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Conference Proceedings

August 5-7, 2009
University of Colorado at Boulder
Boulder, Colorado

Texas AgriLife Research, Texas A&M University
USDA-Agricultural Research Service

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Soil & Water Assessment Tool SWAT

Texas AgriLife Research, Texas A&M University
USDA-Agricultural Research Service

2009 5th International SWAT Conference Proceedings

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5th International SWAT Conference

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2009 5th International SWAT Conference

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Foreword

These conference proceedings consist of papers presented at the 5th International SWAT Conference, SWAT 2009, which convened in Boulder, Colorado, USA. The conference provided an opportunity for the international research community to gather and share information about the latest innovations developed for the Soil and Water Assessment Tool (SWAT) model and to discuss challenges that still need to be resolved to better assess water quality trends. This year, more than 160 people attended from more than 16 countries.

The SWAT model was developed by researchers Jeff Arnold of the United States Department of Agriculture Research Service (USDA-ARS) in Temple, Texas and Raghavan Srinivasan of Texas AgriLife Research, who is the Director of the Texas A&M University Spatial Sciences Laboratory. SWAT is a comprehensive computer simulation tool that can be used to model the effects of point and nonpoint source pollution from the watershed level down to individual streams and rivers. SWAT is integrated with several readily available databases and Geographic Information Systems (GIS).

Over the last decade, several government agencies, a large number of engineers and scientists in the United States and around the world have become SWAT users and have contributed substantial resources to the model. The research community is actively engaged in developing SWAT improvements for site-specific needs and linking SWAT results to other simulation models. Constant updates by the development team make SWAT a model that is constantly evolving to meet the needs of its users.

Due to the versatility of SWAT, the model has been and continues to be utilized to study a wide range of phenomena throughout the world as documented in over 500 peer-reviewed scientific publications. Over 500 scientists and engineers have been trained in the use of the system, and more than 30 universities are using the tool in academic courses. Software, databases, user interfaces and publications are all available on the SWAT website, listed below.

These proceedings contain papers covering a variety of topics including but not limited to large scale applications; site-specific studies; climate change applications; SWAT applications; model development; sensitivity, calibration and uncertainty; biofuel production; plant growth; environmental applications; BMPs; hydrology; sediment, nutrients and carbon; pesticides, pathogens, metals and pharmaceuticals; model development; database and GIS application and development; programming structure, development language and system management; urban processes and management; landscape processes and landscape/river continuum; watershed protection plan development; and instream sediment and pollutant transport.

The organizers of the conference want to express thanks to the organizations and individuals who made this conference successful. Organizations that played a key role in this conference include USDA-ARS, Texas AgriLife Research, Texas A&M University, the University of Colorado, and our sponsors Aqua Terra Consultants, Epsey Consultants, Inc., Montana Department of Environmental Quality, Stone Environmental, Inc. and Tarrant Regional Water District. We would also like to thank the University of Colorado, College of Engineering and Applied Sciences for their assistance and support as well as our countless volunteers, scientific committee, organizing committee and participants who spent their time and money to participate and exchange their scientific knowledge. We would also like to extend our gratitude to Jaclyn Tech for her assistance in recording the conference videos and posting them online. The videos have enabled those who could not attend to share in the conference presentations.

Conference Objective

Soil and Water Assessment

Natural watershed systems maintain a balance between precipitation, runoff, infiltration and water that either evaporates from bare soil and open water surfaces or evapotranspires from vegetated surfaces, completing the natural cycle. The understanding of this hydrologic cycle at a watershed scale and the fate and transport of nutrients, pesticides and other chemicals that affect water quality is essential for the development and implementation of appropriate watershed management policies and procedures.

In recent years, models have become indispensable for understanding natural processes occurring at the watershed scale. As these processes are further modified by human activities, the application of integrated watershed modeling has become increasingly more important in accounting for changing land-water-atmosphere interactions. The combined effects of practices such as agricultural management, water withdraws from surface and groundwater, the release of sewage into surface and sub-surface areas, urbanization, etc. can be better examined through a modeling approach.

The SWAT (Soil and Water Assessment Tool) model has become an important tool for watershed-scale studies due to its continuous time scale, distributed spatial handling of parameters and integration of multiple components such as climate, hydrology, nutrient and pesticide pollution, erosion, land cover, management practices, channel and water body processes.

The 5th international SWAT conference, held at the University of Colorado at Boulder, USA, devoted itself to discussions regarding the application of SWAT to watershed problems worldwide. The 5-day program included 2 days of hands-on SWAT program workshops at both the introductory and advanced levels. The training sessions were followed by three days of conference sessions, covering a variety of topics related to watershed modeling such as hydrology, water quality, land use management, erosion and system analytic topics in calibration, optimization and uncertainty analysis techniques.

Scientists and decision makers associated with research institutes, government agencies and centers for policy making are encouraged to take part in these international conferences in order to become familiar with the latest advances and developments in the areas of watershed-scale modeling and applications.

To learn more about SWAT, go to http://www.brc.tamus.edu/swat/ or contact Raghavan Srinivasan at r-srinivasan@tamu.edu.

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Modeling the Chesapeake Bay Watershed Using SWAT

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Abstract

Chesapeake Bay (CB) is the largest estuary in North America, and has been listed as impaired under the Clean Water Act since 2000. Deteriorating water conditions are largely due to contaminants carried into the Bay by the many tributaries in the CB watershed. The Earth System Science Interdisciplinary Center of the University of Maryland at College Park is developing a Chesapeake Bay Forecast System (CBFS) to perform regional Earth System predictions for the Chesapeake Bay watershed. As the watershed component of the CBFS land module, SWAT simulates the hydrology and water quality of the prominent tributaries in the CB watershed. This paper reports the model configuration and results for Rappahannock, one of the major CB river basins. The data used in this work come from many sources including a project survey, the literature, and various government databases and reports. The complete configuration of the model involved the following steps: watershed delineation and the establishment of HRUs, a sensitivity analysis, balancing the water budget, adjusting crop yields, balancing flow partition, manual and auto-calibration, and validation. The simulated quantities include daily average streamflow and daily loads of sediment, nitrate and phosphate. Calibration results showed satisfactory model simulations for the first three variables and a good prediction of the phosphate load. Validation of the nitrate load also satisfies a set of stringent evaluation criteria. Other variables underperform during validation, especially phosphate, due to several reasons.

The Rappahannock SWAT model currently produces a routine 14-day forecast in an automated system. The system retrieves the 14-day ensemble climate forecast from the CBFS regional atmospheric model, runs SWAT, and then delivers the output to the CBFS ocean model. Eventually, an independent SWAT model will be adopted for each of the major river basins and some of the second-order river basins in the CB watershed.

Keywords: hydrological model, water quality, SWAT, Chesapeake Bay watershed, CBFS

1. Introduction

Chesapeake Bay (CB) is the largest estuary in North America and has been listed as impaired under the Clean Water Act since 2000. One of the clear signs of declining water quality in the CB is the dramatic increase in hypoxic volume in the bay in recent decades. The deteriorating water conditions are largely due to contaminants carried into the Bay by the many tributaries in the CB watershed. The watershed extends over 64,000 mi^2 (165,800 km^2) and partially or entirely includes six states (Delaware, Maryland, New York, Pennsylvania, Virginia, and West Virginia) and Washington DC (Fig. 1). To assist in management and restoration efforts in the vast CB region, it is imperative to identify the sources and to understand the transportation of the contaminants in the watershed. Rapid changes in the environment, such as climate change and urbanization, also call for studies that can predict the future state of the bay and its watershed. A tool that can provide scenario studies will be particularly beneficial to users, ranging from policy makers to farmers, who must make both short and long-term plans.

Figure 1. Chesapeake Bay watershed

The Earth System Science Interdisciplinary Center (ESSIC) of the University of Maryland at College Park (UMCP), with the support of the National Oceanic and Atmospheric Administration (NOAA), is developing a prototype Earth System prediction system, viz. called the the Chesapeake Bay Forecast System (CBFS) to meet the societal needs for the study of Chesapeake Bay region. CBFS integrates atmosphere, land, and ocean (CB estuary) as a regional earth system and seeks to provide predictions and projections at a time scale that ranges from days to decades for the terrestrial and marine ecosystems and other resources (Murtugudde, 2009). In addition to the forecast capabilities, CBFS can also be used in climate change and land use scenario studies or as a decision-making tool, among other potential applications.

One of the fundamental modules of CBFS is its watershed component, which uses the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1994) to simulate hydrology and water quality of the prominent tributaries in the CB watershed. In the CBFS forecast system, SWAT is driven by the weather forecast from the CBFS atmospheric model (Weather Research & Forecasting model or WRF) and delivers its predicted results (flow, sediment and nutrients) to the CBFS hydrodynamic model (Regional Ocean Modeling System or ROMS) and its coupled ecological models to simulate the physical and biogeochemical states and fluxes in the Chesapeake Bay. One of the six major river basins in the CB watershed, Rappahannock River basin (RRB), is chosen as the pilot watershed for applying SWAT. Eventually, an independent SWAT model will be applied to each of the major river basins and some of the second-order river basins on the Maryland shores. This paper will focus on the configurations of and results from Rappahannock SWAT.

2. Model configuration

2.1 Study area

The 2,848 mi^2 (7,405 km^2) RRB (Fig. 2) is located in northern Virginia. About 60% of the 184 mi (294 km) long Rappahannock River is tidal. The dominant land uses surrounding the river are forest (53.9%) and agriculture (38.7%) with one medium sized urban area, the city of Fredericksburg, situated on the fall line where the tidal and non-tidal portions of the Rappahannock River meet. A USGS station is located upstream of the tidal river and collects daily streamflow and water quality data about twice a month. The observations at this site are used for model calibration and validation in Section 3.

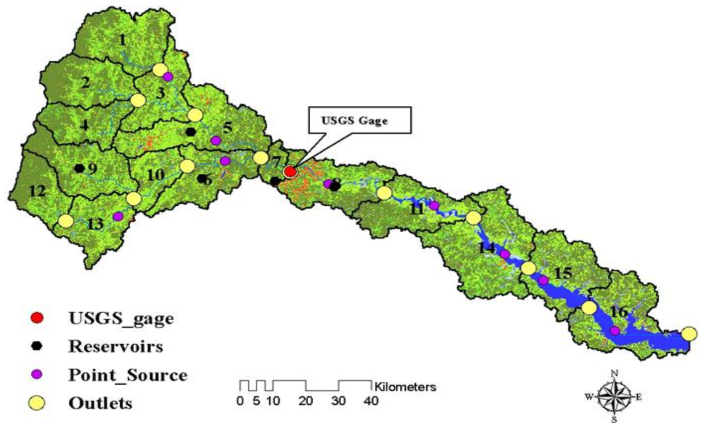

Figure 2. *Rappahannock River basin. The background is the land use map.*

2.2 Watershed setup

The digital elevation model (DEM) data used in CBFS SWAT is the 30 m USGS National Elevation Data (NED). Due to the size of the watershed, the DEM data is aggregated to 90 m to reduce the computing resources required but still retain the accuracy of model predictions (Chaplota, 2005). The primary source of soil data is the USDA Soil Survey Geographic (SSURGO) database. The USDA State Soil Geographic (STATSGO) dataset is used where SSURGO data is not available. The land use data comes from two sources: the year 2002 USDA Crop Data Layer (CDL) map and the year 2000 land use map (Goetz et al., 2000) developed by the Mid-Atlantic Regional Earth Science Applications Center (RESAC) of the University of Maryland at College Park. Both maps are of 30 m resolution. CDL has a high degree of accuracy in agricultural classes as it is based on both satellite imagery and agricultural census data. The advantage of the RESAC map lies in the impervious and developed areas because local GIS maps and the high resolution IKONOS satellite data are used for these categories. The merged CBFS land use map retains CDL agricultural land uses and adopts the remaining classes from RESAC. The CBFS map is composed of 36 land use classes including 24 agriculture, 5 urban, 3 forest, 3 wetland and 1 water. Five reservoirs are included in the model. Reservoir data is compiled from the Army Corps of Engineers National Inventory of Dams (NID) data base. The point source data used by the CBFS SWAT is generated by the Environmental Protection Agency's (EPA) National Pollution Discharge Elimination System (NPDES) and provided by the Chesapeake Bay Program Watershed Modeling (CBPWM) group.

RRB is configured with ArcSWAT interface. Sixteen subbasins (Fig. 2) and 264 HRUs are established with individual slope, soil, and land use data using 10%, 10%, and 5% as the respective thresholds. Most land uses in the watershed amount to less than 5% in each subbasin and are subsequently eliminated from the HRUs. Subbasin 7 is the furthest downstream subbasin that is non-tidal. Its outlet coincides with the USGS gage that serves as the calibration and validation station in this study.

2.3 Management data

Due to the many processes involved, considerable efforts were devoted to the collection and processing of the data used to construct the SWAT management files. The sources for the agricultural management data include a survey of Virginia agricultural extension services, federal, state, and other scientific publications, data provided by the CBPWM group and personnel experiences. The CBPWM group accumulated a wealth of management data for the CB watershed from many years of modeling efforts. However, the differences in watershed configuration and model setup make it difficult to apply many of the CBPWM management data sets to the Rappahannock SWAT without introducing a considerable degree of uncertainty. Hence, repeated failed attempts to incorporate CBPWM data lead to a change in strategy to conducting surveys with extension agencies and resorting to publications.

The agricultural land uses are divided by crop type, including corn, soybeans, small grains and hay, and animal operations. The survey results show that the prevailing crops in RRB are perennial hay and a 2 year rotation of Corn-Winter Wheat-Soybeans-Winter Cover. The primary animal operations in this region are cow/calf production and limited back-grounding for the beef industry. The planting/harvesting/nutrient schedules for crops, listed in Table 1, are established based on the Virginia Agronomy Handbook (2009) and the survey results. The simulation of hay includes a one-year rotation of two fertilizer applications and two harvestings. Row crops follow a two-year rotation of corn, winter wheat, soybeans and winter cover of rye grass. Multiple tillage and fertilization practices are applied throughout the two-year period.

Table 1. *Planting/harvesting/nutrient schedules*

	Tillage	Planting	Fertilizer	Harvesting or harvesting/kill
Hay	-	-	1. 73kg-N/ha after last hard frost; 2. 73kg-N/ha mid-June	1. mid-June, 85% above ground biomass removal 2. early-Sept, 85% biomass removal
Corn for grain	Spring tillage	Early May	1. 165kg/ha of a 28-10-10 fertilizer after emergence; 2. 395kg /ha of a 28-10-10 fertilizer six weeks after planting	Mid-Sept, 50% above ground biomass removal
Winter Wheat	Turbo-till, late-Sept	Mid-Oct	1. 312kg/ha of a 06-24-24 fertilizer after planting; 2. 54kg/ha of anhydrous ammonia in February; 3. 82kg/ha of anhydrous ammonia in March	Mid-June, followed by herbicide application
Soybeans for seeds	Minimum	Mid-June	374kg/ha of a 00-15-00 fertilizer	Early winter
Rye grass	-	Mid-Dec	-	-

The grazing procedure in SWAT is used to simulate the animal operation in RRB. The number of animal units in each subbasin is estimated on a monthly basis from the Census of Agriculture (2002 and 2007). In particular, an adult cow represents 1.2 animal units and a calf 0.5 animal units. Some assumptions are made in this process due to the lack of specific information on the variation of animal population during the year. The grazing statistics reported by Almendinger and Murphy (2007) are employed to estimate the manure produced and biomass removed. Pastures are fertilized with 300 kg/ha of a 15-15-15 fertilizer in the late spring and the late fall to increase biomass yields.

Atmospheric nitrogen deposition has been estimated to account for 20–32% of the total nitrate and ammonium nitrogen load to the CB watershed (Sheder et al., 2002). The original atmospheric deposition data from CBPWM is processed to fit the requirements of Rappahannock SWAT. The concentration of nitrogen in rainfall is an average of the wet atmospheric deposition data for the entire RRB region for the duration of simulation. Since SWAT does not directly simulate dry atmospheric deposition, it is assimilated into the model as a 100-0-0 fertilizer and is applied to all the HRUs on a daily basis.

Other general management practices include consumptive water use that is derived from CBPWM river withdrawal data. A 35 m filter strip is also included to reduce loads of constituents going out of HRUs.

2.4 Modeling Specifics

Rappahannock SWAT utilizes SWAT2005. Green & Ampt infiltration method is used with hourly precipitation data. Potential evapotranspiration is modeled using Hargreaves method due to the lack of relative humidity data for the calibration period.

The SWAT output delivered to the CBFS ocean model, ROMS, includes daily average flow and daily loads of sediment, nitrate, and phosphate. The variables modeled are dictated by the requirements of ROMS and the availability of observed data for calibration. A two-year spin-up precedes the actual simulation period for model calibration, validation and application because the row crops follow a two-year rotation regime.

3. Calibration and Validation

3.1 Calibration

A nine-year calibration period was chosen for Rappahannock SWAT from 1997-2005 with 1995-1996 as the spin-up years. The model calibration involved the following steps: balancing the water budget, adjusting crop yields, balancing flow partition, sensitivity analysis, and manual and auto-calibration. In the RRB region, the annual evapotranspiration to annual precipitation ratio ranges between 0.60 and 0.72 based on a study by Hanson (1991). Event flow to base flow ratio is estimated to be 43:57 as calculated from observed flow and data from Nelms et al. (1997). A sensitivity study was performed on flow, sediment, and various nutrients and the results were referenced in choosing the calibration parameters. CBPWM provided the 1995-2005 precipitation, temperature, and solar radiation data required for calibration. The daily flow and sediment, nitrate and phosphate concentration data at the Fredericksburg site were downloaded for this period from the USGS online database. The SWAT2005 auto-calibration functionality was utilized in the 3-step calibration process, i.e. flow, sediment, and nutrient calibrations. Manual calibration was also performed mainly for balancing the water budget and flow, adjusting simulated crop yields, and nutrient calibration. Table 2 lists the parameters used in flow, sediment, and nutrient calibrations.

Table 2. *Calibration Parameters*

Flow	ch_k2, cn2, gw_delay, gw_revap, smtmp, sol_awc, sol_k, surlag, timp, esco, gwqmn, rchrg_dp
Sediment load	ch_cov, ch_erod, spcon, spexp, usle_c
Nitrate and phosphate loads	filterw, bio_e, biomix, anion_excl, erorgp

The probability exceedance curves of observed and simulated flow and constituent loads are displayed in Figure 3. The distribution of the simulated flow shows good agreement with observations even though it has a tendency to underestimate low flow and compensate by overestimating medium range flow. Both sediment load and nitrate load are adequately simulated with some overestimation, mainly in the medium range. The predicted phosphate reveals an obvious negative bias. The statistics for each of the calibrated variables are given in Table 3. Moriasi et al. (2007) recommended three statistics to evaluate the performance of a watershed model: Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS) and ratio of the root mean square error to the standard deviation of measured data (RSR). They conclude that a model is satisfactory if NSE > 0.50 and RSR < 0.70, and if PBIAS ± 25% for streamflow, PBIAS ± 55% for sediment, and PBIAS ± 70% for N and P. By stringent standards, the simulations of flow and sediment and nitrate loads by Rappahannock SWAT are satisfactory and the simulation of phosphate load is adequate. The ratio of the simulated average annual evapotranspiration to average annual precipitation is 0.61, which falls within the reported range of 0.60 to 0.72. The ratio of simulated annual event flow to base flow is 42:58 versus the observed ratio of 43:57. In addition, the average difference in the simulated and the observed annual total flows is 1.1%. The simulated crop yield for each agricultural land use except pasture was also compared to data from the Census of Agriculture (2002 and 2007) to ensure the two are in agreement.

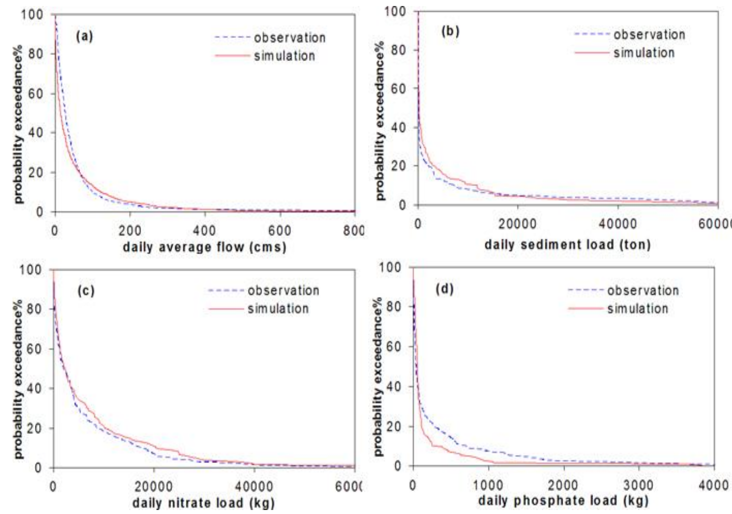

Figure 3. Comparison of probability exceedance curves of observed and simulated (a) daily average flows, (b) daily sediment loads, (c) daily nitrate loads, and (d) daily phosphate loads at Rappahannock River subbasin 7 outlet

Table 3. *Statistics of Calibrated Variables*

Variable	# of observations	NSE	R^2	PBIAS (%)	RSR
Flow	3164	0.70	0.75	4.47	0.55
Sediment load	220	0.62	0.63	-7.84	0.62
Nitrate load	219	0.53	0.74	-23.53	0.69
Phosphate load	224	0.41	0.44	36.57	0.77

3.2 Validation

The validation period was three years from 2006-2008 and the spin-up from 2004-2005. Weather data for validation included 1) temperature data from weather stations operated by the National Weather Service of NOAA, 2) solar radiation data from NOAA satellite remote sensing retrievals, and 3) NOAA stage-IV (radar and gage combined) precipitation data. The statistics for the simulated variables are given in Table 4. Nitrate is the only constituent that passes the criteria set forth by Moriasi et al. (2007). All loads and flow are underestimated as indicated by the positive PBIAS values. Other than the uncertainties in the model, four conceivable factors contribute to the less than satisfactory results: 1) A much smaller sample size compared to the calibration data, 2) the land use map is based on year 2000 and 2002 data and is outdated for the 2006-2008 validation period, 3) management and regulations for agricultural practices have changed noticeably in recent years but are not reflected in the SWAT management files and 4) the entire validation period had lower than average annual flow (Fig. 4). As stated in the calibration section, Rappahannock SWAT underestimates low flow, which is directly responsible for the lower estimated constituent loads.

Table 4. *Statistics of Validated Variables*

Variable	# of observations	NSE	R^2	PBIAS (%)	RSR
Flow	1097	0.38	0.49	22.95	0.79
Sediment load	56	0.44	0.58	59.36	0.75
Nitrate load	57	0.65	0.72	40.97	0.59
Phosphate load	57	-0.16	0.02	97.62	1.08

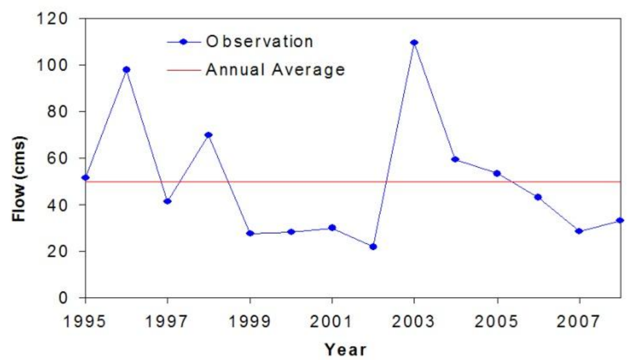

Figure 4. *Rappahannock River annual flow*

4. Application

The Rappahannock SWAT model is currently running in an automated forecasting system. The system consists of four modules that retrieve the ensemble weather forecast data from the CBFS atmospheric model, prepare the two-year spin-up weather data, run SWAT model, post-process SWAT forecast and deliver the data package to CBFS ocean model. The model currently produces routine 14-day forecast and will be used in seasonal to decadal scenario studies in the future.

5. Conclusions

As part of the CBFS project at the Earth System Science Interdisciplinary Center of the University of Maryland at College Park, SWAT is applied to the Chesapeake Bay watershed to predict the flow and constituent loadings entering the Bay. The model calibration results from the pilot river basin, Rappahannock (one of the six major river basins in the Chesapeake Bay watershed), demonstrate satisfactory agreement between simulated and observed flows, sediment and nitrate loads and good agreement for phosphate load. Nitrate load validation also shows satisfactory simulation while the other variables underperform, especially phosphate.

An independent SWAT model will be adopted for each major river basin and some second-order river basins in the CB watershed. Initial watershed configuration has been completed for 4 out of the 5 remaining major river basins. The collection and processing of agricultural management data has proven to be the most difficult and time-consuming part of the Rappahannock SWAT task. It is a foreseeable challenge for other river basins, especially the basins that span to different climate regimes and follow different agricultural management practices.

The complete SWAT modeling system for the CB watershed will be a major component in the CBFS system. It will have a wide range of regional applications from short-term forecasts to seasonal and decadal studies that can account for climate change and decision-making scenarios.

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Integrated Water Resources Management: Implications for Water and Food Security in Iran

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Abstract

Population growth and industrialization are major factors limiting water resource availability in most of Iran. In addition, extended droughts, environmental degradation and worsened climate change scenarios all exacerbate this problem. As agriculture is the largest water user in Iran, there are various attempts to increase irrigation efficiency in the country. A major concern is that traditional techniques used to increase water use efficiency are no longer appropriate. Furthermore, overlapping responsibilities among different agencies often worsen the situation. Hence, there is an emerging need for the design of an integrated approach to water resources management (IWRM) in order to provide services to the growing population and to simultaneously provide adequate and sustainable environmental protection. To design an IWRM for a region, a sound knowledge of water resources, water-crop relationships, climate change impacts, socio-economic conditions and stakeholder interests is necessary.

In this study, we used SWAT to first quantify water resource availability, second, to model the cereal yield, consumptive water use (ET) and crop water productivity (CWP), and third, to assess the impact of climate change on water resource availability and agricultural productivity in Iran. The results were then used to examine stakeholder and government oriented objectives in terms of water and food security through changes in agricultural land use planning. Finally, the possible impact of these changes on socio-economic and environmental factors was considered by employing the concept of sustainability solution space (SSP). This study provides a strong basis for a multi-criteria decision analysis to test the aforementioned strategies on the enhancement of water and food security while taking into account water resources, agricultural productivity and climate change impacts.

Keywords: SWAT, water resource availability, cereal crop water productivity, climate change, sustainability solution space, multi criteria decision analysis

1. Introduction

Population growth and industrialization, in combination with extended drought, environmental concerns, and possible adverse climate change impacts, are the major limiting factors of water resource availability in most parts of Iran. Agriculture is by far the largest water user, accounting for more than 90% of water withdrawals. Self-sufficiency has been a desired national objective for wheat, and that goal was achieved in 2004. However, growing scarcity of water resources and frequent, prolonged droughts are the main concern of sustaining this level of wheat production. In general, irrigation efficiency is low in Iran. The main reasons for this low efficiency include improper design of irrigation facilities, poor maintenance, careless operation, negligible water pricing as well as inefficient division of responsibilities among different agencies (Pazira et al., 1999). Efforts to increase the agricultural water use efficiency have been made by increasing the crop water productivity at plant and field level. However, the process has not been sufficient thus far to meet the country's water demand. This is mainly due to improper agricultural land use, which is practiced every year. Agriculture comprises 12% of the total land area in Iran. Over 60% of that land is devoted to wheat production, about 20% to barley, 5% to rice and the rest of the area is covered by other crops. Cereals are the most water consumptive plants. Of the total water diverted to irrigate cereals, more than 70% is devoted to wheat, which is already exceeds the renewable water resource availability in most of the provinces (Faramarzi et al., 2009b). An appropriate land use planning process is therefore necessary to overcome or mitigate water scarcity in Iran.

The virtual water strategy introduced by Allan (1997) can be seen as one way to improve water use efficiency and to mitigate water scarcity at the regional level by adjusting cropping structure and interregional food trade (Chapagain et al., 2006; Yang et al., 2006). For any given country, water resources can be used more efficiently if crops are produced in the regions or provinces where water productivity of these crops is high. A sound knowledge of crop water productivity (CWP) and water resource availability at fine spatial and temporal resolution is, therefore, of importance for understanding water and food relationships. It is also useful for assessing the feasibility of the virtual water strategy in improving water use efficiency in the country (Yang and Zehnder, 2007). The socio-economic factors and stakeholder analysis are other important factors that need to be analyzed in land use planning and when implementing the virtual water trade strategy.

With this background, Integrated Water Resources Management (IWRM) can be seen as a promising concept to managing this scarce resource in order to service the growing population and to simultaneously provide adequate and sustainable environmental protection (Gregersen et al., 2007). The goal of IWRM is to ensure water availability that will meet all competing demands yet still provide adequate environmental protection. There is great interest in implementing IWRM in Iran. For instance, the Ministry of Energy (with the ultimate responsibility for water in Iran) has initiated IWRM at Zayandehroud river basin, Esfahan, as a case study. This interest in IWRM is also shared by many other central institutions such as the Provincial Government of Esfahan, the Esfahan Environmental Agency and the Water and Sewage Utilities of Esfahan. According to the opinions of the central actors in Esfahan, it is essential that the IWRM takes the following factors into account (http://www.isoe.de):
1) the regional situation and involvement of social factors, 2) the balancing of divergent interests, 3) the creation of conditions that foster cooperation between agencies and 4) Adaptability and openness to future options (constraints and development trends).

A sound knowledge of water resources and crop relations in combination with an assessment of climate change impacts is required for IWRM. To achieve this level of sustainability, it is critical to integrate water resource modeling, land use planning and climate change impact analyses with stakeholder and socio-economic factors (Rahman and Varis, 2005; Allan, 2003).

The Soil and Water Assessment Tool (Arnold et al., 1998) was first used in this study to quantify the water resource availability at subbasin spatial and monthly temporal resolutions and secondly to model the cereal yield (Y), consumptive water use (ET) and CWP in different provinces. Finally, SWAT was also used to assess the impact of climate change on water resource availability and agricultural productivity in Iran. In a further step, the model was used to examine some stakeholder and government oriented objectives in terms of water and food security.

2. Materials and methods

2.1 Study area

Iran, with an area of 1,648,000 km^2, is located between 25 and 40 degrees north latitude and 44 to 63 degrees east longitude. Iran has a wide spectrum of climatic conditions. With annual precipitation of 252 mm per year, the northern and high altitude areas found in the west receive about 1600-2000 mm per year while the central and eastern parts of the country receive less than 120 mm per year. The per capita freshwater availability for the country was estimated at around 2000 m^3 per capita per year in 2000 and is expected to go below 1500 m^3 per capita per year (the water scarcity threshold) by 2030 due to population growth (Yang et al., 2003). Winter temperatures of -20 ºC and bellow in high altitude regions and summer temperatures of more than 50 ºC in the southern regions have been recorded.

Roughly 12% of country's land surface or 18.5 million hectares are devoted to field crop production and horticulture. Irrigation accounts for 90% of total water withdrawals in Iran. Surface water use has been increased through the construction of numerous multi-purpose dams and reservoirs. Groundwater is the main source of potable water in most areas in the central, northeastern and southern parts of the country. Wheat is grown on nearly 60% of the country's total cultivated area and is the largest water user among the other cereal crops grown in the region. It has been regarded as a strategic crop, which is targeted for self-sufficiency by the government. The average yield for irrigated wheat is approximately 3.0 tons per ha compared to 0.95 tons per ha for rainfed wheat.

2.2 Input data

Data used for this study include: the Digital Elevation Model (DEM), a land use map, a soil map, stream network information, daily climate data from about 150 synoptic stations, daily river discharge data from 81 hydrometric stations, daily outflow data from 19 large reservoirs, the statistical rainfed and irrigated wheat yield and area under cultivation, and crop specific fertilizer and planting/harvesting data. The data were compiled from different sources.

2.3 Model setup

Spatial parameterization in this project was performed by dividing the watershed into subbasins based on topography and dominant soil and land use. This resulted in a total of 506 subbasins covering the whole country. Surface runoff was simulated using the SCS curve number (CN) method. Potential evapotranspiration (PET) was simulated using Hargreaves method, and actual evapotranspiration (AET) was determined based on the methodology developed by Ritchie (1972). We selected the automatic irrigation and fertilization option in this study because of the difficulty in obtaining this data for different provinces. In the model, we assumed an unlimited source for irrigation but controlled it through calibration of HI_{act}.

2.4 Calibration setup and analysis

Sensitivity analysis, calibration, validation, and uncertainty analysis were performed for the hydrology, climate change and crop growth. Three different calibration approaches were examined for comparison and to provide more confidence in the results. These include: (i) the "global approach", where only the global parameters were used (26 parameters), (ii) the "scaling approach", where parameters were differentiated by soil and land use (268 parameters), and (iii) the "regional approach", where the scaling approach was used in each of the eight hydrologic regions defined by the Iranian Ministry of Energy (MOE), i.e., each region was calibrated separately. The SUFI-2 (Abbaspour et al., 2007) algorithm was used for parameter optimization. In this algorithm all uncertainties (parameter, conceptual model, input, etc.) are mapped onto the parameter ranges, which are calibrated to bracket most of the measured data in the 95% prediction uncertainty (Abbaspour et al., 2007). For more detail on the data requirements, model setup and development, and calibration setup the readers are referred to Faramarzi et al. (2009a, b) and Abbaspour et al. (2009).

3. Results and discussion

3.1. Modeling water resources

The three calibration procedures resulted in similar goodness of fit for the whole of Iran. We used the results of the 'regional approach' for hydrology, climate change and crop growth because this approach accounted for more spatial variability and a slightly better objective function than the other two approaches. The calibration and validation results were satisfactory for most of the discharge stations as well as irrigated and rainfed yield. The calibrated and validated model was used to calculate the water resources of the country. Figure 1 shows the blue and green water resource availability of the county at subbasin level (Faramarzi et al., 2009).

3.2. Modeling wheat yield and Crop Water Productivity

As wheat covers more than 60% of the country's agricultural area and consumes about 70% of irrigation water in Iran, we modeled wheat yield (Y), ET and crop water productivity with calibration, validation and uncertainty analysis (Faramarzi et al., 2009b). Using our calibrated and validated model, we performed a policy impact analysis to explore the efficiency of objectives proposed in the recent workshop of Iranian-American experts organized by the National Research Council (NRC, 2005). The water and food security issues are as follows:

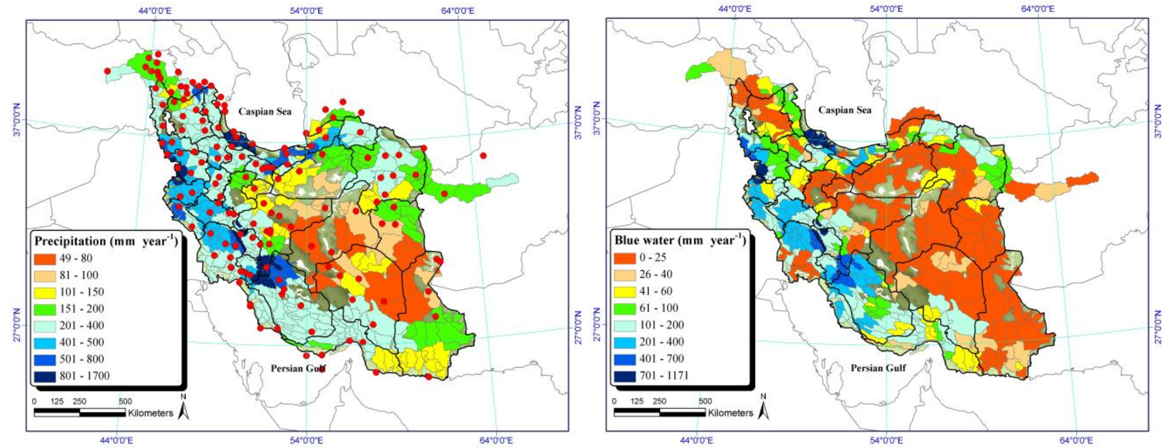

Figure 1. *Average (1990-2002) simulated annual precipitation and internal renewable blue water resources (IRWR) at subbasin level for the entire country.*

- *Y-CWP* relationship in wheat crop showed that a one unit increase in rainfed wheat yield resulted in a lesser additional water requirement than irrigated wheat, leading to a larger improvement in *CWP*.
- An analysis of the ratio of water use to water resource availability revealed that most of the provinces were using more than 40% of their water resources for agriculture. Some provinces reached a ratio of 100% or greater, indicating severe water scarcity and groundwater resource depletion (Figure 2).
- An assessment of improvements in soil available water capacity (AWC) showed an increase in irrigation water use efficiency. The results demonstrated that most of the provinces are more likely to save water by increasing the AWC of the soil through proper management practices. Since wheat self-sufficiency is a desired national objective, we calculated the water requirements for the year 2020 (keeping all factors except population constant) to fulfill the wheat demand. The results showed that 88% of the additional wheat production would need to be grown in water scarce provinces where there would simply not be enough water. For more detail readers are referred to Faramarzi et al. (2009b).

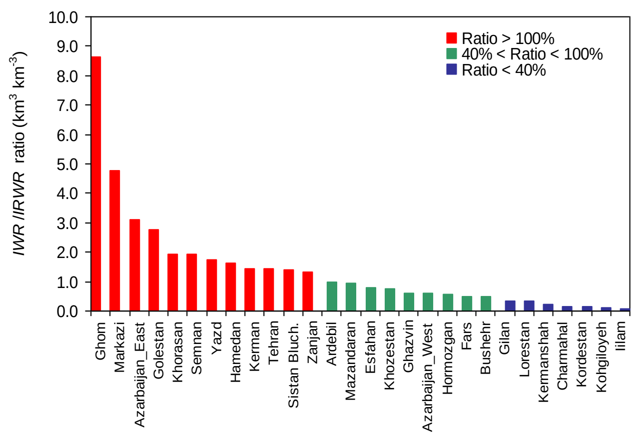

Figure 2. *Ratio of provincial water use to water availability (1990-2002). Data for provincial water use are calculated for 18 main crops across the provinces.*

3.3. Climate change impact assessment on water resources

To get an overall picture of the impact of climate change on water resources, we looked at changes in the various components of the water cycle including precipitation and evapotranspiration distribution, river discharge, soil moisture and aquifer recharge. These variables were then used to quantify the changes in water resources with respect to blue water (river discharge plus aquifer recharge) and green water (soil moisture plus evapotranspiration) with the intention of making our results more useful to the water resources sector of the scientific community. The simulations of the Canadian Global Coupled Model (CGCM 3.1) were downscaled for 37 climate stations across the country for scenarios A1B, B1 and A2 based on the climate data period of 1980-2002. The resulting downscaled formulations were then used to transform the CGCM's predictions of daily temperature and precipitation to regional conditions for the periods 2010-2040 and 2070-2100. For future scenarios, we found that in general wet regions of the country will receive more rainfall while dry regions will receive less. Consequently, river discharge and deep aquifer recharge will increase in the wet provinces and decrease in the dry regions (Figure 3), exasperating the existing water and food production problems. Flooding in the northern and western part of Iran and the prolonged droughts in most of the central, eastern and southern parts of Iran are a historically common occurrence, costing billions of dollars. A further increase in precipitation and blue water resources in the wet regions and a decrease in precipitation and blue water in arid parts of the country could worsen the situation. Our model results were analyzed to explore more about future flooding and drought events in different provinces. More detail can be obtained from Abbaspour et al., 2009.

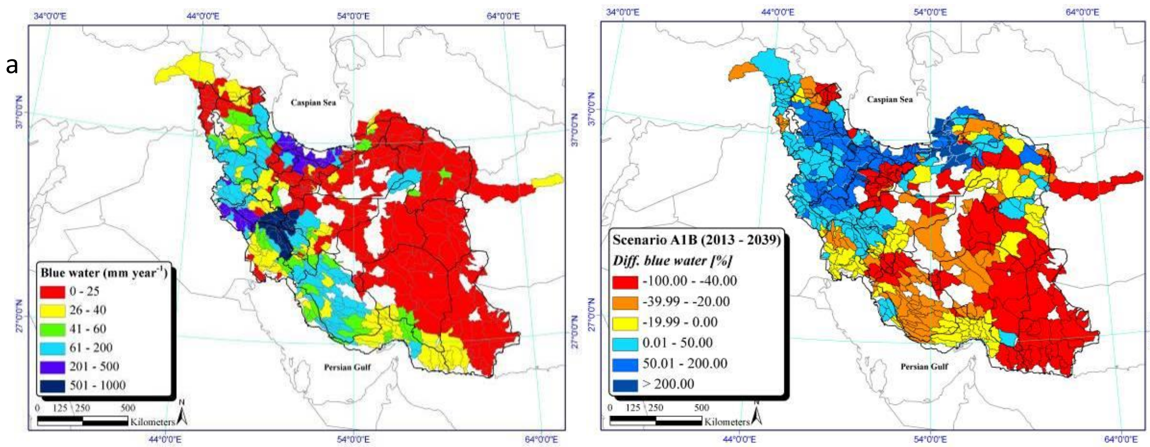

Figure 3. *The anomaly map of 20-year blue water averages for scenario A1B of CGCM. The percent difference is calculated based on the averages of data periods (2013-2039) and (1980-2000, a).*

Given the information gained through this modeling work, we intend to examine the feasibility of applying the intra-country virtual water trade strategy to mitigate provincial and national water scarcity. In this approach, we will consider the water and food relationship as well as climate change impacts on water resources and agricultural production.

3.4. Sustainability solution space

To demonstrate the impact of the changes in agricultural land use on socio-economic and environmental factors, we first modeled sustainability solution space (SSP) using the methodology and tool developed by Wiek and Binder (2005). We then compared the historic situation with the obtained SSP. The SSP model consists of systemic, normative and integrative modules, which include both the stakeholder and scientific views. For each indicator, a sustainability range is defined, i.e., a minimum and maximum value is set according to the selected criteria. Finally, the integrative module merges the normative module and the system module. In this study, five indicators were identified to describe the main socio-economic and water problems. These are: rural-urban justice (RUJ), farm income (FI), income stability (IS), water scarcity ratio (WSR) and wheat self-sufficiency (WSS). Figure 4 compares the average historic (1992-2004) values of the indicators, depicted with red line, with their SSP for different provinces. The water scarcity indicator is outside of the SSP for most provinces in the country. In further work, we will compare the scenario outcomes of possible land use planning with the obtained SSP to explore the sustainability of the scenarios.

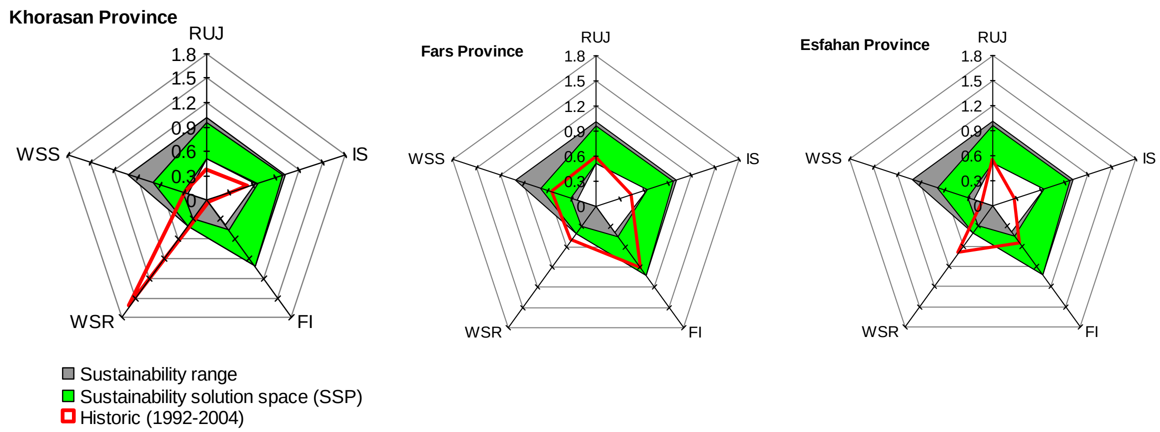

Figure 4. *Comparison of historic (1992-2004) trends with the sustainability solution space of the system criteria at different provinces.*

Conclusion

The results of water resource availability, crop yield and water productivity at a high spatial and temporal resolution revealed that most of the provinces in the country lack agricultural sustainability in terms of water and food security. Furthermore, climate change has an adverse impact on the water availability in most of the central and eastern provinces.

Given the knowledge we obtained through this research, a feasibility assessment of intra-country virtual water trade, taking stakeholder interests and socio-economic conditions into account, is outlined to assess the possibilities of managing the water resources of Iran to alleviate water scarcity and ensure food production.

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Application of SWAT Model to Investigate Nitrate Leaching in Hamadan-Bahar Watershed, Iran

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Abstract

The application of large amounts of mineral and organic fertilizers in intensive agricultural regions of Hamadan-Bahar watershed in western Iran contributes to excessive nutrient loads in soils and groundwater bodies. Nitrogen leaching into groundwater from agricultural land is a common global problem. We employed SWAT to examine the effects of agricultural management on nitrate leaching in Hamadan-Bahar watershed. Groundwater supplies approximately 80% of the water consumed in Hamadan, with the remainder coming from surface water reservoirs. Objectives of this study are to investigate temporal and spatial variability of nitrate leaching in Hamadan-Bahar plain and suggest best management practices (BMP) to reduce nitrate leaching in the future. The SWAT model is calibrated and validated with uncertainty analysis using the SUFI-2 (Sequential Uncertainty Fitting, ver. 2) procedure. Measured daily discharge data from 7 discharge stations and 1 measured daily nitrate station at the outlet of the watershed were used in this procedure. We further calibrated the model for crop yield to improve confidence in soil moisture, evapotranspiration, water percolation from the root zone and plant uptake of nitrogen. The calibration and validation results are quite satisfactory. This validated model will be used along with an optimization routine for BMP analyses.

Keywords: SWAT model, SUFI-2, Hamadan-Bahar watershed, Iran, nitrate leaching, groundwater

1. Introduction

In Hamadan-Bahar watershed, water shortages have become an increasingly serious problem. Groundwater has become the major source of water for drinking, domestic, industrial and agricultural sectors in this region. One of the major problems affecting groundwater quality is the leaching of nutrients from the soil, which is particularly evident in agriculture-dominated areas (Jalali, 2005; Jalali and Kolahchi, 2008). The application of large amounts of mineral and organic fertilizers in regions of the Hamadan-Bahar plain with intensive agriculture contributes to excessive nutrient loads in soils and groundwater bodies (Jalali, 2005; Nadafian, 2007; Rahmani, 2003). Nitrogen leaching from agricultural land is a common problem in many regions with intensive agricultural production. In regions where nonpoint source pollution is dominant, regional models are often the only feasible way to examine the impacts of land use change on pollutant concentration. Hydrologic models are useful tools for determining the probable effects of agricultural practices on local hydrology and aqueous geochemistry. Also, hydrologic models of nitrate leaching could help to determine the amount of nitrate loss from root zones and, therefore, the potential impact on nitrate concentration in groundwater. Direct measurement of the impacts of agricultural management on groundwater quality is too technical for most consultation and monitoring services. The Hamadan-Bahar Plain is a region where nonpoint source nitrate loading has substantially impacted groundwater nitrate concentrations (Jalali, 2005; Nadafian, 2007; Rahmani, 2003). These lands are located in the vicinity of drinking water wells, so it is of great interest to determine how management practices will impact groundwater nitrate concentrations.

Against this background, the aim of this study is first to calibrate and validate a SWAT model of Hamadan-Bahar watershed with uncertainty analysis taking crop yields for potato, irrigated wheat and rainfed wheat into account. Our second objective is to predict temporal and spatial variability of nitrate leaching dynamics for the present agricultural situation. In this paper we only focused on calibration of the discharge and crop yield.

In this study, we used the program SUFI-2 (Abbaspour et al., 2004; Abbaspour et al., 2007) in SWAT-CUP (Abbaspour, 2007), which combines calibration and uncertainty analysis. This program is linked to SWAT in the calibration package SWAT-CUP (SWAT Calibration Uncertainty Procedures). Using SUFI-2, it was possible to handle a large number of parameters and measured data from many gauging stations simultaneously.

2. Materials and methods

2.1 Description of the study area

The Hamadan-Bahar watershed in western Iran has an area of 2460 km^2 and is situated between longitudes 47° 49' E and 48° 16' E and latitudes 34° 35' N and 35° 56' N (Fig. 1). In Hamadan-Bahar watershed, most of the rivers originate from southern heights (Alvand Mountains). The outlet of the watershed is Koshk Abad in the north-eastern portion of the watershed. Mean elevation of the watershed is about 2038 m above sea level. The climate of the region is semiarid with a mean annual precipitation of 324.5 mm and mean annual temperature of 11.3 ^{o}C.

In Hamadan, groundwater supplies 88% of the water consumed. Land use in the Hamadan-Bahar watershed is predominantly agricultural, with major crops being wheat and potato. Table 1 summarizes the annual amount of N-fertilizers applied on potato growing Hamadan and Bahar agricultural lands according to data from the Information Center of Ministry of Jahade-Agriculture of Hamadan. For wheat, an average of 150 kg per ha urea is applied in these regions. The main aquifer is 480 km^2 in area, of which 52.5% is under irrigated land.

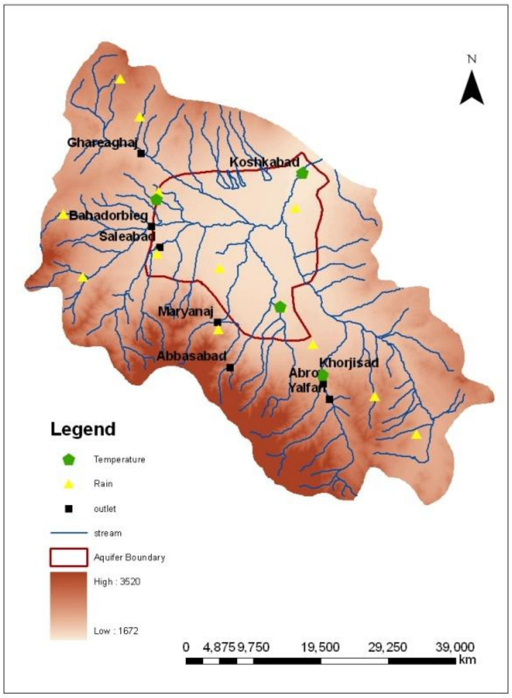

Figure 1. *The Hamadan- Bahar watershed, river network, aquifer and meteorological station*

Table 1. *Average applied fertilizer for potato cultivation in Hamadan and Bahar regions during 2004-2007*

Fertilizer	2004-2005	2005-2006	2006-2007	Mean
Hamadan				
Urea (kg ha^{-1})	791	905	301	666
Hen manure (ton ha^{-1})	28	21	24	24
Bahar				
Urea (kg ha^{-1})	390	482	393	422
Hen manure (ton ha^{-1})	9	15	10	11

2.2 Model inputs

In this study, we used Arc-SWAT version 2.1.4 (Winchell et al., 2008). The most recent available GIS maps for topography, land use and soils were used. Table 2 gives an overview of the model input data. Typical management practices such as crops grown, fertilizer application and tillage operations for different land uses were gathered from state agricultural statistics, the statistical yearbook of Information Center of Ministry of Jahade-Agriculture of Hamadan and personal communication with some farmers.

The simulation period for calibration was 1997–2008. The first 3 years were used as a warm-up period to mitigate the unknown initial conditions and were excluded from the analysis. The validation period was 1989–1999, also using 3 years as warm-up period.

Table 2. *Model data source for the Hamadan-Bahar watershed*

Data type	Scale	Source
Topography	1:25,000	National Cartographic Center of Iran
Plain soil	1:50,000	Hamadan Agricultural and Natural Resources Research Center
Mountain soil	1:250,000	Planning and Management Organization of Hamadan Province
Land use	1:100,000	Natural Resources Organization of Hamadan Province
Weather	20 Station (daily rainfall) 4 Station (daily temperature)	Hamadan Meteorological Organization and Hamadan Regional Water Authority
Reservoir	Daily outflow	Hamadan Regional Water Authority
Spring and Qanats	4 station (monthly loading)	Hamadan Regional Water Authority
Stream network	1:50,000	Hamadan Regional Water Authority
Discharge	8 Station (daily rainfall)	Hamadan Regional Water Authority
Crop yield	2 city (annual yield)	Center of Ministry of Jahade-Agriculture of Hamadan
Nitrate	6 Station (Monthly)	Sampled by Authors

2.3 Model Calibration Procedures

The Hamadan-Bahar SWAT model was calibrated and validated based on river discharge data from 7 gauging stations as well as rainfed wheat, irrigated wheat and potato yield data. Most SWAT model calibrations have been performed by comparing the simulated surface runoff, and/or sediment yield and nutrient concentration in runoff against observations at the watershed outlets (e.g., Abbaspour et al., 2007; Arabi et al., 2008; Behera and Panda, 2006; Du et al., 2006; Schuol et al., 2008). On the other hand, few studies (e.g., Faramarzi et al., 2009) have evaluated the performance of SWAT on the growth part, particularly yield prediction. In agricultural watersheds, correct simulation of crop yield ensures a more reliable simulation of evapotranspiration, soil moisture and groundwater recharge.

The program SUFI-2 (Abbaspour et al., 2007) was used for a combined calibration, validation and uncertainty analysis. Previous studies showed that the SUFI-2 program is very efficient in calibration and uncertainty analyses of large-scale (Schuol et al., 2008; Yang et al., 2008; Faramarzi et al., 2009) and small scale watersheds (Abbaspour et al., 2007; Rostamian et al., 2008).

In SUFI-2, parameter uncertainty accounts for all sources of uncertainties. The degree to which all uncertainties are accounted for is quantified by a measure referred to as the P-factor, which is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU). Another measure quantifying the strength of a calibration/uncertainty analysis is the so called R-factor, which is the average thickness of the 95PPU band divided by the standard deviation of the measured data. SUFI-2, therefore, seeks to bracket most of the measured data (large P-factor, maximum 100%) with the smallest possible value of the R-factor (minimum 0).

In order to compare monthly measured and simulated discharges and crop yield, we selected the follow objective functions, respectively:

$$\Phi = \begin{cases} |b|R^2 & if\ |b| \le 1 \\ |b|^{-1}R^2 & if\ |b| > 1 \end{cases} \tag{1}$$

$$MSE = \frac{1}{n\sigma^2}\sum_{i=1}^{n}\left(Y_{obs} - Y_{sim}\right)_i^2 \tag{2}$$

where the coefficient of determination R^2 represents the discharge dynamics, b is the slope of the regression line between the monthly observed and simulated runoff, *n* is the number of observations, σ^2 represents the variance of the observation, Y_{obs} is actual crop yield (ton ha^{-1}) and Y_{sim} is the SWAT predicted crop yield (ton ha^{-1}).

3. Results and discussion

Based on calibration in previous studies (Abbaspour et al., 2007; Schuol et al., 2008; Yang et al., 2008; Rostamian et al., 2008; Faramarzi et al., 2009), 24 parameters related to streamflow and 2 parameters related to crop yield were selected. The results of the monthly discharge simulation for calibration are shown in Figure 2a, 2c and 2d and validation results are shown in Figure 2b and 2e for two hydrometric stations. For Koshkabad and Abbasabad, an R-factor of less than 1 indicates a good calibration result. However, the P-factor for Koshkabad is small. Based on the management map illustrated in Figure 3, most parts of the watershed are under intensive agriculture, yet constructed artificial groundwater recharge stations on the rivers and small dams for irrigation affect calibration and validation results. Therefore, a careful examination of the calibration results for Koshkabad station shows that a large number of unbracketed data fall into the region of base flow due to insufficient accounting of agricultural water use in the model. Nevertheless, as illustrated in Figure 2, the flow dynamic is quite well simulated for these stations. In the first calibration of the Abbasabad hydrometric station, the model couldn’t predict the base flow (Fig. 2c) because at this station the base flow of the river is supplied by springs. In a second attempt, we imported the spring in this subbasin as a point source. The new results are shown in Figure 2d. The P-factor value increased from 18% to 40% after importing the spring data.

Figure 4 shows the simulated potato crop yield for Hamadan city. The annual calibration results for yield as well as the average annual validation results (1992-1999) are quite satisfactory.

4. Conclusions

In this study, the well-established, semi-distributed SWAT model, in combination with the GIS interface ArcSWAT and SUFI-2 calibration procedure, was successfully applied to simulate the runoff and crop yield for the Hamedan-Bahar watershed with uncertainty analysis. One of the difficulties and limitations within this study is the lack of data on the amount of irrigation water removed from rivers and a lack of sufficient discharge data for springs. These data help to predict the base flow. However, considering the complexities of this watershed and the large number of interactive processes taking place, the results of the SWAT model are very satisfactory. We calibrated crop yield because in agricultural watersheds the relationships of crop growth and soil moisture, evapotranspiration, water percolation from the root zone and plant uptake of nitrogen are important. Based on the results obtained in this study, SWAT is assessed to be a reasonable model to simulate watershed processes and watershed management studies. After nitrate calibration, the model developed herein will be used to examine spatial and temporal leaching of nitrate from the soil profile and implementation of alternative BMPs to alleviate the aquifer nitrate problems.

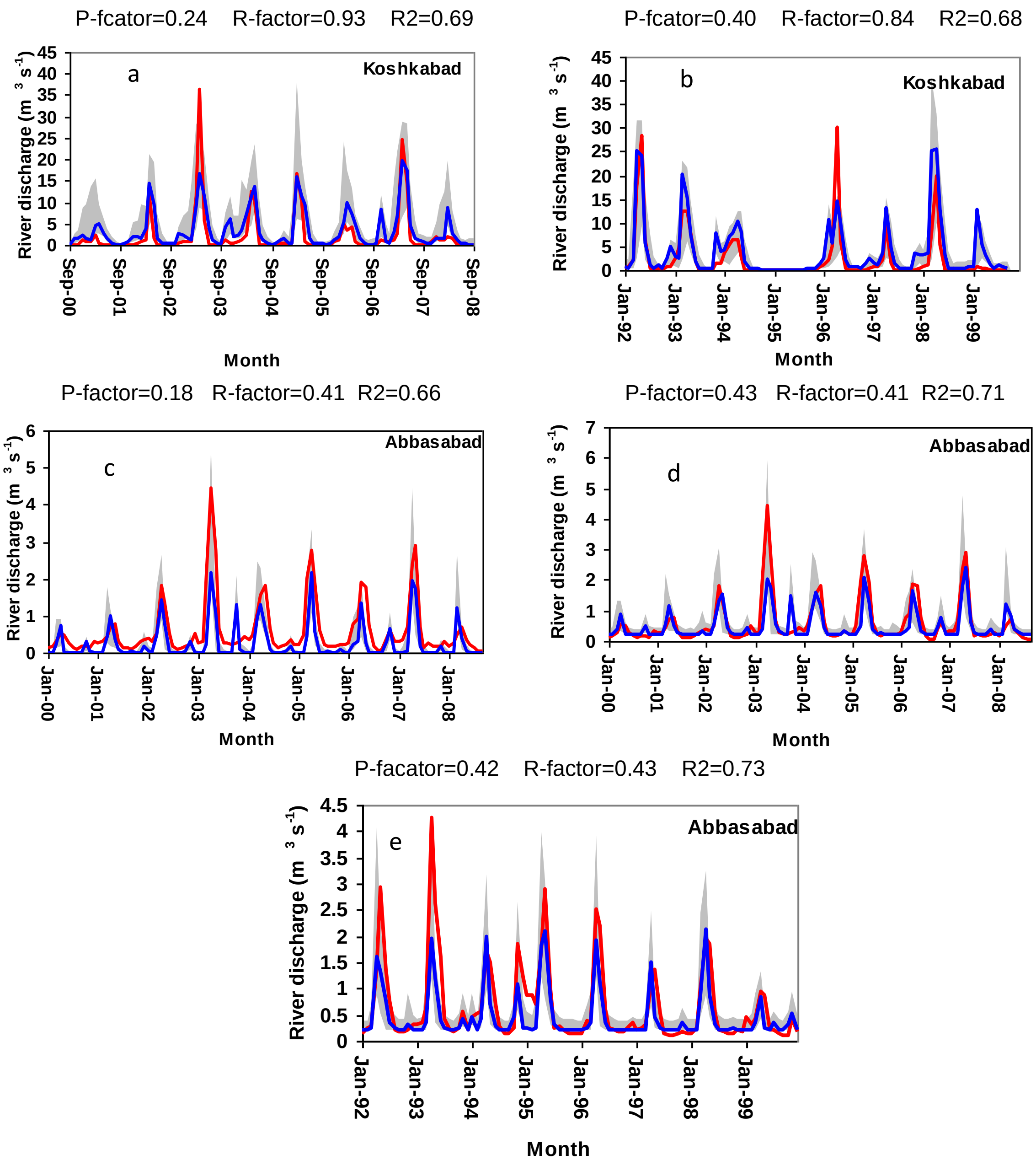

Figure 2. *Calibration and validation results are shown for two hydrometric stations. The red and blue lines are observation and best simulation, respectively, and the gray band expresses the 95% prediction uncertainty band.*

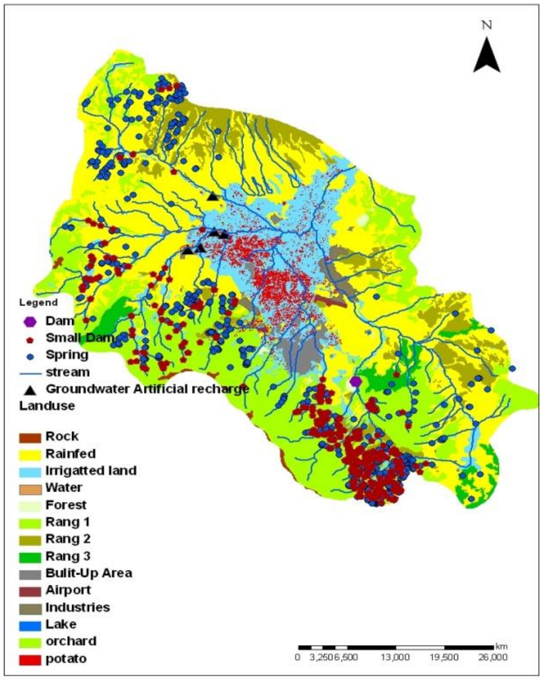

Figure 3. *The management map of the Hamadan-Bahar watershed shows the location of groundwater artificial recharge, dams and agricultural activities.*

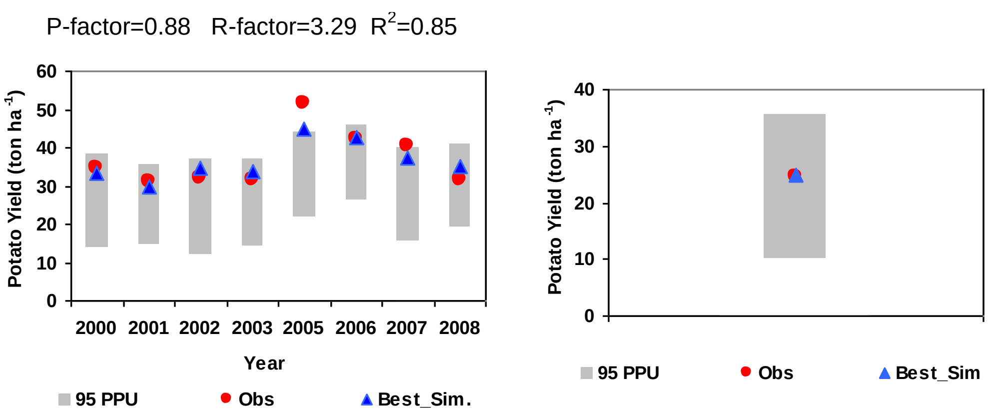

Figure 4. *Calibration (left) and validation (right) results of crop yield for potato for Hamadan city*

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How To: Applying and Interpreting the SWAT Auto-calibration Tools

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Abstract

Watershed-level modelers have expressed a need for a better understanding of uncertainty related to hard-to-measure input parameters and to the remaining internal processes of a model through ongoing discussions within the USDA-ARS Conservation Effects Assessment Program and the broader international research community. One water quality model of interest in this regard is the Soil and Water Assessment Tool (SWAT), which is being used internationally to aid in assessing the effects of various conservation practices. This paper defines and explains the main outputs provided by the three components of the SWAT Auto-calibration Tool: parameter sensitivity analysis, parameter uncertainty and model uncertainty. The goal of this paper is to aid future users by demonstrating a straightforward process for applying and interpreting the results of the Auto-calibration Tool relative to a specific watershed or region. The paper is intended to serve as a reference guide to the Auto-calibration Tool user community.

Keywords: calibration, parameter uncertainty, sensitivity analysis, user-oriented guide

1. Introduction

A set of tools have been developed for SWAT that evaluate parameter sensitivity, aid in model calibration and assess parameter and model uncertainty. These tools were created by Van Griensven (2005) and have been included into SWAT2005 and the ArcSWAT interface. The objective of this paper is to demonstrate a straightforward process for using these tools to analyze the parameter sensitivity and uncertainty associated with a particular watershed project. This work addresses the need for publicly available guidelines for applying and interpreting results from these tools. Due to space limitations, this proceedings paper will focus on understanding tool outputs. A more complete discussion of the tools is planned for journal publication with feedback from the SWAT conference.

SWAT response was evaluated for 16 hydrological parameters. Two parameters, CN2 and SOL_AWC, were varied by multiplying their initial parameter values by a percentage given as the range in the User Input Interface of ArcSWAT. The remaining 14 parameters were varied systematically within the ranges, independent of their initial values. Parameters can be varied identically for all or some HRUs and varied individually for all or some of the remaining HRUs. For example, when SURLAG is varied identically for all HRUs, it changes to the same value for all HRUs whereas CN2 changes by the same percentage from the initial value. When varied by individual HRU, SURLAG changes to a value within the given range, and the change for each HRU is independent from the change for any other HRU. Similarly, for each HRU, CN2 changes by some percentage from its initial value in that HRU. The percentage change method is more similar in impact to the within-range method when HRUs are allowed to vary individually rather than as a group. However, the percentage change method still maintains any new values within a constant interval of the initial value. In contrast, the within-range method only restricts the new value to a given range. Thus, the initial value has more lasting impact when the percentage change method is used for individually varied HRUs. In this study, the only channel-based parameter considered, channel hydraulic conductivity (CH_K2), was allowed to vary across all four channel reaches. The remaining HRU-based parameters were allowed to vary individually across all 123 HRUs within the watershed.

2. Sensitivity analysis

Sensitivity analysis demonstrates the impact that change to an individual input parameter has on the objective function value and can be performed using a number of different methods. The method in ArcSWAT combines Latin Hypercube (LH) and One-factor-At-a-Time (OAT) sampling. During the sensitivity analysis, SWAT runs (p+1)*m times, where p is the number of parameters being evaluated and m is the number of LH loops. For each LH loop, a set of parameter values is selected such that a unique area of the parameter space is sampled. That set of parameter values is used to run a baseline simulation for that unique area. Then, using one-at-a-time (OAT), a parameter is randomly selected, and its value is changed from the previous simulation by a user-defined percentage. SWAT is run on the new parameter set, and then a different parameter is randomly selected and varied. After all parameters have been varied, the LH algorithm locates a new sampling area by changing all parameters.

The number "m" determines the number of sub-ranges into which each parameter range is divided. For example, if m = 10, one LH loop will sample a parameter of range 0 to 150 within the sub-range of 0 to 15; another loop will sample within the sub-range of 15 to 30 and so on. The user specifies the percentage of change in the parameter value that will be used in the OAT variations within the parameter range specified in the user interface. So, if a range is from 0 to 150, a 5% parameter change means the parameter value varies by 0.05*(150-0) = 7.5 units. However, another parameter with a range of 0 to 1 will vary only 0.05*(1-0) = 0.05 units. Selection of the number of LH loops and the parameter change percentage should be made jointly, as they are both a function of the parameter ranges.

Evaluation of parameter sensitivity is determined by calculating 1/4th * the percent difference between the objective function output values of the simulation runs directly before and after a parameter value is changed (Eqn. 1). Since only one parameter is varied for each simulation run within each of the "m" loops, each parameter accumulates "m" sensitivity values. The sample mean and variance for each parameter's "m" sensitivity values are calculated. Then parameters are ranked in order of decreasing sensitivity based on decreasing ranked mean order.

$$\text{ParSen}_{\text{i}} = \frac{50 \times |Y_i - Y_{i-1}|}{(Y_i + Y_{i-1})} \qquad \text{(Eq. 1)}$$

where Y_i is the value of the objective function for simulation run *i*. The "sensout.out" output file summarizes the inputs used for the sensitivity analysis and the results.

The tool can determine sensitivity analysis in comparison to measured streamflow, using a "sum of squares" or "sum of squares ranked" objective function on the daily values. The average daily flow of the simulation run or some other user-selected measure can be used on the modeled output only. Outputs of parameter sensitivity analysis performed with observed data are listed under the heading "OBJECTIVE FUNCTION 1". These included the ParSen results per loop and then the maximum, variance and mean values of those ParSen results, as calculated by input parameter. A parameter ranking is also provided, with those parameters having highest mean ParSen value receiving a rank of 1. Outputs of parameter sensitivity analysis performed only using modeled data have the header "OUTPUT VALUE 1" followed by same respective information as the evaluations using measured data. Parameter rankings are also provided in the "sensresult.out" file.

Figure 1 shows the results of a sample analysis of 16 hydrologic parameters with regard to streamflow from a small watershed in the ridge and valley physiographic region of Pennsylvania. For both objectives, SOL_AWC has the largest mean value, ranking it most sensitive, while CH_K2 is ranked the least sensitive. Since all parameters changed value by a consistent 5%, the most sensitive ranking corresponds to the parameter that individually produced the highest average percentage of change in the objective function value of the model.

Higher variance for the indicated parameters (not shown), in combination with the highest mean value, suggests that these parameters most affect the calibration of the model but also have some interaction with other parameters or other aspects of the model. In contrast, a top ranking parameter with little to no variance would indicate no room for flexibility in that parameter's value while still maintaining the high value of the tested objective function.

When determining the most influential parameters, it is also useful to consider the difference in impact between the ranking using measured data and that of using modeled data. The analysis using measured data provides an overall "goodness-of-fit" estimation between the modeled and measured time series, whereas the analysis using only modeled data identifies the impact of tweaking a parameter value on some measure of modeled output (average streamflow in this example). The first analysis identifies the parameters that are affected by the characteristics of the study watershed and those to which the given project is most sensitive. The later analysis may help identify parameters that improve a particular process or characteristic of the model.

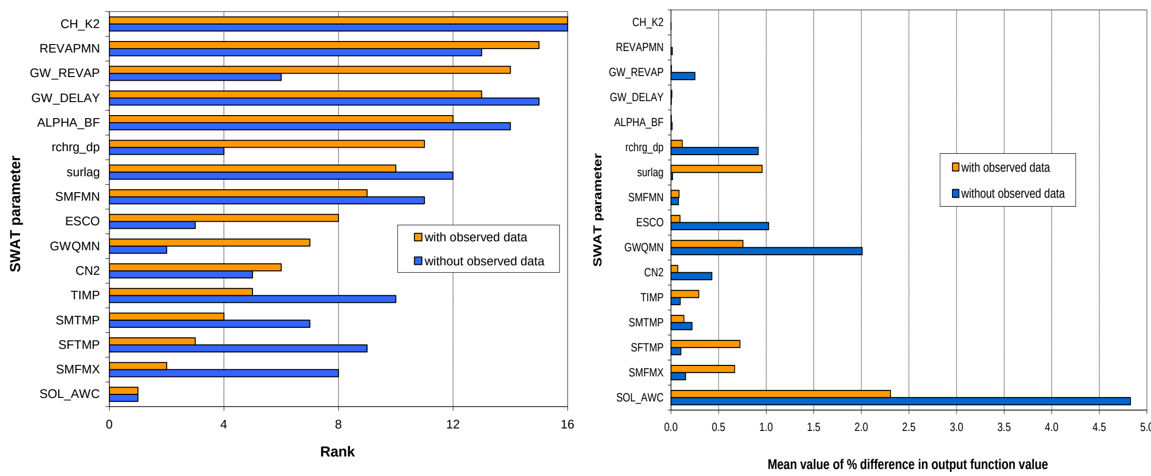

Figure 1. *Sensitivity rankings of 16 SWAT parameters on modeled and measured streamflow*

* The 1/4th factor is apparently due to a small math error and will be submitted for correction. However, for those users looking at current or previous runs in ArcSWAT or SWAT2005, Equation 1 is the value that is currently being calculated. Figure 1 shows the “true” mean, i.e., the current SWAT output times 4. The same rankings hold regardless of which “mean” value is used.

3. Parameter Calibration and Uncertainty

The Auto-Calibration and Uncertainty Analysis option in ArcSWAT provides three options under the “calibration method” pull-down box: ParaSol, ParaSol with Uncertainty Analysis, and SUNGLASSES. The first two focus on parameter calibration and uncertainty while the third addresses model uncertainty.

3.1 ParaSol and ParaSol with Uncertainty Analysis

The first, ParaSol, calibrates the model to the user-supplied output by optimizing the values of the user-specified parameters with a user-supplied objective function (typically “sum of squares” or “sum of squares ranked”). It also tracks the average value (or other specified statistic) of the modeled output. For ParaSol with Uncertainty Analysis, ParaSol is run as normal to find an optimal calibration set. Then, each simulation that was performed during the ParaSol optimization process is grouped into a “good” or “not good” category based on whether or not the objective function value of the run falls within a user-defined confidence interval (CI). This confidence interval is defined by the user input of “90%”, “95%”, or “97.5%” probability and the corresponding statistic of either a chi-square or Bayesian distribution.

The SWAT Auto-Calibration and Uncertainty Analysis window facilitates all necessary data entry. Data specifics are available in the ArcSWAT help. However, a few input parameters are explained briefly in Table 1 as user-supplied values from the interface for these parameters may be overwritten by a calculation in the current program code.

Table 1. *Code-calculated parameters for SWAT Auto-Calibration and Uncertainty Analysis*

NGS: Number of complexes in initial population	= user-value used
NPG: Number of points in each complex	= 2*"noptmax" + 1, where
"noptmax" = min("nopt",16), and "nopt' = number of parameters to optimize	
NPT: Number of points in initial population	= NGS * NPG
NPS: Number of points in subcomplex	= 1+ "noptmax"

The main output file for ParaSol and for ParaSol with Uncertainty Analysis is "parasolout.out". This file summarizes the input parameters and reports the Nash-Sutcliffe value for the initial run. The middle of the file records the process of the optimization routine and can be rather lengthy, but the final results of the routine are summarized in the last section (or two sections when including Uncertainty Analysis) at the bottom of the file. In particular, the maximum and minimum parameter values for all solutions in the Parasol Uncertainty Analysis CI are listed at the bottom of the "parasolout.out" file. The values are listed horizontally, left to right, in the same parameter order as appears vertically, top to bottom, in the input summary at the top of the page. Also given is the percentage of the input parameter range that is covered by the max-min range. The smaller the percentage is, the more sensitive that parameter is to being precisely calibrated, assuming the user-input range was not grossly inaccurate or there are not extreme parameter interactions. The ranges of values resulting from the parameter values of these solutions are shown in Figure 2a, after normalizing as a percentage of ParaSol's user-defined input ranges. For example, the minimum and maximum values for SURLAG were 3.70 and 9.38 respectively. The user-defined input range for SURLAG was 0.5 to 10. Thus, the normalized range for SURLAG is 0.34 to 0.93. In contrast, the normalized range for SOL_AWC is only 0.03 to 0.07. In general, the shorter the bar for a parameter, the more critical that parameter is to a good calibration. Also, the location of the bar indicates which end of the user-supplied parameter range provides the "better" values for a good calibration.

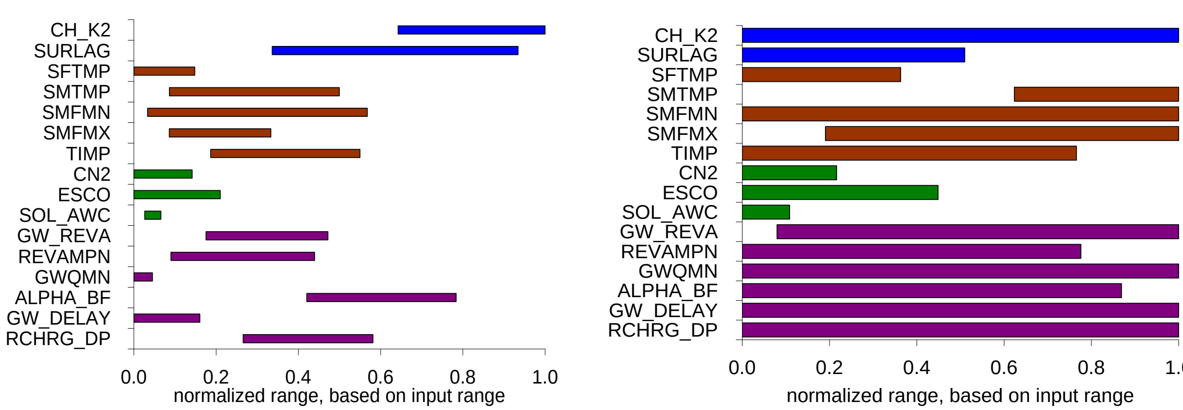

Figure 2. *Normalized range of parameter ranges for solutions within a) the Parasol Uncertainty CI of the best found solution set and b) the SUNGLASSES CI*

ParaSol maintains a record ("goodpar.out" file) of all solutions having an objective function value within the Uncertainty Analysis CI and of the objective function value of the optimal solution found by SWAT ("bestpar.out") as well as others ("uncobjf.out"). The tool should automatically calculate the maximum and minimum time series for the Uncertainty CI ("minval.out" and "maxval.out") based on all "good" simulations. These can be plotted with a measured time series and a best solution time series, as shown in Figure 3, to delineate the inclusive boundaries for all "good" time series. The optimum run usually lies within these boundaries but is not guaranteed to. The good parameter set is defined as all sets for which the optimal function value (not a particular time step value) lies within the specified CI. Thus, in a time series or other type of evaluation, the good parameter set generally defines an uncertainty around the optimum but not necessarily a predetermined confidence interval.

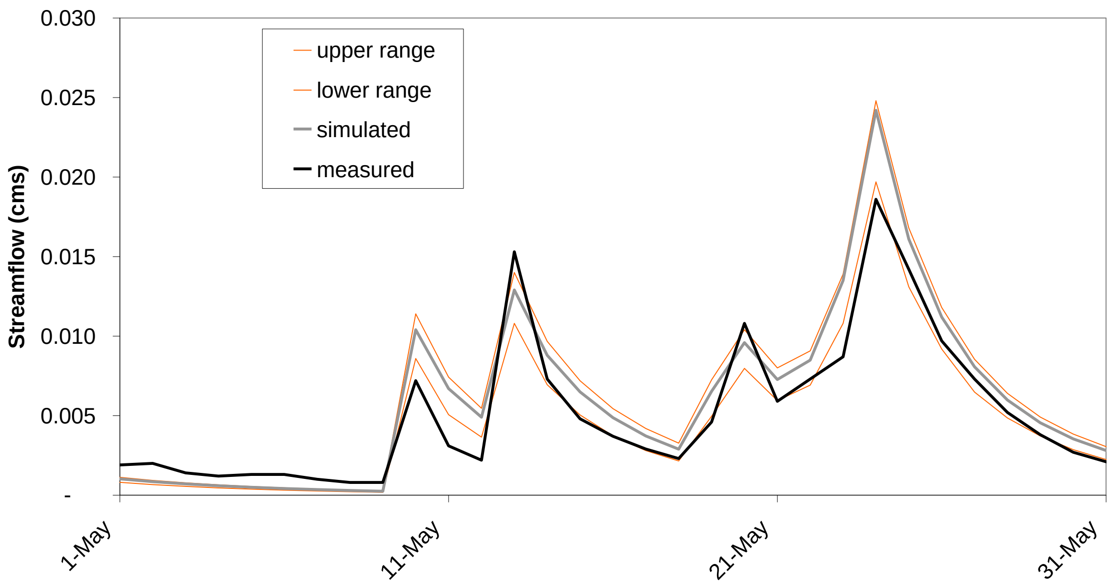

Figure 3. *Excerpt of time series showing Parasol Uncertainty CI*

3.2 Sunglasses

The third option of the Auto-calibration Tool, SUNGLASSES, ranks all simulation runs by their global optimization criterion (GOC) as in Figure 4. The GOC is similar to but, in the case of multiple objective functions, not exactly the same as the objective function value (e.g., "scegoc.out" versus "sceobjf.out"). The optimal solution has the lowest GOC (731 in the Figure 4a), and the GOC for the Parasol Uncertainty Analysis CI is slightly higher (744). SUNGLASSES continues up the ranked list of GOCs until it reaches a solution for which the percent bias of the objective function spans zero. For example, this happens for GOC = 791 with percent bias of 1.0272 (Figure 5). The GOC corresponding to this solution provides the threshold for the SUNGLASSES CI bounds. All simulation runs with GOCs equal to or higher than this CI-bound GOC are included in the SUNGLASSES solution set.

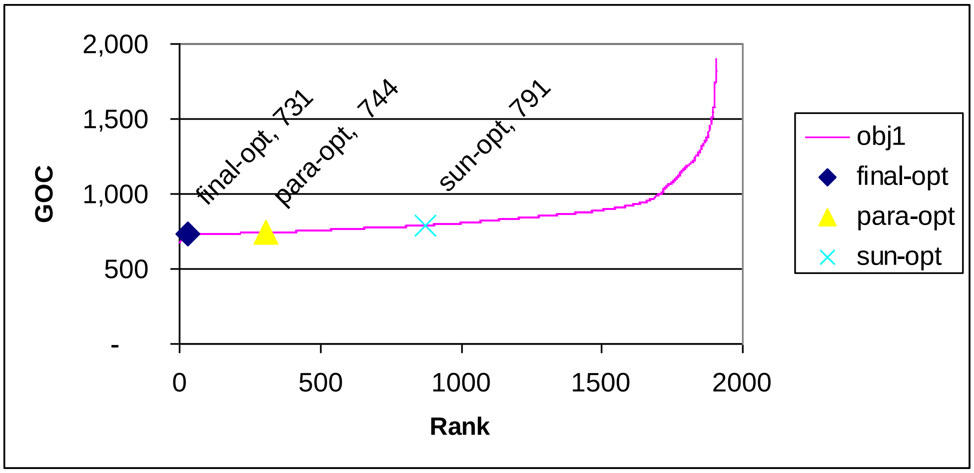

Figure 4. *Sorted GOCs for entire optimization process with optimum, Parasol CI threshold, and SUNGLASSES threshold indicated*

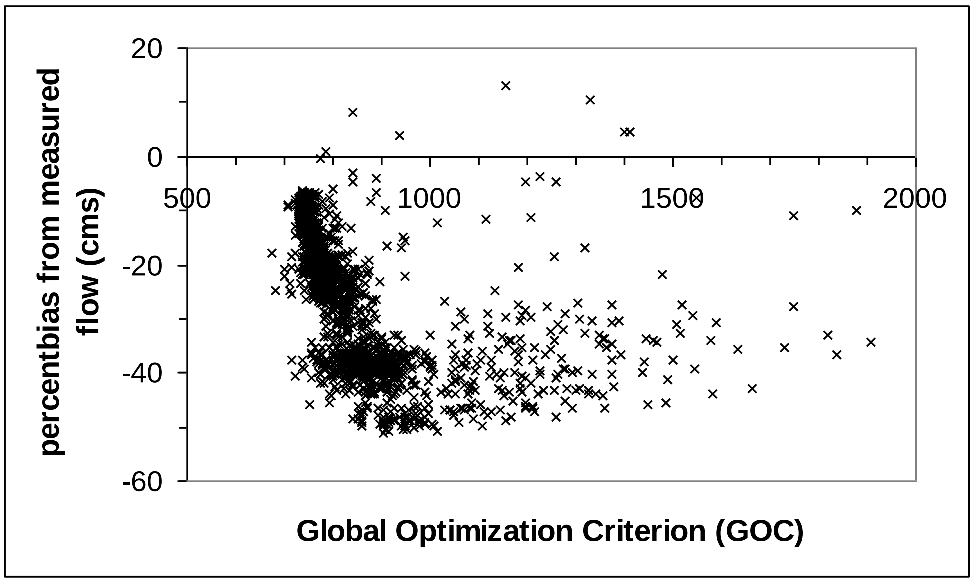

Figure 5. *Percent bias values and GOCs for all simulations*

The main output file for SUNGLASSES ("sunglasses.out") is identical to that of Parasol with Uncertainty Analysis but contains an additional section at the end that summarizes the impact of expanding the GOC threshold. The maximum and minimum parameter ranges corresponding to this threshold are given in the same format as in "parasolout.out" and can also be plotted (Figure 2b).

For all simulation runs with GOC values less than the threshold GOC, SUNGLASSES creates a file of the parameter values ("SGgoodpar.out") and of the objective and model output values ("uncobjf.out" and "uncresponse.out"). The minimum and maximum times series values should be given in "minval.out" and "maxval.out" for the entire simulation run. Figure 5 shows the SUNGLASSES max-min time series values combined with the ParaSol CI and the optimum and measured time series. The parameter values and objective functions for all simulation runs are given in "sceparobj.dat".

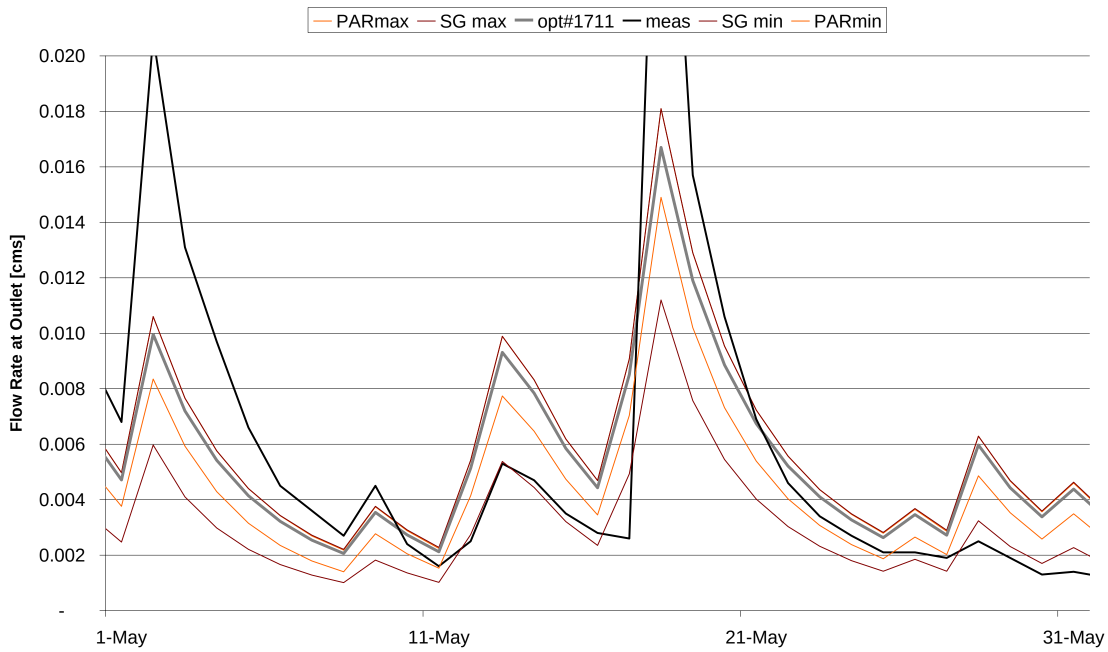

Figure 4. *Excerpt of time series showing SUNGLASSES CI and ParaSol CI with modeled optimal solution and measured data*

4. Conclusion

The Auto-calibration Tool in ArcSWAT provides a user-friendly method for specifying various inputs including calibration parameters and desired widths of uncertainty confidence intervals. It also facilitates specification of measured data sets and the desired output parameters and objective functions. The text-based summaries from the three components of the Tool can be used to determine the optimal parameter set for calibration purposes, parameter sensitivity ranges and corresponding objective function ranges. Time series graphs, with or without parameter and model uncertainty bounds, can be created from additional output files to facilitate comparison between the amount of variation in the model results and the measured data.

References

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Event-Based Hydrologic Calibration of Field-Scale Watersheds in Southwestern Wisconsin Using the SWAT Model

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Abstract

Simulation models are increasingly being used to test how alternative management scenarios can reduce the export of phosphorus from agricultural watersheds. Calibrating these models using short term monitoring records at watershed outlets can lead to questions about the appropriate combination of parameter changes, especially when parameters are strongly correlated. This can be particularly important for the hydrologic calibration. The research in this paper involved determining and comparing the sensitivity of common hydrologic calibration parameters in the Soil and Water Assessment Tool (SWAT) model with individual runoff events at the field-scale. The volume and composition of runoff from alfalfa and corn fields at the University of Wisconsin - Platteville Pioneer Farm were measured over a period of six years. Although, SWAT2005 was used with a daily time-step, model results were summarized on an event basis in order to be consistent with field collection efforts. SWAT was used with PEST, a nonlinear parameter estimation tool, to evaluate parameter sensitivity and uncertainty when using different calibration techniques. The results show improvement in model fit using a temporally varied NRCS curve number (CN) rather than a single value representative of the entire simulation. The field-scale watersheds were acceptably calibrated to individual storm events (S2, R^2 = 0.70; S3, R^2 = 0.51). Analysis of parameter sensitivity and parameter correlation indicated that the temporal variation of the CN improved calibration, yet the soil parameters AWC and ESCO were highly sensitive in hydrologic event-based calibration. The correlation of these parameters suggests that achieving a unique solution is difficult with the SWAT model.

Keywords: field-scale, curve number, parameter sensitivity, calibration, PEST

1. Introduction

Runoff from agricultural land can substantially accelerate nutrient transfer from land to surface waters and lead to eutrophication in both lakes and streams. For example, in the U.S. approximately 20% of the lake area is impaired by nutrient enrichment (USEPA, 2004). The need to reduce agricultural runoff and slow nutrient transfer has led to the use of modeling tools such as SWAT, which simulates hydrology and nutrient movement. Characterizing runoff and nutrient transport is challenging because of the variability of sources, sinks and transport processes (Gburek and Sharpley, 1998). This variability reflects the dynamic nature of land management that is further complicated by temporal changes in runoff source areas driven by precipitation and landscape conditions.

Landscape processes that accelerate nutrient transfer are complex and heterogeneously expressed. Watershed models simplify the processes by aggregating data both spatially and temporally and also by reducing the mechanistic detail simulated. In many water quality models, the relatively simple NRCS curve number (CN) formulation is used with a daily time step to simulate the hydrology. The CN equations are described in detail elsewhere (NRCS, 1985) and will not be repeated here. While the use of the curve number approach in this type of continuous simulation has been questioned (Garen and Moore, 2005), it remains likely that it will be an important component of many water quality simulation tools into the foreseeable future. Selection of an appropriate curve number has important implications for runoff volume estimates and therefore strongly influences nutrient export predictions and impacts the management practice changes required to meet certain goals or regulations.

This study examines some of the issues related to CN selection and application during daily time-step modeling with SWAT. This is a relatively simple approach to hydrologic modeling. For example, it does not separately account for multiple storms that could occur within a single twenty-four hour period. In addition, it relies on a previously questioned association between soil moisture and the CN (Van Mullem et al., 1993). Researchers have not found a very significant relationship between soil moisture and CN. Furthermore, research has shown that the variation in CN linked to soil moisture may be much smaller than the range sometimes cited for the dry and wet condition curve numbers, CN1 to CN3, respectively. To evaluate the application of the CN in SWAT, the study described here used runoff data collected from individual runoff events from small, homogeneous watersheds to explore the variability of runoff curve numbers on an event-basis. Parameter estimation tools were used to explore the correlation between runoff curve number and other hydrologic parameters typically used in SWAT calibrations.

2. Study Area

The Upper Fever River watershed (UFRW) in southwestern Wisconsin's Lafayette County is the location of this study. The UFRW drains 7.8 square kilometers of primarily agricultural land east of Platteville, Wisconsin. The Upper Fever River joins the Galena River and ultimately the Mississippi River. The 174 hectare (ha) University of Wisconsin – Platteville Pioneer Farm is in the southern region of the UFRW (Figure 1). Pioneer Farm is a working farm that "focuses on discovering new applications that can offer the farmer both environmental stability and economic viability while complying with environmental regulations and guidelines" (Southwest Badger, 2007). The farm manages approximately 134 ha of tillable land. Pioneer Farm uses edge-of-field outlet flumes, stream gauges, soil testing and other methods to the study environmental impacts related to farming practices and conservation measures. Edge-of-field refers to a field's crop landscape, terraces and grassed waterways as they contribute to the field's hydrologic outlet. Conservation practices such as terraces, contour strips, grassed waterways, and filter strips have been installed to reduced sediment and nutrient loss from the farm's cropland. In conjunction with detailed management records, Pioneer Farm is developing baseline conditions regarding the impact of various agricultural best management practices in southwestern Wisconsin.

Most of Pioneer Farm's 134 hectares of tillable land is used to maintain the farm's dairy operation, and the remainder is used to support beef and swine. Pioneer Farm's tillable land is broken into 27 fields. Crops are grown using a dairy forage rotation: three years corn (C), one year oats (O) and three years alfalfa (A). The dairy forage rotation is varied throughout the farm so as to create contour strips that prevent water and sediment erosion. Conventional tillage, the most common system for corn, is applied to all fields on Pioneer Farm. Conventional tillage holds < 15% residue cover on the fields after planting. Within SWAT, tillage impacts the runoff potential represented by the CN and the biological mixing of soils and residue burial. For fertilizer applications, liquid manure is injected into the soil.

For the scope of this study, two field-scale watersheds are used to simulate edge-of-field discharge. Sub-area S2 is an 8.87 ha watershed in the northwestern corner of Pioneer Farm and S3 is a 5.16 ha watershed on the eastern edge of Pioneer Farm. S2 and S3 are single crop (corn and alfalfa) watersheds.

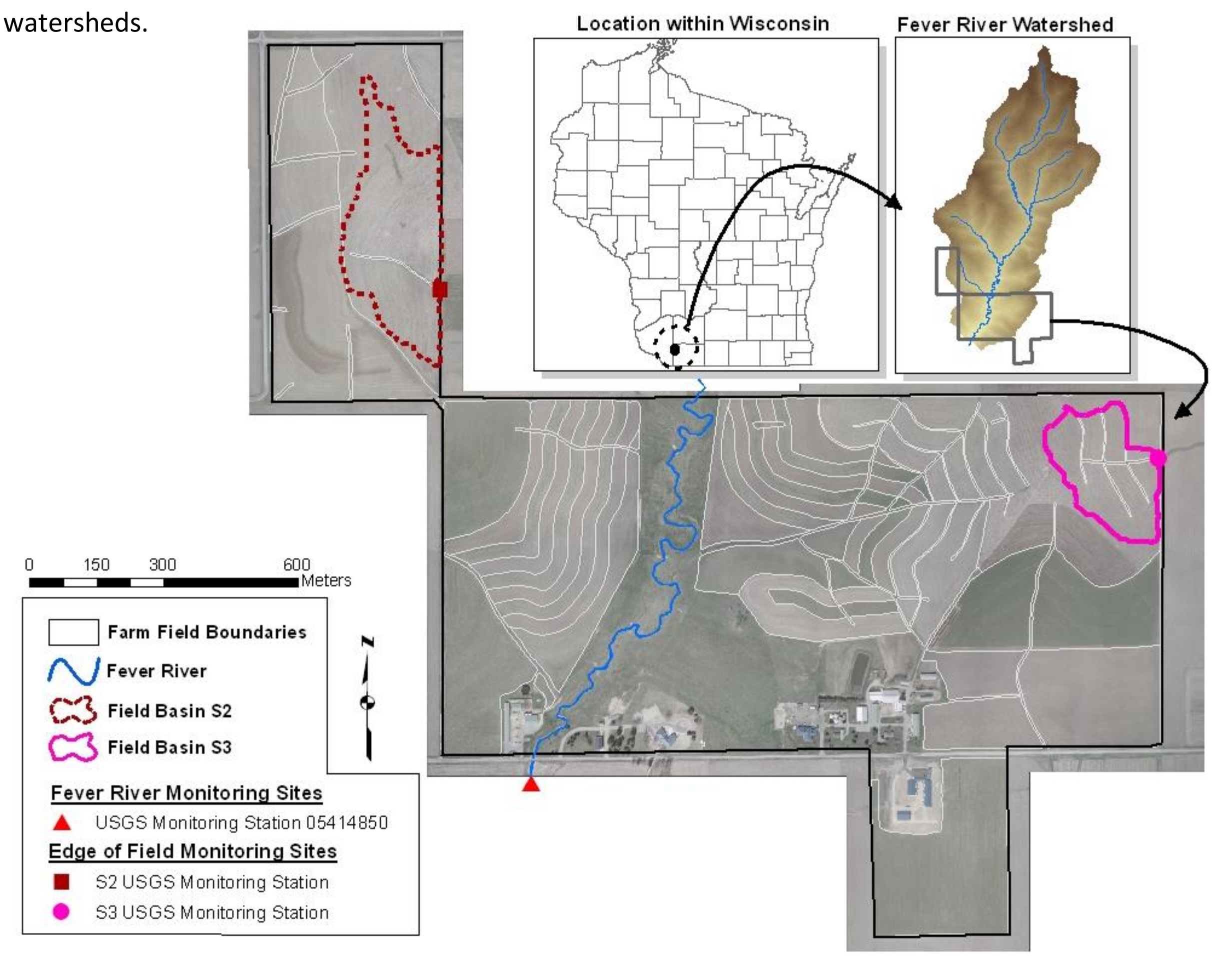

Figure 1. *Study area location within the Upper Fever River watershed, southeastern Wisconsin*

3. Methodology

3.1 Field Monitoring

Pioneer Farm has multiple edge-of-field monitoring stations located at the surface outlet of agricultural fields to monitor flow, sediment and water chemistry from individual storm or snowmelt events. The edge-of-field represents all components of the field watershed including the cropped land, terraces, and grassed waterways. Grassed waterways are used as a preferential path to funnel the individual field-scale watersheds toward the monitoring station. Two of Pioneer Farm's edge-of-field monitoring stations were used in this study: S2 (USGS Station 424314090240601) and S3 (USGS Station 424302090225601).

At each edge-of-field and in-stream monitoring station, water quality samples were taken via an ISCO3700R™ stainless steel, refrigerated autosampler during each measurable event. Individual samples were proportionally mixed into a single sample representing the flow-weighted average concentration over the duration of the storm. The measured flow volume and known concentrations are used to calculate sediment and nutrient loads.

3.2 Model Inputs

A SWAT model was developed for the two small watersheds. Each watershed was modeled as a single HRU within a single subbasin. The ArcSWAT interface uses topographic inputs to delineate the watershed boundaries. The individual field-scale watersheds delineated from monitoring stations S2 and S3 each have an ephemeral grass waterway contributing to the station. Depending on storm event intensity, water moves laterally across the field's terraces before traveling down gradient, along the grass waterway, toward the H-flume.

Soil characteristics are used to determine soil moisture properties within SWAT. According to the NRCS soil survey, the UFRW has soils with a silt loam texture. Tama soils, listed as the dominant series, are generally well-drained (USDA, NRCS 2006). Borings at Pioneer Farm confirmed the silt loam texture and found that the unconsolidated layer was one to four meters thick.

Field-scale SWAT simulations used daily maximum and minimum air temperature and total precipitation collected from Pioneer Farm MET station between January 1, 2003 and December 31, 2007. For dates prior to 2003, the daily median precipitation from four edge-of-field monitoring stations was used. All simulations used the Hargreaves method of evapotranspiration.

3.3 SWAT Simulations

The results from the SWAT simulation were aggregated on a daily basis corresponding to the way that runoff events were monitored at Pioneer Farm and were then compared to the monitored flow volume. A pre-processor using Python script aggregated the multi-day events from the SWAT output prior to PEST evaluation. PEST input required the date, measured value, an acceptable input variable range and current values of the input variables. Evaluation of SWAT's discharge simulation for each field basin was made based on individual storm events in field watersheds S2 and S3. This study focused on non-winter discharge events (April 1 – November 31) between June 2002 and December 2007. During that time, watershed S2 and S3 had a total of 41 and 27 measured events, respectively. The model simulated 8 years (2000 – 2007), but the first two years were used to initialize the simulation and were not included in the analysis.

Discharge was calibrated by simultaneously adjusting a set of the model input parameters to improve the fit between observed and predicted data. The model input parameters were selected based on previous SWAT studies (White and Chaubey, 2005; Lenhart et al., 2002; Heuvelmans et al. 2004) and by auto-calibration of model parameters. Parameter estimation (PEST) software was used to evaluate model parameters and their sensitivities. PEST, a freeware tool, assists with data interpretation, model calibration and predictive analysis (Doherty, 2004). PEST can be used with any model by reading a model's input and output files in order to find optimum values and sensitivity for each input parameter. PEST allows for a large number of parameters to be fitted from nonlinear models like SWAT. PEST performs iterations using the Gauss-Marquardt-Levenberg algorithm. The parameters used for surficial, field-scale hydrologic model calibration were the crop curve number (CNOP), soil available water capacity (AWC), soil hydraulic conductivity (SOLK) and the evapotranspiration coefficient (ESCO). Due to small variations, a single average AWC and SOLK was used to represent all three soil horizons.

Flow simulation results were taken from the surface flow output (SURQ) in the subbasin output file (output.sub) of the SWAT model directory. The SURQ is the surface runoff contribution to streamflow in the main channel during the time step (mm H_2O). The SURQ alone was used because there is no permanent flow at the upland stations.

4. Results

4.1 Event Runoff Curve Numbers

The measured runoff volumes and precipitation depths were used to estimate curve numbers for each runoff event using the method of Hawkins (1993). Figure 2 shows that most of the runoff events on these fields were relatively small storms that correspond to relatively high (e.g., > 70) event runoff CNs. The variation of curve numbers plotted against event precipitation shows how runoff events observed at relatively low precipitation levels would require relatively high curve numbers. The line in Figure 2 shows that there is a practical lower boundary for curve numbers that represent a runoff amount that is 0.1% of the incident precipitation. The calculated curve numbers for runoff events from these fields follow the "standard" behavior pattern described by Hawkins in that they appear to move asymptotically towards an event curve number with increasing storm size.

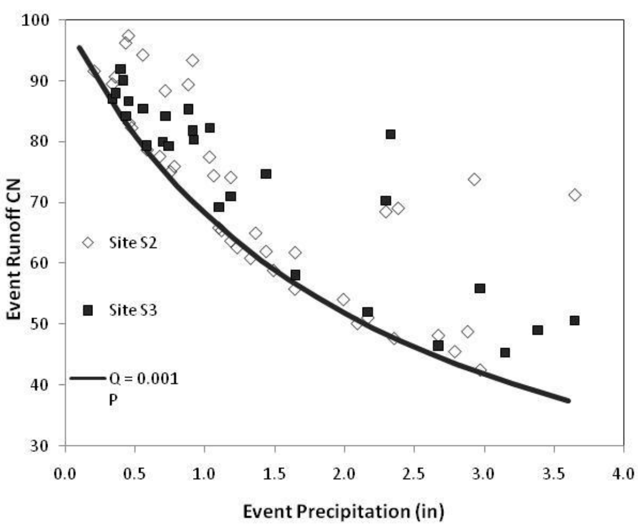

***Figure 2**. Calculated event runoff curve numbers for runoff events at S2 and S3.*

The variation of event curve numbers reflects a range of event conditions such as precipitation intensity, soil moisture levels, canopy interception and field conditions. The asymptotic curve number that is observed at a relatively large storm size ranges from 50 to 70 in these fields. As expected, runoff events that precede days with little rain are likely to have lower CN than those following wetter conditions.

4.2 SWAT Calibration of CN

Runoff events from watersheds S2 and S3 were used to calibrate the SWAT model using PEST. To evaluate the impacts and sensitivities of calibration in this study, several different calibration strategies were compared: 1) fixing all parameters except a single CN, 2) fixing all parameters and using three, variable CNs (corn, tillage and alfalfa), 3) allowing hydrologic parameters (AWC, ESCO and SOLK) and three CNs (corn, tillage and alfalfa) to vary within reasonable limits (Table 1). In all three cases, the results are compared in terms of the coefficient of determination and the ability to match the runoff volume.

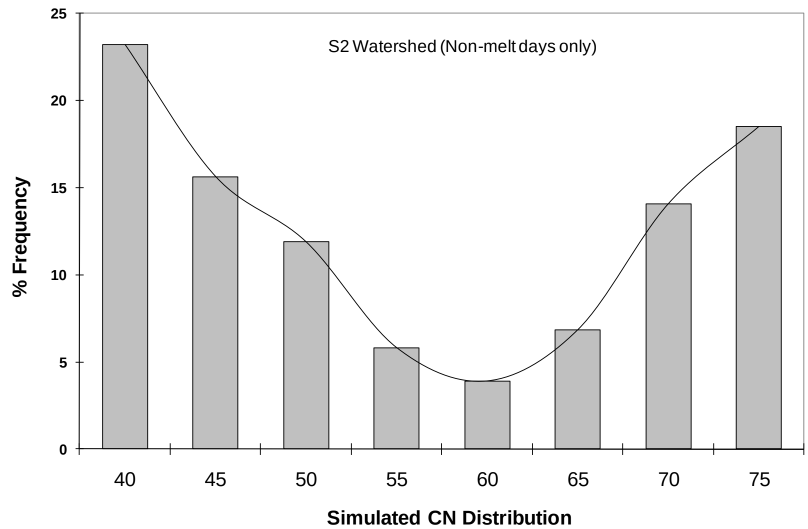

Figure 3. *Frequency distribution of daily SWAT simulated CNII*

Table 1. *Calibration strategy summary*

Calibration Strategy	Calibration Strategy Description
#1 – Single CN, Fixed Parameters	Single CNII, remaining hydrologic parameters remained fixed at default value
#2 – Multiple CN, Fixed Parameters	Multiple CN (Corn, Tillage, Alfalfa), remaining hydrologic parameters fixed at default value
#3 – Multiple CN, Variable Parameters	Multiple CN (Corn, Tillage, Alfalfa) hydrologic parameters (ESCO, AWC, SOLK) variable

The first strategy involved calibrating a single CN while fixing the other parameters based on default values for these conditions. This CN was applied to corn, alfalfa and periods between crops. The SWAT input CN is that for antecedent runoff condition II (CN2) between wet CN3 and dry CN1. As shown in Table 2, the fitted CN typically falls within the middle of the 50-70 range calculated for the larger storm events.

During the SWAT simulation, the CN will vary daily based on soil moisture. Figure 3 shows a histogram of non-melt, daily CNs from the SWAT simulation of S2. As expected, the curve number varies across a relatively wide range between CN1 and CN3. The figure shows that in the SWAT simulation very few days had a CN close to the CN2 condition. In contrast to the calculated CNs, the SWAT simulated output also shows many days with low CNs. These are days that would not result in runoff for all but extremely large storms.

The second calibration strategy fit the runoff events with a SWAT model with multiple CNs, reflecting separate crops and management practices (corn, alfalfa, or tillage). The CNs were incorporated as operational within the SWAT management file. The results indicated a departure from the asymptotic relationship between curve numbers simulated using a single CN. Instead, the CN was dependent on the tillage practice, which typically had a higher CN than corn or alfalfa. In comparison to the single curve number simulation, calibrating to a temporally varying CN improved the ability to simulate runoff events. Overall, the multiple CN simulation was within 15 percent of the measured values with an R^2 of 0.67 and 0.48 for fields S2 and S3, respectively.

The third calibration strategy allowed several hydrological parameters (AWC, SOLK and ESCO) and three CNs (corn, tillage and alfalfa) to vary within reasonable bounds. Figure 4 shows the results of a best-fit calibration for watershed S2 that used six parameters: corn CN, alfalfa CN, tillage CN, AWC, SOLK, and ESCO. All variables had a set calibration of +/- 20 percent of the default value. The calibration of all six parameters resulted in a better calibration than strategy #1, the single CN simulation, but only a modest improvement over strategy #2, the multiple CNs alone (Table 3). This limited improvement likely reflects the relatively high correlation between the AWC, ESCO and CN. Adjustments to one parameter can be compensated for by changes in another, resulting in little overall improvement in the ability to describe the events. The overall change in the objective function is relatively small across this range, but it requires substantial variation in the AWC and CN to accomplish a similar fit to the measurements. The SWAT model was able to capture most, but not all, of the events. All the events were weighted equally during calibration; therefore, because the objective function was based on a squared residual, the larger runoff events were very important in determining the CN. The smaller runoff events had a much greater percent error with respect to the simulated runoff volume.

Table 2. *Calibrated parameters per calibration strategy*

			S2 Calibration Strategy			S3 Calibration Strategy		
	Default	**Range**	**#1**	**#2**	**#3**	**#1**	**#2**	**#3**
CN2	77	45 – 85	56	–	–	62	–	–
CN - Row Crop	77	61 – 85	–	77	75	–	62	62
CN – Alfalfa	59	47 – 71	–	47	49	–	62	61
CN – Tillage	80	60 – 88	–	84	85	–	79	81
ESCO	0.95	0.40 - 0.98	–	–	0.98	–	–	0.86
AWC	0.22	0.17 - 0.27	–	–	0.25	–	–	0.17
SOLK	32.4	25.4 - 39.0	–	–	25.40	–	–	25.40

Table 3. *Model results per calibration strategy*

	Field S2 Calibration Strategy			Field S3 Calibration Strategy		
	#1	**#2**	**#3**	**#1**	**#2**	**#3**
% Flow Diff.	-63%	-15%	-21%	-24%	-14%	-7%
R^2	0.05	0.67	0.70	0.46	0.48	0.51

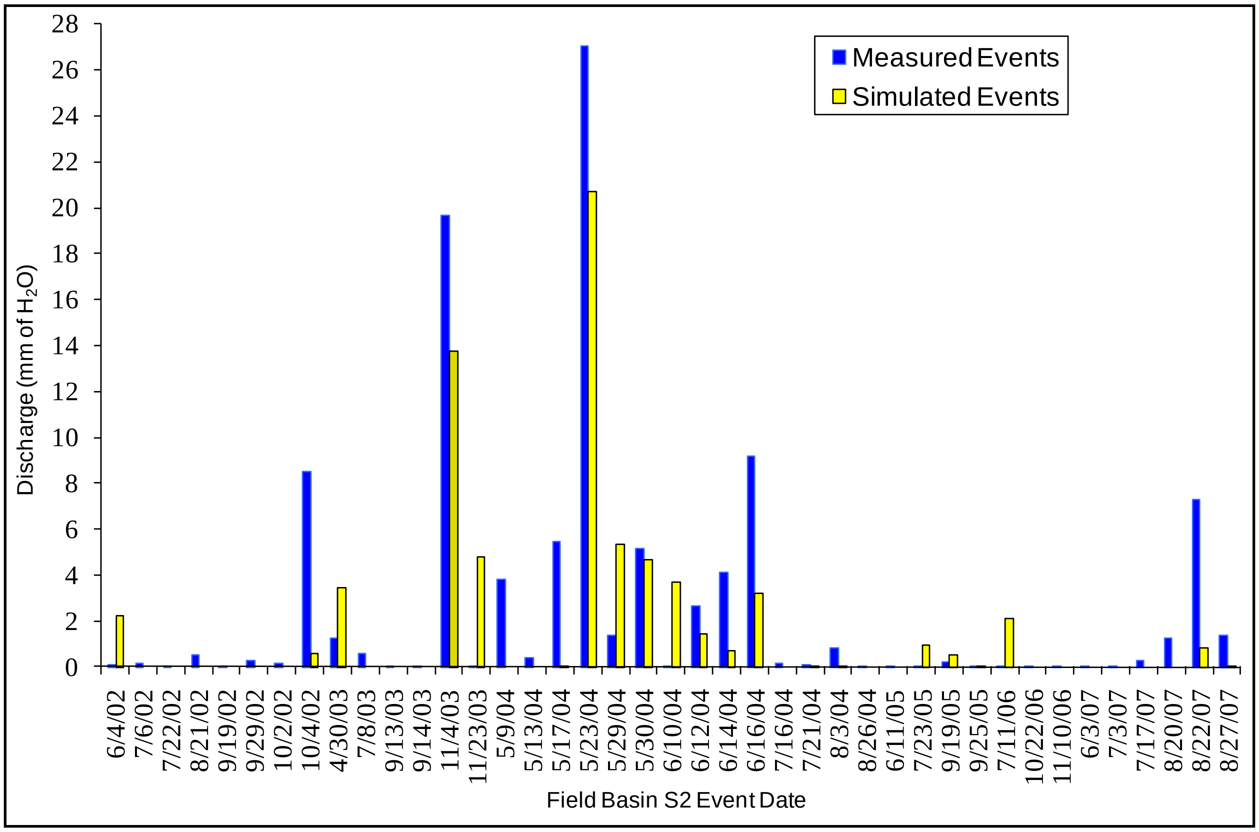

Figure 4*. Field basin S2 measured vs. simulated event discharge calibration*

4.3 Parameter Sensitivities

An important consideration in calibrating the SWAT model, which uses a soil moisture adjustment for the daily curve number, is the extent to which several hydrologic parameters are likely to be correlated. Multi-parameter calibration was used to explore parameter sensitivity and correlation. Parameter sensitivity analysis can help limit the number of parameters used in calibration and provide the modeler with an understanding of model behavior. The use of PEST in conjunction with SWAT indicated that AWC and ESCO were the two most sensitive parameters out of the six used for calibration strategy #3. The sensitivity of the CN varied depending on what calibration strategy was applied. To assess parameter correlation, the CNOP for row crops was plotted in response to incremental changes in the AWC and ESCO. PEST works to minimize the objective function, so the CN value was pushed to its upper or lower bounds in each case for S3 and the same was done with ESCO for S2. The different variations of ESCO/CN and AWC/CN illustrate that developing unique solutions within SWAT is difficult.

5. Conclusions

This study showed that SWAT simulations with a daily time-step and a CN based on soil moisture were able to describe runoff from many of the storms occurring in the small watersheds at the Pioneer Farm in southwestern Wisconsin. Evaluating the daily CN showed that it was sensitive to soil moisture and was generally considerably higher or lower than the CN2. Not surprisingly, adding more curve numbers improved the ability to describe these storms. Because CN updating is based on soil moisture, the simulation is sensitive to other parameters that relate to soil moisture. However, these can be strongly correlated with the CN, leading to a series of similar solutions with little improvement in overall model performance. Modelers should be aware of the correlation between soil moisture and CN and be cautious about making large adjustments in these correlated parameters.

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Preliminaries to Assessing the Quality of SWAT Parameter Confidence Intervals

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Abstract

While the Soil and Water Assessment Tool (SWAT) is typically calibrated and validated based on streamflow, the prediction of quantities related to contaminant transport or other phenomena are often of greater interest than the prediction of streamflow itself. The reliable prediction of these quantities hinges upon the quality of the SWAT parameter confidence intervals. Various methods have been proposed for providing unbiased parameters with relatively narrow confidence intervals. These methods may be tested by comparison with field data if the field data is abundant in its spatial and temporal coverage. The soil moisture data set of the Little River Experimental Watershed (LREW) is such a data set. For facilitating the comparison of the results of various methods against the field data, minor modifications of the SWAT code are proposed. These changes were made to keep the number of SWAT hydrologic response units (HRUs) at a minimum and simulation times conveniently short without introducing aggregation errors that would degrade parameter confidence intervals. It was found that aggregation to 102 HRUs provides simulated streamflow values very close to that of a very large reference number of HRUs (10,372) for sub-watershed I of LREW. The Nash-Sutcliffe Efficiency of the former relative to the latter scenario is 0.9954 when the parameters are uninhibited by a calibration process. Also, providing ten relatively thin soil layers, as opposed to the typical three to five soil layers found in the soil database, allows for a noticeable difference in simulated streamflow while increasing simulation time by approximately 10%.

Keywords: confidence intervals, soil moisture, parameter, SWAT, Little River Experimental Watershed, calibration, hydrologic model, streamflow, watersheds.

1. Introduction

SWAT models are often evaluated according to how well they predict streamflow. The ultimate concern is often not the predication of streamflow itself, but how well the model, once calibrated with observed streamflow, is able to predict other phenomena, such as the fate and transport of contaminants or the need for irrigation. These phenomena are predicted via the parameter values of the streamflow-calibrated model.

The literature provides clear examples of parameters becoming distorted from their true values as an algorithm seeks to improve the model's ability to predict streamflow (Oudin et al., 2006). At times, parameter values from nearly opposite ends of the naturally occurring spectrum enable the model to predict streamflow well (Abbaspour, 2008). However, given this situation, the model would obviously not perform well in estimating sediment transport or in describing other phenomena that may be of primary concern to SWAT users. How then can SWAT users know whether a model that predicts streamflow well is really of much use for predicting quantities other than streamflow?

Theoretical explanations for parameter distortion have been presented (Huard and Mailhot, 2006). Attempts have been made to reduce or eliminate the distortion of parameters in the calibration process by, for example, introducing terms into a Bayesian analysis in which the rules of statistics are more closely followed (Yang et al., 2008). However, the actual reliability of the parameter estimates or of their confidence intervals are not tested and indeed typically cannot be tested through any practical means. Attempting to introduce other signals into the calibration process, signals that are more directly relevant to the quantities of primary concern, is also attempted often. However, such signals may themselves be difficult to measure accurately or extensively enough to cover their spatial and temporal variability and thus may contribute little to improving parameter estimates.

Occasionally, quantities closely associated with various parameters are accurately measured at a great enough diversity of points and with a great enough frequency over a long enough period of time to be quite useful. Such is the case in some experimental watersheds like the Little River Experimental Watershed (LREW) in southwestern Georgia with its soil moisture probes. The soil profile plays a pivotal role in the hydrologic cycle of watersheds. First, it acts as an interface between two basic sets of parameters — those acting at or above ground level (for SWAT these include CN2, SURLAG, CANMX and others) and those acting below ground level (for SWAT these include DEP_IMP, RECHRG_DP and others). Secondly, the soil profile acts as an interface between subgroups of parameters that act below ground level because it exerts influence over the portion of water reaching the stream as lateral flow (SOL_K, SOL_Z and others) and the budgets of underlying aquifers (REVAPMN, DEP_IMP, RCHRG_DP and others). Accurate SWAT model prediction of soil moisture in the profile on a daily and hourly basis, especially when those measurements are not used in the calibration process, suggests parameter reliability, but discrepancies indicate otherwise. Methodologies designed by Yang (2007) and others to reduce parameter bias may finally be put to the test, and progress may readily be made in improving models, their calibration procedures and uncertainty analyses.

The LREWswI offers a unique opportunity for such testing. Calibrated SWAT models for the LREW tend to have simulated peaks that lag behind measured streamflow peaks by one day (Bosch et al., 2004). The streamflow response to rainfall in LREWswI is apparently altered by riparian storage, and the SWAT code was modified such that curve numbers could more readily account for the degree of saturation in the riparian zone (White et al*.,* 2009). The most current SWAT code does not include this structural change in the equations. However, this characteristic of the LREWswI, coupled with its abundant soil moisture data set, provides an excellent opportunity to test the methodology developed by Yang et al. (2007, 2008). In this methodology, an autoregressive parameter is applied to supposedly compensate for structural inadequacies in hydrologic models, thereby improving streamflow prediction and therefore the quality of parameter confidence intervals. The soil moisture data set can be used to help assess the performance of the code modifications by White et al. as well as the methodology of Yang et al. and others.

However, in order to efficiently use the soil moisture dataset of experimental watersheds, such as that of LREW, some modifications of the SWAT software are necessary, as discussed herein.

2. Methods and Data

2.1 Description of Watershed and Data

The 334 km^2 Little River Experimental Watershed (LREW) is in southwestern Georgia, U.S.A. It lies within the Coastal Plain physiographic region, which is characterized by broad, flat surfaces that dip gently seaward (Shirmohammadi, 1987). Stream channel slopes within the watershed vary from 0.1% to 0.4% (Bosch, 2007). SSURGO data for sub-watershed I of the LREW (LREWswI) show a soil profile having 1 m to 2.5 m of mostly sand. At the bottom of the profile is a clay layer, samples of which reveal a maximum transmission rate of approximately 0.1 mm per day (Rawls and Asmussen, 1973). This clay layer is believed to act as an aquiclude for the entire watershed, preventing seepage loss (Bosch et al., 1996). Figure 1 shows the SSURGO soil data for LREWswI, which is approximately 50 km^2 at the upstream end of the watershed and is the focus of this study.

Although there are several experimental watersheds in the U.S. and elsewhere that have extensive soil moisture measurements, LREWswI was selected because its shallow underlying impermeable layer reduces uncertainty in balancing the water budget and in some of the SWAT model parameters. It was also chosen because of its similarity to an ungauged watershed of interest to the authors.

A variety of parameters were obtained from ftp://www.tiftonars.org, which is maintained by the Southeast Watershed Research Laboratory (SEWRL) of the United States Department of Agriculture's Agricultural Research Service. Information drawn from this website included daily precipitation records from 15 evenly distributed, continuous rain gauges within LREWswI, daily streamflow records, and 30-minute soil moisture data at five sites each with probes at depths of 50 mm, 200 mm, and 300 mm as well as numerous shape files and a land use classification raster. SSURGO data and the 10m DEM were obtained through the NRCS website at http://datagateway.nrcs.usda.gov. The University of Georgia's Coastal Plain Experimental Station, located approximately 20 km southeast of the LREWswI outlet, provided daily temperature, humidity, wind and solar radiation data. The locations of the soil moisture probe sites are shown in Figure 1, and the land use, soil and slope classes for each of the sites are shown in Table 1. The subbasin numbers are those of the automatic delineation executed by the SWAT model.

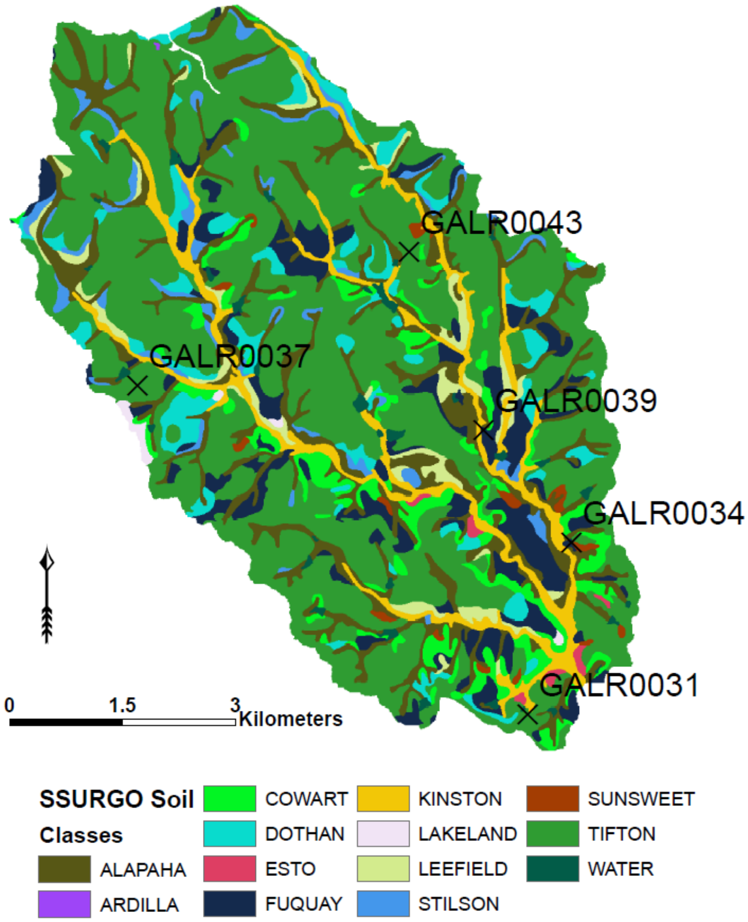

Figure 1. *Soil moisture sites and SSURGO soil classes for sub-watershed I of the Little River Experimental Watershed*

Table 1. *Land use, soil and slope categories for each of the five soil moisture measurement sites of LREW sub-watershed I*

Soil Moisture Site	Subbasin	Land Use	Soil	Slope
GALR0031	23	Corn silage	Tifton	1% - 3%
GALR0034	21	Corn silage	Fuquay	> 3%
GALR0037	7	Spring barley	Tifton	1% - 3%
GALR0039	13	Eastern gamagrass	Fuquay	1% - 3%
GALR0043	3	Summer pasture	Tifton	> 3%

2.2 Beginnings of the Development of the SWAT Model

While the full development of a SWAT model for LREWswI is to be achieved at a future date, the early steps and related considerations are as follows.

2.2.1 Watershed Delineation

Under the "Watershed Delineation" tab of ArcSWAT, the automatic watershed delineation options were employed, and the 25 subbasins generated were accepted. Slight adjustments were then made to account for the presence of highways and a particularly flat area where the automatic delineation process did not successfully match the boundary location identified by Agricultural Research Service.

Alternatively, a finer division of more numerous subbasins may be worthwhile. In particular, as seepage from lateral flow and/or a surficial aquifer is a dominant contributor to streamflow, it may be worthwhile to select the minimum subbasin size such that all streams witnessed in the field appear as reaches in the SWAT model. In this way, the length of the path of lateral flow and surficial aquifer flow will be more accurately represented. The identification of such stream locations is to be verified and the SWAT watershed delineation adjusted as necessary.

2.2.2 Calibration and Validation Years

As of this writing, sub-daily streamflow values are yet weeks away from being available in a usable form. Therefore, although sub-daily data are available for precipitation and other weather parameters, only daily data were used for the SWAT model. The years 2001-2003 were fairly dry. Therefore, 2000 and 2001 were selected as warm up years, while calibration and daily output were limited to the years 2002-2004. The years 2005 and 2006, the latest years for which the full set of data are available, and 2007, as it becomes available, will be used for validation.

2.2.3 Acquiring Soil Moisture Output and Defining Soil Layers

SWAT allows for defining up to ten soil layers, and the average soil moisture for each layer of each HRU may be calculated and printed to an output file on an hourly, daily or monthly basis. The SSURGO data typically indicated three to five soil layers. The soil moisture probes are at depths of 50 mm, 200 mm and 300 mm and lie within the first one or two SSURGO-defined soil layers at each of the five soil moisture measurement sites in LREWwsI. The SSURGO-defined layers were divided more finely (Narasimham, 2009) so that each sensor lies within a relatively thin soil layer. Deeper layers were also divided more finely (though to a lesser extent) to improve accuracy. For example, for the Fuquay soil, SSURGO identifies the uppermost layer to a depth of 305 mm, the second to a depth of 1524 mm and a third to a depth of 1829 mm. These three soil layers, each with their own unique set of properties, were further divided to be a total of ten layers, having bottoms at depths of 20, 40, 60, 100, 150, 250, 305, 700, 1524 and 1829 mm. The first seven layers maintained properties identical to those of the SSURGO-defined first layer, and the eighth and ninth layers maintained properties identical to those of the SSURGO-defined second layer. The SWAT model was run to observe how SWAT output might be affected by the layer refinement and to measure the increase in simulation run time due to calculations at additional layers.

Presently, SWAT provides an “all or none” option for soil moisture output. The soil moisture is printed into an output file for all soil layers and HRUs or for none. The resulting soil moisture output file size was noted.

2.2.4 Defining HRUs for Model Performance and Conveniently Short Simulation Times

The first step in obtaining soil moisture output from SWAT is to properly define the HRUs in the “HRU Definition” dialogue box. Land use thresholds must be set low enough to include the land uses in all soil moisture probe subbasin locations, as listed in Table 1. Alternatively, if the land use threshold must be made undesirably low to include all land uses at the soil moisture sites, land use exemptions may be made. Thresholds must also be selected for soil and slope, and exemptions cannot be made for these. Lowering thresholds and including land use exemptions to provide HRUs that match the soil moisture sites may substantially increase the number of HRUs and simulation run times while doing essentially nothing to improve model performance. Therefore, the increase in the number of HRUs beyond what would otherwise be used was determined, and the change in model run time and performance was noted. The computer used has an AMD Athlon™ 64 Procecessor 3400+, 2.40 GHz, with 448 MB of RAM.

Without consideration of the soil moisture sites, thresholds for soil were generally set twice as high as those for land use because of the lower number of soil categories, and because the soil categories tended to be sandy with similar properties. Also, the slope threshold was in all cases set at 0% because the slopes were categorized into only three broad categories for this relatively flat area - 0%-1%, 1%-3% and >3%.

As previously discussed, model performance is ideally to be assessed not only on how well the model predicts streamflow, but also in regard to the reliability of the calibrated parameters for predicting other quantities that may be of more immediate concern than streamflow. Therefore, it is important to assess how the aggregation of spatially distributed data into relatively few HRUs may lead to parameters becoming distorted in the calibration process. This assessment is best made by comparing streamflow simulations for various numbers of HRUs prior to attempting any calibration. In particular, we began with all threshold settings at 0% to provide the minimum amount of aggregation possible for the particular arrangement and number of subbasins of the delineated watershed. For the SWAT-delineated LREWswI with 25 subbasins, the resulting number of HRUs is 10,732. This is considered the maximum or reference number of HRUs. Simulated streamflow is then generated. The process is repeated for various other threshold settings corresponding to lower numbers of HRUs. Simulated streamflows are compared with those of the reference number of HRUs. Visual comparisons are helpful. To provide a statistical basis of comparison, R^2 and the Nash-Sutcliffe Efficiency (NSE) may be calculated for each threshold setting relative to the reference setting. In all cases, the ten soil layers, the default parameter values and the Plant ET option were used. The simulation time for each threshold setting was also noted.

3. Results and Discussion

Results from the methodology described in 2.2.4 are shown in Table 2. The percentages in parenthesis refer to the land use and soil thresholds, respectively. Only in the case with 577 HRUs were land exemptions made which included all four of the land use categories that lie within the five soil moisture sites. The difference between using 10,732 HRUs and as few as 102 HRUs is not substantial, as evidenced by the NSE value of 0.9954. Also, the simulation run time of 102 HRUs is kept conveniently small at 0.33 minutes. However, to provide HRUs that match the sites of the soil moisture probes, the four land use categories of the soil moisture sites must be exempt because their percent areas in the subbasins of concern fall well below the specified thresholds. It was found that lowering the threshold to include all four land uses without exemptions would create over a thousand HRUs, an undesirable alternative. Once the land use exemptions were made for the 15%-30% threshold combination, it was noticed that site GALR0039 still did not have a matching HRU because the Fuquay soil class fell well below the 30% threshold in subbasin 13. As there is no way to exempt soil classes, the threshold had to be lowered from 30% to 14%. The land use exemptions and the lowering of the soil threshold increased the total number of HRUs from 102 to 577 and the simulation run times from 0.33 min to 1.8 minutes, respectively. This latter run time exceeds the former by a factor of about five and severely jeopardizes the feasibility of performing MCMC or other parameter calibration and uncertainty analyses which may require tens of thousands of runs. Although it was not possible for the author to calculate the NSE for this case (due to encountering an error when running land use exemption scenarios in the recently released ArcSWAT 2.3.3), the runtime of 1.8 minutes is from approximately the same number of HRUs acquired strictly by reducing thresholds.

Table 2. *Changes in model streamflow simulation and run times due to changes in the HRU definition*

	25 HRUs	102 HRUs (15%, 30%)	182 HRUs (10%,18%)	577 HRUs (15%,14 %, exemptions)	10,732 HRUs (0%,0%)
Simulation Time (min)	0.11	0.33	0.58	1.8	45
R-squared	0.7693	0.9991	0.9996	-----	unity
NSE	0.5075	0.9954	0.9975	-----	unity

One should be cautious in assuming that very high NSE values, say above 0.9900, are adequate for selection of the proper number of HRUs. Differences between the simulation at 102 HRUs and 10,732 HRUs are not substantial but are noticeable. Whether they are unimportant is left to the modeler's discretion. If an increase in the number of HRUs is desired to reduce discrepancies, the improvement made by lowering the thresholds will be much more dramatic than adding exemptions, which occupy relatively small areas. For example, one notices that simply lowering the land use and soil thresholds to 10% and 18%, a combination used in a previous study of a sub-watershed within LREWswI (Bosch et al*.,* 2004), would bring the NSE approximately halfway from 0.9954 to unity while adding only about 15 seconds to the simulation run time for the computer used in this study.

It is also important to modify code such that the SWAT soil moisture output will be limited to the HRUs of concern. Otherwise, when daily output is selected as the time scale, the result is a text data file with millions of calculated values or tens of millions if an hourly scale is selected. Dealing with such voluminous data sets for various scenarios quickly becomes a wearisome process.

When the three to five soil layers were restored in the case of 102 HRUs, simulation time decreased from 0.33 minutes to 0.30 minutes. This 10% difference may be of a concern to some users. A comparison was made between the two results by treating the ten-layer scenario as the observed data. The resulting NSE was 0.9946. Once again, it should be noted that in the context of comparing various levels of aggregation against some reference level of refinement, even NSE values clearly above 0.9900 might not be satisfactory to the SWAT user. The simulated streamflow records for these uncalibrated models should be compared. For this case in particular, it was noticed that a section of the simulated values in October and November of 2002, those ranging from 0.3 mm to 15 mm, contained some differences in streamflow values that were quite noticeable, with the differences ranging from 1 mm to 3 mm. However, this was clearly the time of greatest discrepancy over the three-year period.

Default parameter values were used in all of the above comparisons. The performance of aggregate numbers of HRUs relative to a reference number (such as 10,732) may vary depending on the parameter values. Thus, after choosing an efficient number of HRUs to begin the calibration process and after calibrating the model, it may be worthwhile to compare the simulated output at the chosen number of HRUs to that of the reference number using the calibrated parameters. If the difference is still small, one may be fairly confident that the reduction in HRUs from that of the reference number caused very little additional parameter distortion than would have occurred had the model been run at the reference number of HRUs.

This method of selecting optimal thresholds offers advantages over selecting optimal thresholds based on calibration runs. Calibration processes tend to reduce the effect of aggregation, as seen in the resulting differences in simulated streamflow. This happens because streamflow is coerced into matching the observed data perhaps by distorting parameters rather than properly adjusting them. Also, this method only allows for comparison against the maximum possible number of HRUs, which is not practical during calibration due to lengthy simulation times.

4. Conclusion

Even methods for calibrating hydrologic models that provide parameter confidence intervals of good quality must ultimately be tested against field data. Minor modifications to the SWAT code that allow the user to more precisely define HRU exemptions and the printout of soil moisture calculations will be a positive step toward such testing.

Dividing soil layers into thinner layers may improve model performance (which is to be evaluated not only by streamflow prediction, but by the quality of the parameter confidence intervals as well) without a substantial increase in simulation time.

Comparing simulated streamflows for various HRU-defining threshold levels of aggregation against a reference level is a quick and effective method of dramatically reducing simulation times without significantly degrading the quality of parameter confidence intervals.

Acknowledgements
The authors would like to thank Dr. David Bosch of SEWRL and Dr. Gerrit Hoogenboom of the University of Georgia for their generous assistance in providing data.

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Implementation Issues for the SWAT Model in Urban Areas

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Abstract

Modeling of creek systems in the Austin, Texas area using the Soil and Water Assessment Tool (ArcSWAT) is being done to assess the impacts of urban development scenarios and the benefits of Best Management Practices (BMPs). Extensive data available in the Austin area was provided as model input for this urban area. During the process of calibration, physical systems and characteristics of urban areas were identified that could not be directly represented by current SWAT input parameters. These urban characteristics include: 1) stormwater systems that route water contrary to topographic delineations, 2) the physical characteristics of conveyance systems, such as shape and constrictions of pipes or culverts that allow no local floodplain overflow, 3) configurations of flood and water quality control ponds, 4) subsurface inputs from leaking infrastructure, 5) urban vegetation options and 6) extremely rapid runoff and response. Some problems have been addressed by preparing model input with equivalent characteristics, such as burning in channels where storm sewers exist and modifying channel dimensions to provide the same flow capacity. Finding a function like reverse shallow water pumping may be sufficient to simulate an urban input such as leaking infrastructure. To address some concerns, the City of Austin is working with Texas AgriLife Extension Service personnel who are developing model capabilities to include further BMP modeling capabilities and a smaller time step. However some issues, such as large diversion channels, have not yet been successfully addressed.

Keywords: urban, time step, infrastructure, vegetation, Austin

1. Introduction

The Soil and Water Assessment Tool (SWAT) is being used to model creek systems in the Austin, Texas area in order to assess the impacts of urban development scenarios and the benefits of Best Management Practices (BMPs). ArcSWAT (SWAT developed with an ArcGIS interface) allows the user to easily import many layers of geographic data and simulate undeveloped lands and various management scenarios. The intent of the model exercises is to quantify and interpret the effects of urbanization as well as various stormwater runoff control measures on both hydrology and water quality. The City of Austin (COA) has a large extent of nonurban areas both within its extra-territorial jurisdiction (ETJ) and outside.
These are situated at the headwaters of large creek systems from which runoff flows inward towards the city center and into Lady Bird Lake. This lake is a segment of the Colorado River, which flows through downtown Austin. Therefore, the City's master planning process strives to look at both the benefits that can be achieved by addressing current problems, primarily in the highly developed urban watersheds, and the potential problems that may develop as growth continues outward into the City's watersheds and outlying suburban areas and bedroom communities. The land management and nonurban capabilities of the SWAT model are appropriate for the highly divergent mix of urban and nonurban land within the area. However, this study also highlights urban characteristics that are difficult to model.

During the calibration process for urban watersheds, physical systems and characteristics of urban areas were identified that could not be directly represented by current SWAT input parameters. These urban issues include:

- stormwater routing and physical characteristics of those systems, such as pipes,
- characteristics of constructed features such as water quality treatment ponds and leaking water lines,
- characteristics of pervious, urban areas and their associated vegetation and management, and
- characteristic rapid response of runoff.

As each issue is discussed below, a description will be provided of the equivalent model input that was used to simulate the condition. Altered and additional functions that have been addressed in cooperation with Texas AgriLife Extension Service and Texas A&M and issues to be addressed in the future (Glick, 2009) are also discussed.

SWAT has extensive input parameters. These include the ability to import large quantities of geographic data and extremely detailed elevation data. The user can also alter soil properties down to the subbasin or hydraulic response unit (HRUs) level, yet there are some physical attributes where the input is more limited. The limitations can sometimes be overcome, but sometimes they must be recognized and planned for accordingly.

2. Urban Stormwater Routing

In urban areas, stormwater systems frequently route water contrary to topographic delineations. An example of this is storm sewers that route water that would normally fall in a different creek watershed to another. Figure 1a shows an example of this type of situation with a delineated watershed and extended boundary due to underground routing. One solution is to burn in creeks with added storm sewers that reroute significant portions of water as shown in Figure 1b.

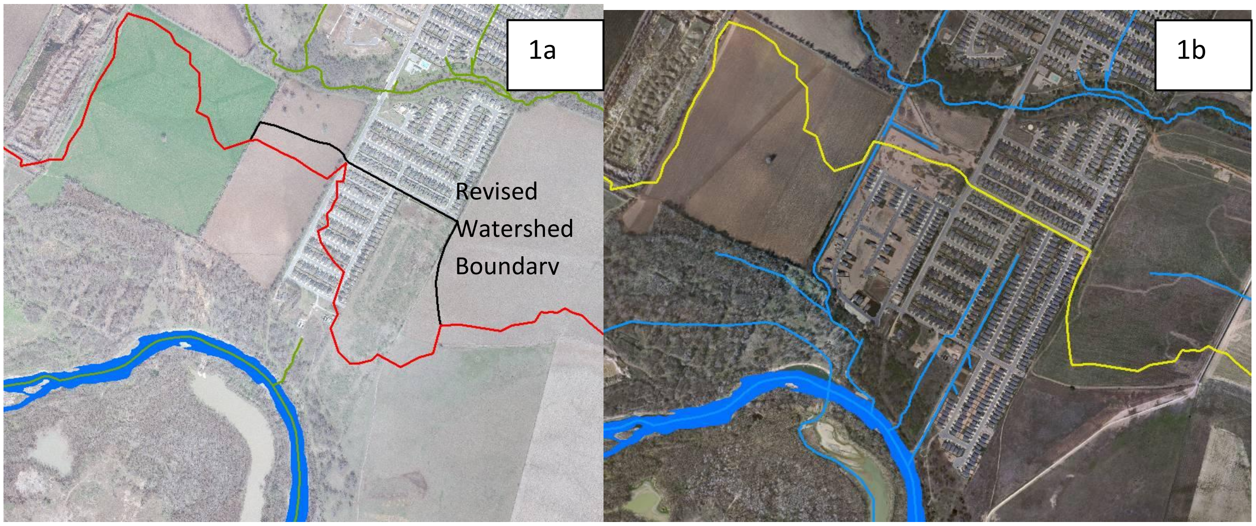

Figure 1. *Watershed boundaries redefined by stormwater systems*

Simulation of other routing patterns may not have a solution. Creeks in highly populated urban areas may have a bypass, tunnel or other overflow system that provides an additional alternate route to move floodwaters around urbanized areas. An example in Austin is a bypass on East Bouldin Creek that diverts floodwaters to Lady Bird Lake during high flows, as shown in Figure 2. This bifurcation of streams can be important hydrologically and is not currently a possible stream network configuration in SWAT. Important environmental impacts may need to be assessed before construction of flood diversions. For example, a tunnel that is nearly a mile long and approximately seven meters in diameter is planned to reduce the size of the 100-year floodplain of the lower Waller Creek watershed by an estimated 11 hectares. This will allow denser development and redevelopment in a very desirable area of downtown Austin. The ability to assessing biological impacts by simulating flow effects from this diversion would be useful to the City.

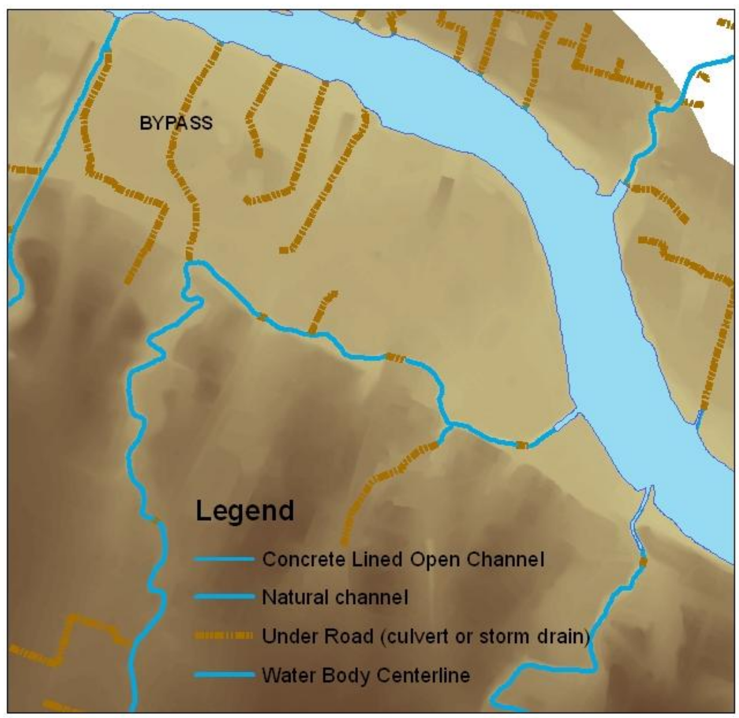

Figure 2. *East Bouldin Creek flood diversion*

3. Channel Dimensions and Floodplain Functions

Some physical characteristics of channels are not readily represented in SWAT, particularly with the default assumptions of trapezoidal channels. In SWAT, the assumed shape of a channel is a trapezoidal cross-section with a shallow, wide floodplain. The trapezoidal channel may work well in agricultural or undeveloped areas, but the default size and shape do not represent urban channels and storm sewers well nor do they reflect the function of urban high flow and flood conditions.

Not only are urban areas characterized by enlarged channels with steep side slopes, but underground pipe systems need to be included because they change both the direction and the characteristics of the flow. In particular, and perhaps most significantly, pipes cause constrictions in flow and lack a floodplain.

One solution that will allow for more accuracy in the flow volumes is to analyze cross-section data, usually available in flood models, and simulate an equivalent cross-sectional area. Although this solution may not address the erosion component or the issue of constrained flow in pipes, it will carry an equivalent flow rate before overflow is enacted. Because urban channels are enlarged, the occurrence of flood flows is infrequent. This may be due to the fact that the model will not simulate large peak flows well because they do not reflect channel and pipe constraints.

4. Urban Impoundment Structures: Flood and Water Quality Ponds

SWAT currently provides two options for impounding water: ponds (including wetlands, depressions, etc.) and reservoirs. The City of Austin requires a multitude of constructed flood, erosion and water quality control ponds, the benefits of which are of great interest. Alterations in regulatory requirements or design criteria may need to be evaluated to maximize these benefits. Although reservoirs may simulate flood storage ponds (with no permanent storage), the pond function does not address water quality design options. For example, Austin reservoirs are designed primarily to prevent sedimentation and encourage filtration. The function of these ponds is primarily to accept and treat the first flush of runoff, while bypassing higher flows. The captured water is filtered and released through a subdrain. Since the capture is based on flow rather than area, the current SWAT options do not address the treatment functions well. To address this concern, the City has contracted with Texas AgriLife to provide four pond functions for the primary types of water quality and small flood structures seen in the Austin area.

5. Leaking Infrastructure as a Water Source

The City has used SWAT to add sources and losses of water in modeled urban watersheds as well as movement between soil layers and the deep aquifer. Pumping from the shallow or deep aquifer and irrigation operations used for maintenance of lawn areas can be incorporated into the model. In addition, point source inputs are allowed. However, in the Austin area, trickling baseflow, sometimes from a localized area, provides evidence of more widespread inputs in the form of leaking infrastructure. Studies from 2007 in the Austin area (City of Austin, 2009) and other Texas cities (Alan Plummer Associates, 2007) show that reporting utilities in Texas experienced a total water loss of up to 12.3 percent or 57,260 cubic meters $x10^4$ per year from reported and unreported losses from the distribution system. Over a service area of 139,340 hectares, that volume constitutes a noticeable amount of water.

An attempt was made to simulate this water source by using the shallow water aquifer pumping ability in SWAT. Theoretically, a negative pumping rate would introduce water to the shallow aquifer to simulate leaking water lines. A loss rate in residential areas was estimated based on usage rates. Initially the model would not accept negative values, but upon the request of the City, Texas AgriLife modified the acceptable ranges to take negative values. The function for accepting relatively low flow rates is still being revised because formatting of the parameter was planned for pumping rates, and fractions below 0.1 are not written to text files. If this capability should continue to be developed, it may be sufficient to simulate urban infrastructure inputs.

6. Vegetation

SWAT has a comprehensive database of crops and land covers including Rangeland – Brush, Bermuda grass and multiple other vegetation types that are typical of the Austin area. It also includes the capability to change the parameters for each vegetation type. The limitation found within the Austin area is that pervious areas classified as urban are automatically assigned to have Bermuda grass as the vegetation. An aerial view of the central Austin neighborhoods, Figure 3, demonstrates that perhaps the leaf area index for Bermuda grass is not representative of the large expanse of tree canopy cover that can be seen below. There are some ways to work around this, notably copying the Bermuda vegetation (e.g., Bermuda1) as an alternate crop and providing the desired vegetation in the named vegetation field for Bermuda. Thus, one set of desired vegetation parameters can be provided for pervious urban areas. However, this creates an inability to provide multiple vegetation choices or multiple management parameters for urban pervious areas. Real conditions include poorly maintained Bermuda lawns, while others have highly maintained St. Augustine lawns with extensive tree canopy. On large lots in the hilly suburbs, vegetative cover frequently consists of cedar, brush and native landscaping on rocky soils. Examining the impacts of management options, such as the conversion of lawns to native landscaping, would require some of the same vegetation and management options for urban pervious areas as are available for crop areas.

Figure 3. *Typical Central Austin Vegetation – aerial 2006*

7. Rapid Response in High Impervious Cover Areas

The land uses in Austin, like any urban area, are characterized by increased impervious cover. This, combined with hilly terrain and intense, short-duration rainfall patterns, results in rapid runoff response to rainfall that requires a shorter time-step to accurately model. The most common version of SWAT currently allows the use of sub-daily rainfall if Green-Ampt routing is selected, but the output and routing are simulated on a daily basis. COA has contracted with Texas AgriLife to modify the SWAT code in order to simulate most processes on a 15-minute time step. Careful consideration of available rainfall data is required if the model is to be operated using the Green-Ampt option. This option simulates runoff based on rainfall exceeding infiltration. If the intensity of the rainfall data at a given time-step does not reflect the actual intensity of the event, the simulated runoff will be lower that the observed runoff. For example, a 10-minute rainfall event with an intensity of 75 mm/hr would be simulated as 12.5 mm/hr if hourly rainfall is used and produce little or no runoff.

Even an hourly time step is sometimes insufficient to characterize the response when an hourly rainfall can be up to 250-500 mm, the type of rain causing flash floods. To evaluate the response of the surface soils to high intensity rainfall, a smaller time-step is needed because those effects are rapidly transmitted downstream in a highly urbanized area. Austin has a very 'flashy' rainfall/runoff pattern, and frequently the peaks can be missed completely because the real storm was split over a time period not well simulated by the model. The response of water quality ponds which capture first flush phenomena cannot be adequately modeled with a large time step.

8. Conclusions

The ArcSWAT model has extensive capabilities for modeling upland processes and a multitude of vegetative and management combinations, making it an ideal model for evaluating changes from nonurban to urban conditions and evaluating management options. However, its basis in agricultural simulation and management becomes apparent when applying it in an area with intense urban development with extensive and specific available data. As with all models, not all physical characteristics and configurations can be input specifically and must be simulated with an equivalent description. In some cases, SWAT has the capability of simulating an equivalent system. Other urban systems are not as well represented. Developments being made by Texas AgriLife include 1) a 15-minute time-step, 2) four additional impoundment options, and 3) the ability to input a distributed water source into the shallow aquifer. These capabilities will assist greatly in both the simulation capability of the model in urban areas and the evaluation of management strategies for controlling urban flows and improving water quality.

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Predicting Aquatic Life Potential under Various Development Scenarios in Urban Streams using SWAT

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Abstract

We applied SWAT to evaluate the impacts of different development conditions on the health of a stream's aquatic life in a watershed in the Austin, Texas area. The Walnut Creek watershed was simulated by employing land use maps developed in 2003 and weather data from 2002-2003. The model calibrated well with a Nash-Sutcliffe ratio of 0.872. The model was adequately validated using an estimated land use map based on aerial photographs from 1964 and weather from 1964-1970. A third SWAT model was developed using a projected build-out land use map. The three models were run using weather data from 2002-2004, resulting in simulations of streams under different levels of development. The built-out watershed had higher peaks and less baseflow compared to the less developed watersheds. Hydrologic metrics for each development condition were computed at eleven locations in the watershed. The hydrologic metrics correctly reflected changes in development with decreased baseflow, more dry periods, more total dry time and more variable flow in general. These metrics were used to compute an aquatic life potential (AQP) for each condition at all eleven locations. The AQP indicated decreases in aquatic health that varied with development conditions and by location in the watershed. This tool may be used to help planners and regulators evaluate decisions before they are implemented rather than waiting for a decline in aquatic health to evaluate.

Keywords: SWAT, aquatic life, modeling, urban, land use

1. Introduction

Changes in land use associated with urbanization of previously undeveloped areas can have a significant impact on the hydrologic regime and aquatic health of a stream. The most readily observable impacts, flooding and erosion, are often associated with changes in the hydrologic regime. Modeling has been used for many years to evaluate and mitigate these impacts. However, degradation of aquatic health has usually been associated with increases in nonpoint source pollution. Scoggins (2000) proposed that changes in hydrology, rather than nonpoint source pollution, may control aquatic health in some areas. If this is the case, continuous hydrologic simulation may be used to predict the impacts of different development scenarios on aquatic life.

The Watershed Protection and Development Review Department (WPDR) of the City of Austin, Texas (COA) is tasked with, among other things, protecting the aquatic resources in the Austin area, including aquatic life resources. This is normally accomplished in two ways: first, by installing water quality controls in already-developed areas and second, by implementing development regulations to minimize the impacts of any new development. There is ongoing monitoring of the impacts on aquatic health, yet this strategy is flawed because once degradation in aquatic health is detected, it is often irreversible.

Roesner and Rohrer (2006) proposed a protocol based on changes in hydrology to help designers and planners consider aquatic health when designing new developments. Their relationship between aquatic health and hydrologic metrics was based on data collected by Booth et al. (2001, 2004) in the Seattle area. Because these relationships were developed for perennial streams and not the intermittent streams found in semi-arid areas like Austin, WPDR examined twenty years of USGS streamflow data and 10 years of COA aquatic health information to develop a relationship to estimate aquatic life potential (AQP, scale 0-100) based on hydrologic metrics (Glick et al*.,* 2009). Majid (2007) demonstrated that the Soil and Water Assessment Tool (SWAT) (Neitsch et al*.,* 2005) could be used to simulate different types of urban development. Combining these two studies could result in a framework to evaluate different development scenarios with respect to the aquatic health of a stream instead of the chemical and physical properties as has been done in the past. This paper reports the results of a test case of this paradigm in the Austin area.

2. Methods

Walnut Creek is a 145.8 km watershed stretching from northwest Austin through the central part of the city and emptying into the Colorado River to the east of Austin (see Figure 1). US Geological Survey (USGS) and COA have operated a flow-gauging station in the lower portion of this watershed since 1966. COA has been collecting aquatic life data at eleven locations in this watershed since 1993. The COA Flood Early Warning System (FEWS) has been collecting 1-mm event rainfall at approximately 90 rain gauges in the Austin area (including 18 in the Walnut Creek watershed) since 1987. In 1964 the watershed was approximately 21% developed. By 2003 it was 71% developed and is expected to be fully developed (10% open space) by 2040. These factors combine to make it a good test case for predicting AQP under different development scenarios.

A SWAT model for the Walnut Creek watershed was developed and calibrated using a 3.048-m (10-ft) digital elevation map (DEM) generated from LIDAR data collected by COA in 2003, SURRGO soils data, land use maps developed by WPDR based on zoning and 2003 aerial photography, FEWS rainfall data and temperature data from the National Weather Service (NWS) station at Austin, Texas (Camp Mabry). This model was run for five years, 2000-2004, with the first two years as a warm-up period and omitted from further analyses.

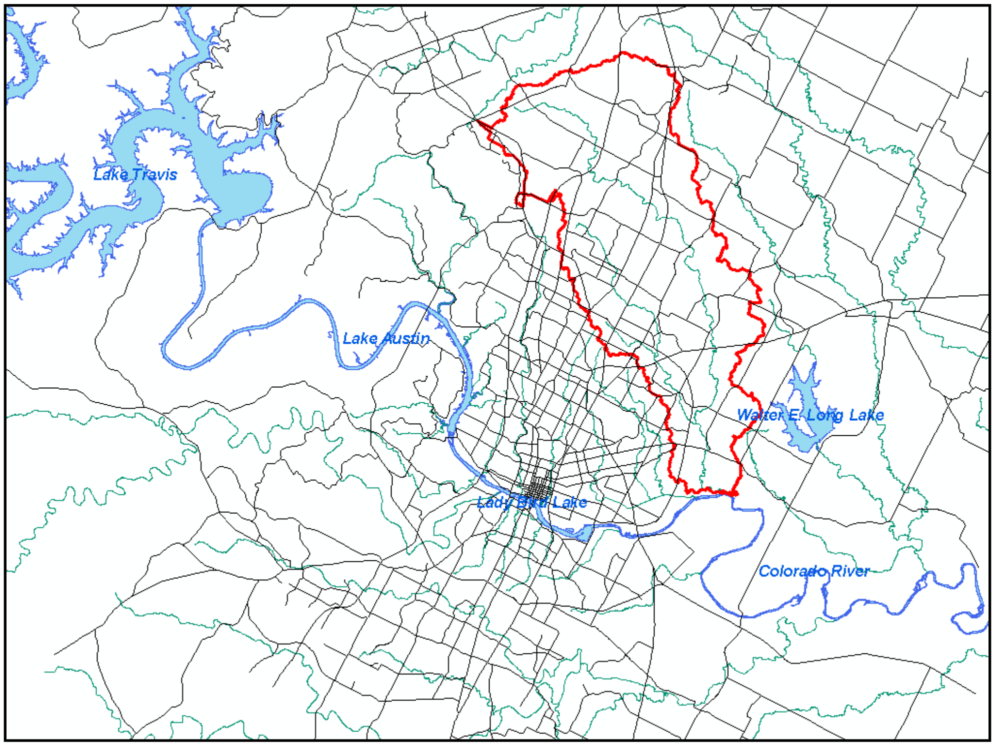

Figure 1. *Walnut Creek watershed study located in Austin, Texas*

Once the model was calibrated for 2003 land use, a second SWAT model was developed using the same calibration factors and data with the exception of the land use coverage and weather data. WPDR staff used the 2003 land use and historical impervious cover maps to characterize historical land use in the study area. The historical impervious cover map was developed using 2003 planimetric maps and 1964 aerial photographs. Land parcels with impervious cover identified in the aerial photographs of 1964 were assumed to have their 2003 land use, and areas without impervious cover were assumed to be undeveloped (pasture). The land use maps for 2003, 1964 and 2040 are presented in Figure 2. NWS rainfall and temperature data from Austin, Texas (Mueller Airport) were used because FEWS rainfall and the Camp Mabry weather station did not exist during the validation period. This model was run for 9 years (1964-72) with the first three years used as a warm-up period and omitted from further analyses. This model was used to validate the calibration.

A third SWAT model was developed using the validated model parameters and other data except that land use coverage reflected full build-out of the watershed, expected to occur around 2040. WPDR staff compared 2003 land use, zoned use and future use to determine study area build-out. The purpose was to identify which one had the highest development potential and assign a future use based on that potential. Undeveloped areas not covered by a zoned or future land use were randomly assigned a future use. All three models were then run using FEWS rainfall and temperature data from the National Weather Service (NWS) station at Austin, Texas (Camp Mabry) for five years (2000-2004), with the first two years as a warm-up period that was omitted from further analyses.

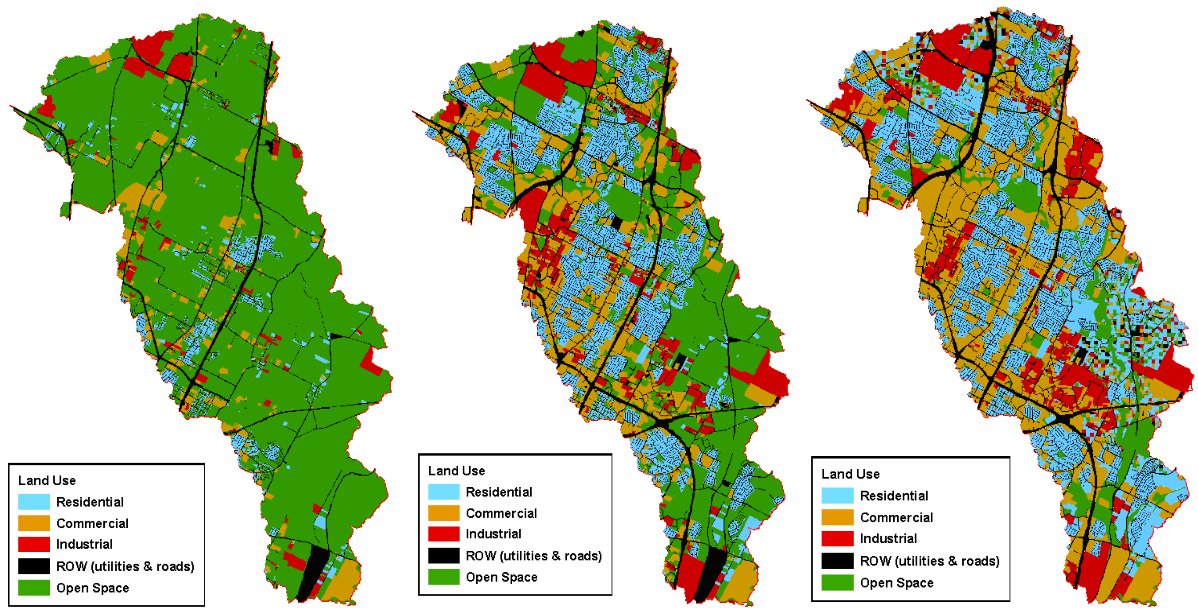

Figure 2. *Land use assumptions for Walnut Creek watershed: land use for 1964 is on the left, 2003 in the center and 2040 (full build-out) is on the right.*

Five hydrologic metrics were computed: 1-pass baseflow fraction (BF1), the fraction of time that flow was less than 0.003 cms (T_{dry}), the average number of dry periods per year (F_{Ln}), the 90th percentile flow rate (Q_{90}) and the fraction of time flow exceeds the mean flow rate (T_{Qmean}). These factors, either individually or in combination, have been suggested as possible indicators of aquatic health in streams. The AQP was then computed at eleven locations in the Walnut Creek watershed based on the 1964, 2003 and 2040 land use conditions.

3. Results and Discussion

Automatic watershed delineation was used with a 25 ha threshold resulting in 298 sub-basins. The automatic delineation did not follow known watershed boundaries in all cases, primarily due to underground storm sewers changing flow direction, but this was negligible. Three slope categories were used: 0-1, 1-5 and >5%. Minimum HRU thresholds were set at 5% for all soils, slopes and land uses except residential areas. These were exempt from the threshold limits, resulting in approximately 4500 HRUs. The channel dimensions were adjusted using DEM data to reflect the wider and deeper channels found in urban areas. Other calibration factors included lowering the curve numbers by 3, setting alpha baseflow to 0.03, raising groundwater delay to 60, lowing ESCO to 0.85, lowering SURLAG to 2 and increasing available water capacity by 3%. Management options included grazing on agricultural land, lawn maintenance (irrigation, fertilization and frequent mowing) in residential and commercial areas and biannual mowing on other urban land uses (see Figure 2 for the 2003, 1964 and 2040 land use maps).

The resulting model predictions compared well to the observed flow (see Figure 3) but there were some shortcomings. The Nash-Sutcliffe (Nash and Sutcliffe, 1970) ratio for the model is 0.872, but the model under predicts total flow by 12%. It appears that the model predicts peaks well but does not predict low-flow conditions well, especially during dry conditions. This may be due to small leaks in water and wastewater distribution and collection systems entering the larger system. Research in the Austin area has indicated that the majority of low flow in some creeks is from non-natural sources. Providing the ability to add water to the system to represent these leaks may help in calibrating low flows in urban areas.

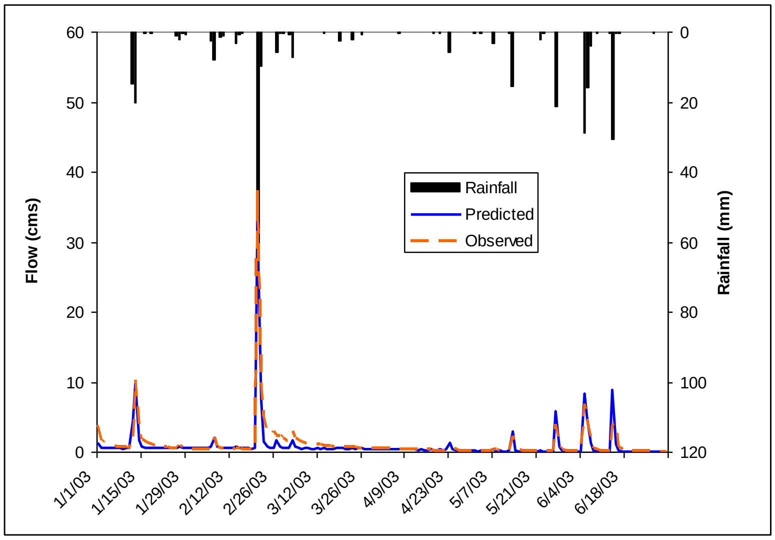

Figure 3. *Calibration run 2002-2004 predicted and observed flows in Walnut Creek watershed (Austin, Texas), N-S = 0.872*

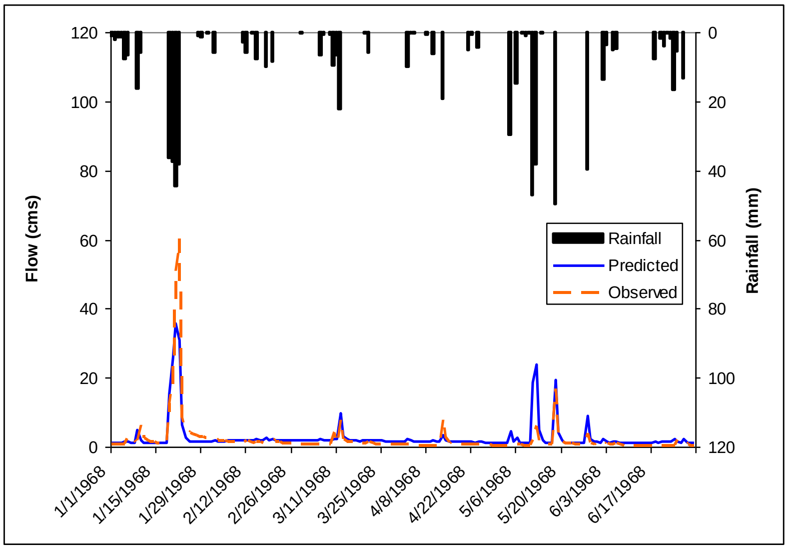

Figure 4. *Validation run 1967-1970 predicted and observed flows in Walnut Creek watershed (Austin, Texas), N-S = 0.437.*

The validation model that used the 1964 land use data did not perform as well as the calibration model, but it is acceptable (Figure 4). The Nash-Sutcliffe ratio was 0.437. The model under predicted peaks and over predicted low flow and total water yielded. These discrepancies may be due to several factors, primarily land use assumptions. The land use was based on aerial photography taken in 1964 when there was little development in the watershed, but the calibration period was three to six years later. Development during the intervening period could explain some of the difference. Using a single rain gauge outside of the watershed and assumptions on agricultural practices during this period could also explain some of the differences.

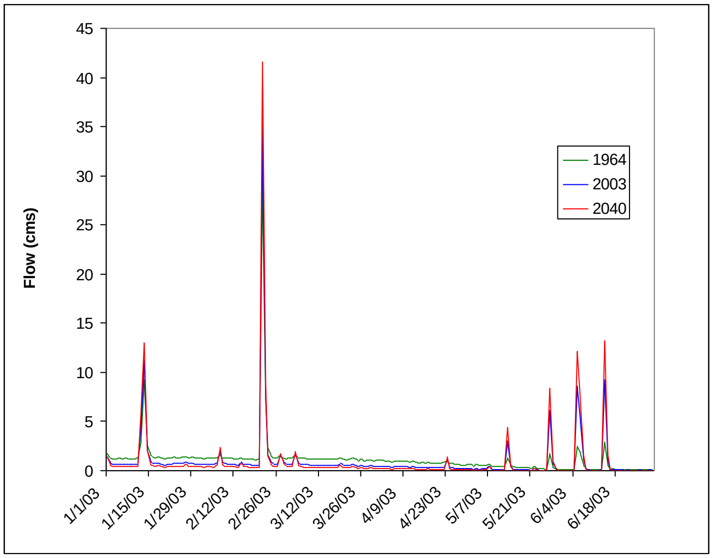

Figure 5. *SWAT simulated flows in Walnut Creek watershed (Austin, Texas) using land use data from 1964, 2003 and 2040 and weather data from 2002-2004*

The model runs that employed the three different years of land uses produced expected results (Figure 5) with the less-developed watershed exhibiting lower peaks and more baseflow than the partially developed and fully developed watersheds. This can also be seen in changes to the hydrologic metrics (Table 1). In general, as development increases the fraction of flow that is baseflow decreases, the 90^{th} percentile flow rate increases and the amount of time that the flow exceeds the mean flow rate increases, indicating a more “flashy” stream. These factors are important to aquatic health because highly variable flow may disturb habitat. The fraction of time the creek is dry increases and the number of dry periods also increase with increased development. This are important for two reasons: first, if there is no flow the aquatic life cannot survive and second, if there are numerous wet-dry cycles (as opposed to seasonal wet-dry cycles) the biota may not be able to establish and complete a life cycle before the flow stops. It should be noted that these two metrics T_{dry} and $F_{Ln}$where not modeled well. During the calibration period the T_{dry} and F_{Ln} were zero.

WPDR has been collecting aquatic life scores as part of their Environmental Integrity Index (EII) since 1996 (COA2008). Glick et al. (2009) proposed predicting the potential for aquatic life (AQP) as a function of either F_{Ln} and Q_{90} or BF1 and T_{dry} after relating measured aquatic life scores to various hydrologic metrics. Due to the shortcomings of the current SWAT model in predicting dry periods, AQP was predicted using the following relationship (Table 2):

$$AQP = 72.883 – 27.651\ T_{dry} + 27.359\ BF1$$

The Little Walnut and Buttermilk branches of Walnut Creek, at the southwestern part of the watershed, were the first portions of the watershed to develop. The flows from the SWAT model at the six monitoring sites in these braches indicate an average decrease of 12.3 points in AQP between 1964 and 2003. However, because these areas were virtually fully developed by 2003, the decrease in AQP between 2003 and 2040 was only 1.8.

In the main branch of the creek, the decreases between 1964 and 2003 were not as dramatic. Two factors could be influencing this. First, this portion of the watershed contains most of the remaining open spaces, and second, development regulation put in place in the 1980s may have mitigated some of the impacts. The average decrease in APQ was 7.3. The decrease in AQP between 2003 and fully developed is 4.4 on average to a maximum score of 73.3. While this is not as bad as AQP predicted and seen in L. Walnut and Buttermilk, it would still be impaired.

Table 1. *Hydrologic metrics for Walnut Creek watershed at eleven COA monitoring locations using SWAT simulated flow and land uses representing 1964, 2003 and 2040*

Sampling Location	BF1			T_{dry}			F_{Ln}			Q_{90}			T_{Qmean}		
	1964	2003	2040	1964	2003	2040	1964	2003	2040	1964	2003	2040	1964	2003	2040
Walnut 801	0.52	0.31	0.23	0.036	0.060	0.089	6.3	6.7	8.0	1.50	1.89	2.37	0.727	0.875	0.870
USGS 08158600	0.53	0.32	0.24	0.029	0.047	0.075	7.0	8.0	9.7	1.57	1.99	2.50	0.733	0.875	0.869
Walnut 803	0.55	0.33	0.16	0.448	0.547	0.753	15.3	23.7	30.0	0.02	0.01	0.02	0.669	0.869	0.879
Walnut 804	0.61	0.39	0.31	0.026	0.070	0.070	5.0	7.3	7.7	0.63	0.69	0.74	0.717	0.871	0.870
Walnut 805	0.60	0.34	0.27	0.043	0.094	0.127	5.3	8.0	11.3	0.13	0.15	0.17	0.727	0.875	0.873
Buttermilk 1601	0.39	0.19	0.16	0.319	0.552	0.637	20.3	26.0	29.7	0.04	0.06	0.07	0.822	0.879	0.878
Buttermilk 1602	0.36	0.19	0.17	0.400	0.609	0.690	21.7	27.3	29.3	0.03	0.04	0.05	0.878	0.878	0.878
Buttermilk 1603	0.42	0.20	0.18	0.456	0.758	0.779	19.0	29.7	29.7	0.02	0.03	0.03	0.838	0.875	0.878
L. Walnut 601	0.41	0.18	0.16	0.253	0.489	0.552	20.0	28.3	28.7	0.32	0.48	0.56	0.756	0.871	0.871
L. Walnut 603	0.29	0.15	0.15	0.769	0.847	0.835	28.0	27.3	27.7	0.01	0.01	0.01	0.881	0.866	0.868
L. Walnut 604	0.43	0.15	0.15	0.452	0.789	0.779	17.0	29.3	29.7	0.02	0.03	0.04	0.789	0.868	0.867

Table 2. *Aquatic life potential (AQP) for Walnut Creek watershed at eleven COA monitoring locations using SWAT simulated flow and land uses representing 1964, 2003 and 2040*

Sampling Location	Aquatic Life Potential		
	1964	2003	2040
Walnut 801 (mouth)	86.1	79.7	76.7
USGS 08158600	86.6	80.3	77.4
Walnut 803	75.5	66.8	56.4
Walnut 804	88.9	82.2	79.4
Walnut 805	88.1	79.6	76.8
Buttermilk 1601	74.7	62.8	59.7
Buttermilk 1602	71.7	61.3	58.5
Buttermilk 1603	71.8	57.4	56.3
L. Walnut 601	77.1	64.3	62.0
L. Walnut 603	59.5	53.6	53.9
L. Walnut 604	72.2	55.2	55.4

Development restrictions are currently in place in this watershed that limit development areas and provide for more open space than would otherwise be required. The use of water quality BMPs, in addition to traditional flood controls, are also required for new developments. Unlike flood controls, water quality BMPs capture and treat smaller, more frequent runoff events. If these BMPs can be designed to extend the flow and mimic natural flow regimes, increasing the baseflow component and decreasing the length of time the creek is dry, the impacts of development on aquatic life due to changes in hydrology might be mitigated. An aggressive plan to retrofit existing developments with these types of controls may also reduce the impacts on reaches that are currently degraded. To fully investigate these possibilities a version of SWAT that will model hydrology on a sub-hourly time-step would be required.

4. Conclusions

Assessing the impacts of future development on the aquatic health of a stream has traditionally focused on changes in nonpoint source pollution, but the changes in hydrology may be just as important, if not more so. If locally valid relationships between hydrology and aquatic health are available, modeled flows can be used to evaluate the impacts of different development scenarios.

SWAT successfully simulated the changes in hydrology as a watershed in the Austin, Texas area developed. Biohydrologic relationships developed by COA staff in combination with flow simulated by SWAT predicted aquatic life potentials distributed across the watershed, accurately reflecting the degree of land use change. This paradigm can be applied in other watersheds to evaluate existing regulations, proposed changes in regulations and urban retro-fit programs, allowing limited funds to be used more efficiently.

Acknowledgements

The authors wish to acknowledge the assistance of other WPDR staff in the Environmental Resources Management Division, especially Robbie Botto for developing past and future land use maps and Chris Herrington for assistance in developing AQP relationships. We would also like to acknowledge the support of the citizens of Austin, Texas for financially supporting this study.

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Validation of the SWAT Model for Sediment Prediction in a Mountainous Snowmelt-Dominated Catchment

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Abstract

Federal and state agencies across the United States are currently tasked with Total Maximum Daily Load (TMDL) development to ensure compliance with the Clean Water Act of 1972. In the northwestern part of the country, the TMDL effort is particularly challenging due to the complicated nature of expansive watersheds, steep mountainous topography and orographic precipitation. This is especially true for sediment, which is a primary pollutant of concern. Modeling, in combination with field source assessments, has historically been used to estimate watershed sediment yields and associated source contributions. However, even with widespread use of these methods, little has been done to validate the sediment prediction performance of modeling tools in forested mountain regions. The purpose of this paper is to present an eight-year simulation period (1985-1992) for the Lamar River in Yellowstone National Park, Wyoming USA where daily suspended sediment discharges are compared with simulated loads from the Soil and Water Assessment Tool (SWAT). Findings suggest that SWAT is a suitable tool for simulation of sediment yield in mountainous snowmelt-dominated catchments based on Nash-Sutcliffe efficiencies of >0.81 and >0.86 for daily and monthly streamflow and > 0.51 and >0.78 for daily and monthly sediment as well as simulated and observed streambank erosion contributions of 76 and 72 percent, respectively. Information gleaned from this study is applicable to the high-elevation areas of Idaho, Montana, and Wyoming, USA or those with similar hydrophysiographic constraints.

Keywords: model, snowmelt, sediment, mountainous watersheds, auto-calibration, SWAT

1. Introduction

Nonpoint source pollution is a leading cause of water quality problems in both the United States and worldwide (USEPA, 1991). Of all pollutants, fine sediment is the most prevalent and the most difficult to quantify. This is presumably because continuous suspended sediment data collection is expensive and inherently variable. A number of modeling tools have been developed to assist in watershed sediment yield estimation such that suitable TMDL planning conclusions can be made. These include: (1) the Soil and Water Assessment Tool (SWAT), (2) Generalized Watershed Loading Functions (GWLF) model, and (3) the Hydrologic Simulation Program Fortran (HSPF) (Borah and Bera, 2004). SWAT, in particular, has been used extensively for sediment modeling and TMDL planning (Borah et al., 2006). However, very little is known about the performance of the model in steep, mountainous, snowmelt-dominated catchments. The purpose of this paper is to present an eight-year simulation (1985-1992) for the Lamar River in the Rocky Mountain region of Yellowstone National Park (YNP) where predicted daily suspended sediment loads, surface erosion rates and landscape and bank erosion contributions are compared with observed data to validate the model.

2. Study Area

The Lamar River is a tributary of the Yellowstone River and drains approximately 1,709-km^2 of the Absaroka-Beartooth mountain range in the northeast corner of Yellowstone National Park (Figure 1). The watershed has a mean basin elevation of 2,570 meters, with an average watershed slope of 29.5 percent. Portions of the watershed lie in both southern Montana and northwestern Wyoming, and climate in the basin is markedly seasonal, with long cold winters and short summers. Strong topographic gradients extend from the valleys onto the Beartooth Plateau and Absaroka Range, causing significant variability in climate. As a result, average annual precipitation ranges from approximately 350-mm in the valleys to nearly 1000-mm in the mountains. The distribution of precipitation is typical of mountainous regions, with valleys peaking in the spring and mountain and plateau regions in the winter. Mean temperatures are approximately 1.0º C, with highs approaching 25.0º C in the summer months and lows of -15.0º C in the winter. Watershed hydrology exhibits a strong snowmelt signal and is principally runoff from steep mountainous slopes. Mean annual streamflow is approximately 25 m^3 per second while annual runoff peaks routinely reach 275 m^3 per second. Land cover consists of primarily Douglas fir and Engelmann spruce (81.9%), with valleys of dry grasslands (5.7%) and sagebrush steppe communities (10.8%). Ewing (1996) reports YNP is unmanaged, which makes it favorable for watershed model testing.

The Lamar River has historically been a major contributor of suspended sediment to the upper Yellowstone River. In 1985, suspended sediment sampling was initiated in response to concerns that Yellowstone Park's Northern Range was over-grazed. Data was collected from 1985-86 and was continued for a period of four years following the fires of 1988. These published daily sediment discharge data were used in model calibration for this study. A second effort used in model validation was the radionuclide tracer studies completed by Whiting et al. (2005). Relative landscape contributions (e.g. rill/interill erosion, landslides or slumps) and bank erosion were quantified in the watershed over the course of seven sampling events during snowmelt and spring runoff in 2000.

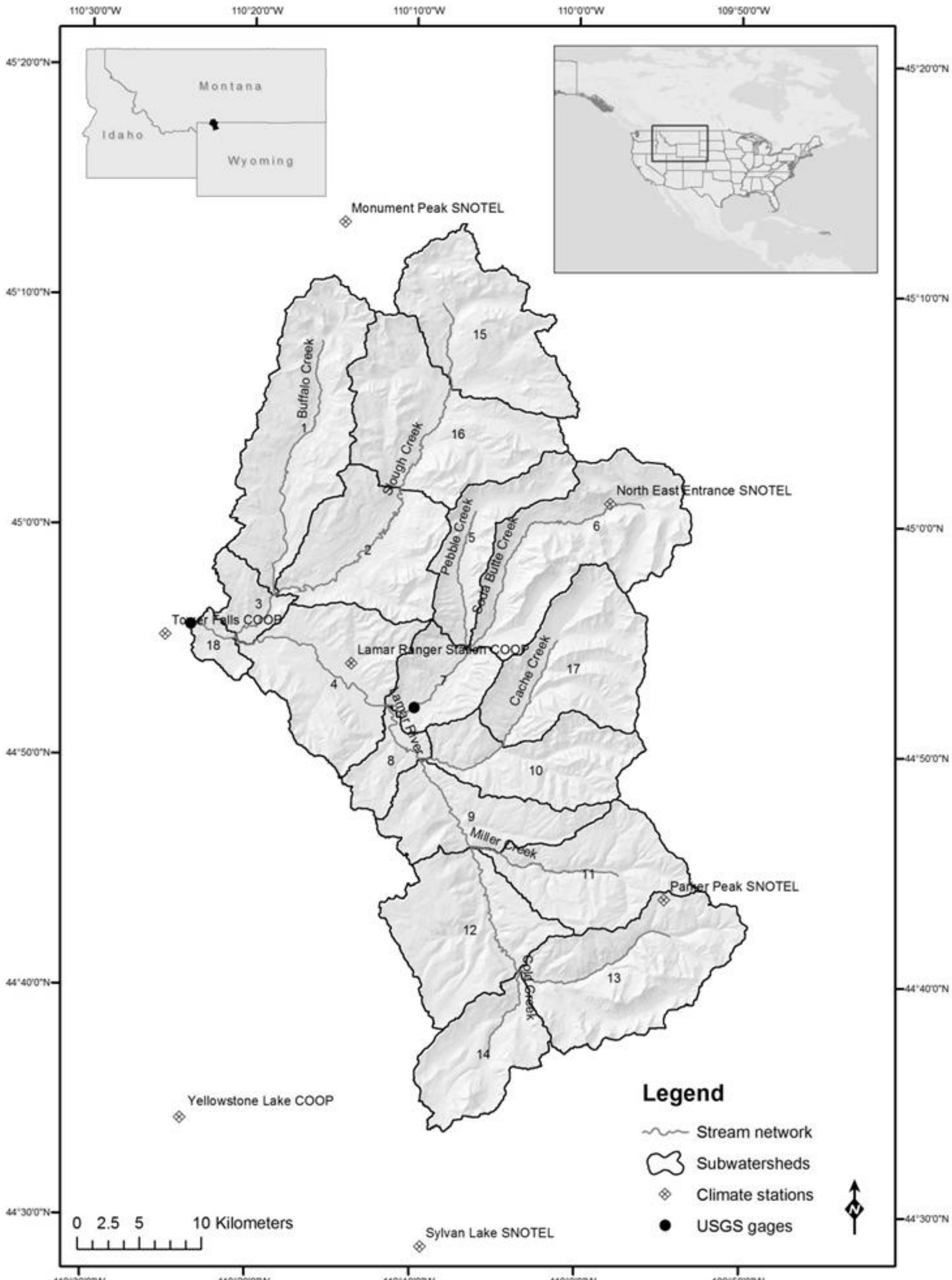

Figure 1. *Lamar River watershed showing sub-watershed delineation, hydrography, USGS gage site and associated climate stations*

3. Model Development

3.1 Model Input

Fundamental input data used for SWAT model development are shown below:

- National Elevation Dataset (NED), 1:24,000 scale high-resolution.
- National Hydrography Dataset (NHD), 1:24,000 scale stream topology.
- National Land Cover Dataset (NLDC), 30-m land cover grid.
- STATSGO Soils, 1:250,000 scale generalization of detailed soil survey.

3.2 Watershed Delineation, HRUs, and Management

The watershed delineation for the Lamar River was established using 6th code HUC boundaries and resulted in a delineation of eighteen total sub-watersheds. HUC areas fell roughly along the upper limits recommended for sub-watershed delineation by Jha et al. (2004) thereby minimizing the influence of slope aggregation, non-linear formulation of the runoff energy factor and simplification of routing processes on model simulations. HRUs were then defined using all possible soil and land use combinations, resulting in 459. Management files for each HRU were written according to known activities occurring in YNP and included the following: (1) ungulate grazing on rangeland and (2) forest wildfire. In order to simulate grazing, large herbivore consumption was set at 450 kg per ha per year and dry dung deposition at 200 kg per ha per year based on field studies conducted by Frank and McNaughton (1992). Wildfire disturbances were simulated using a harvest and kill command, which was followed by regeneration of grass in the fall. Fire related runoff parameters were adjusted according Canfield et al. (2005), and the effect of vegetation removal on soil erosion was simulated by modifying the minimum USLE_C according to the documented increase in sediment yield from Ewing (1996).

3.3 Climate

Observed daily precipitation, temperature, wind speed, solar radiation and relative humidity were obtained from seven weather stations in close proximity to the Lamar River watershed. Because the spatial and temporal distribution of hydrometerological conditions in mountainous environments is highly variable, five elevation bands were defined in each subbasin such that orographic effects in the watershed could be properly simulated. Precipitation and temperature lapse rates were specified using site data and were 950 mm/km and -1.5 ˚C/km. The unusually low temperature lapse rate was attributed to cold climatic conditions and winter temperature inversions that cause deviations from traditional environmental lapse rates.

4. Model Parameterization

Default model parameters were used to the extent possible in the Lamar River, and much of the initial model setup was completed in AVSWATX. Runoff curve numbers (CN2) were adjusted for slope to reflect the steep topography of the region, and MUSLE factors were parameterized as follows: (1) USLE_K was taken directly from a modified version of the STATSGO database, (2) USLE_LS was derived from slope and slope steepness from the DEM (which were subsequently modified for each HRU) and (3) default cover management factors were used (USLE_C).

5. Model Calibration and Validation

A typical split-sample calibration-validation was used for the Lamar River SWAT model and consisted of a three-year warm-up period, two years of calibration (1985-1986) and four years of validation (1989-1982). Auto-calibration was first completed using the automated shuffled complex evolution algorithm to obtain a best-fit parameter set, and then parameters were manually adjusted based on desired system response and watershed knowledge (Van Liew et al., 2005). Twenty-five parameters that govern snow accumulation and melt, precipitation runoff and subsurface flow were optimized either through the auto- or manual calibration procedure. The sediment calibration was completed according to the “weight of evidence approach” discussed by Donigian and Love (2003). Landscape loadings were first optimized to a target range consistent with the literature, and then transport capacity and sediment re-entrainment parameters were adjusted to account for any discrepancy between the observed and simulated data. Five sediment parameters that govern landscape and streambank erosion were calibrated in SWAT on the Lamar River. These include the average overland flow length, channel routing transport coefficient and exponent, channel erodibility factor and bank cover factor.

6. Results and Discussion

6.1 Hydrology

Simulated and observed mean daily streamflow for the 1985-1986 calibration and 1989-1992 validation period are shown in Figure 2. Visual inspection of the rising, falling and peak flows of the hydrographs indicate that SWAT performs excellently over a wide range of hydrologic conditions. Daily NS_E for the calibration was 0.81 while the monthly value was 0.86. PBIAS was 3.6 percent. NS_E for the validation period was 0.87 for the daily value and 0.93 for the monthly value, and PBIAS was -10.9 percent. Watershed response was consistent with that of forested areas in which lateral throughflow, lateral unsaturated flow or macropore flow are the dominant hydrologic processes (Montgomery and Deitrich, 2002). Over 55 percent of the simulated hydrologic flux in the watershed was shallow lateral flow. Much of the remaining percentage was groundwater flow.

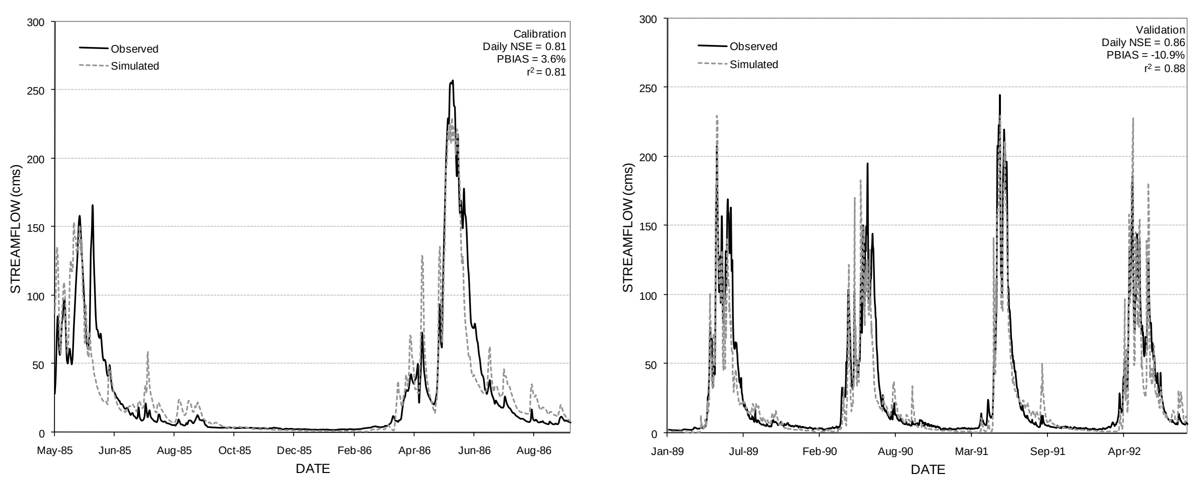

Figure 2. *Simulated and observed daily streamflow for the Lamar River watershed, Yellowstone National Park for the two-year calibration and four-year validation period*

6.2 Sediment

Measured and simulated daily suspended sediment loads for the Lamar River are shown in Figure 3. Both individual storm events and the overall sediment hydrograph are adequately reproduced. Daily and monthly NS_E values were 0.62 and 0.81 for the calibration and 0.51 and 0.78 for the validation, respectively. This in itself suggests that SWAT performs adequately in mountainous regions. PBIAS was less than desired for both the calibration and validation (-25.9% and -16.3%) and is a result of the calibration being weighted toward observed depth-integrated sediment samples rather than published USGS daily sediment discharges (which are computed). Model efficiency statistics for both the streamflow and sediment calibration are shown in Table 1.

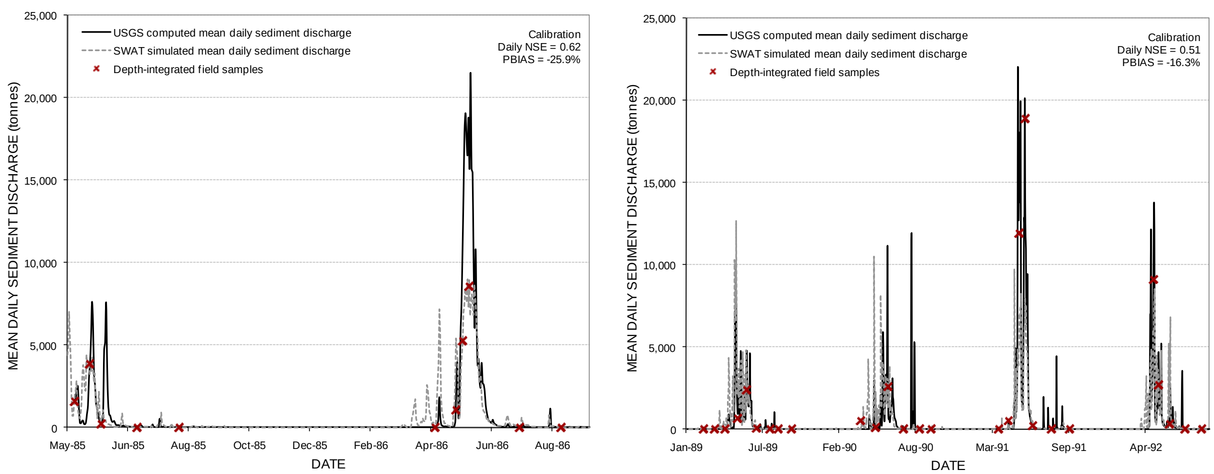

Figure 3. *Simulated and observed daily sediment load for the Lamar River watershed, Yellowstone National Park for the two-year calibration and four-year validation period*

Table 1. *Model efficiency statistics showing PBIAS and daily and monthly NS_E for streamflow and sediment prediction in the Lamar River SWAT model*

State-Variable	Period	PBIAS (%)	NS_E (daily)	NS_E (monthly)
Hydrology	Calibration (1985-1986) Validation (1989-1992)	3.6 -10.9	0.81 0.86	0.86 0.93
Sediment	Calibration (1985-1986) Validation (1989-1992)	-25.9 -16.3	0.62 0.51	0.81 0.78

Following the daily sediment calibration, predicted erosion rates were reviewed to address the adequacy of the model in simulating landscape erosion. Simulated annual erosion rates of 1.66 tons per ha per year for rangeland, 1.07 tons per ha per year for sagebrush, 0.06 tons per ha per year for forest and 0.24 tons per ha per year for burned forest are consistent with regional estimates and are considered satisfactory for the purpose of this study. Following confirmation of the predicted landscape erosion rates, bank erosion source contributions from SWAT were compared to the published ratios reported by Whiting et al., (2005). Over the entire simulation period (1985-1992), simulated values in SWAT were within 5 percent of the observed data. The bank erosion contribution from the calibration of SWAT was 76 percent, compared to that of 72 percent from the radionuclide tracing study.

In critique of the sediment calibration, there are literally an unlimited number of combinations and associated calibrations that can be attained by modification of landscape and channel sediment re-entrainment parameters in SWAT. In every instance, it is up to the modeler to make judgments regarding appropriate parameter selection so that processes are accurately simulated. This means that the user should not only be familiar with the model's theoretical limitations and assumptions, but also the watershed processes they are attempting to describe. In the case of the Lamar River, hydrologic flux and landscape associated sediment production were found to be very sensitive to HRU overflow flow length and slope. Significant efforts were made to parameterize these values appropriately. However, it is believed that further development of SWAT should be initiated to more thoroughly estimate these parameters as part of the initial GIS pre-processing. In regard to channel calibration, two things were noteworthy. First, SWAT regressed channel dimensions are not appropriate for the Lamar River and required modification. Due to their direct effect on sediment transport, it is recommended that this modification be completed in future studies were appropriate. Secondly, findings from the Lamar River study suggest that the literature range for the sediment transport parameter exponent should be expanded to better represent snowmelt driven systems. An upper limit of 3.0-3.5 might be a good first estimate based on calibration of SWAT in the Lamar River. A value of 3.2 was used in the calibration and was justified based on the verified contribution of streambank erosion as well as analysis of the velocity-sediment relationship at the watershed outlet.

6.3 Implications

The implication of these findings toward TMDL development should not go unmentioned. A long-standing problem in the development of watershed allocations has been estimating nonpoint source loads. Most often, managers wish to know something about the relative contribution of landscape and streambank sediment sources in their watershed. This typically leads to a discussion with modelers about "which model is appropriate for my watershed". Findings from the Lamar River study answer this question in regard to the use of SWAT for watersheds in the Rocky Mountains.

Conclusion

The complex nature of the detachment and movement of soil particles presents a significant challenge for estimation of sediment yield in steep, mountainous, snowmelt-driven catchments. The Soil and Water Assessment Tool (SWAT) was applied to the Lamar River in Yellowstone National Park to estimate net sediment production and the relative contribution from both hillslope and streambank erosion sources. A 2-year calibration and 4-year validation period were simulated from 1985-1992 to assess the reliability of the tool for TMDL planning purposes. Based on daily NS_E values of 0.81 and 0.86 for hydrology and 0.62 and 0.51 for sediment yield, our results suggest that SWAT provides reasonable predictions of water and sediment discharge for mountainous, snowmelt-dominated catchments. Two supporting lines of evidence were used to validate this statement including a comparison of simulated erosion rates with that of regional literature based studies and confirmation of simulated landscape and bank erosion source contributions with that of published ratios for the watershed. The combined success of the efforts illustrates the utility of the model for sediment prediction in snowmelt-dominated catchments.

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Migrating a complex environmental modeling system from a proprietary to an open-source GIS platform

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Abstract

The MapWindow development team, in collaboration with Idaho State University, the EPA and Texas A&M University, have developed a new open source water assessment tool named Open Soil and Water Assessment Tool (OpenSWAT). This is a continuous, time series model useful for modeling the hydrology and point-source pollutants of large and small scale watersheds. This model is useful for hydrologists, engineers and resource managers who wish to answer important questions related to watershed management, such as predicting pollutant concentrations and streamflow characteristics. This project is instrumental for extending existing technologies like the Better Assessment Science Integrating Point & Nonpoint Sources (BASINS) program created by the EPA and serving as a critical link to the open source SWAT editor created by Texas A&M University. This paper discusses the performance, operations, limitations and assumptions involved with this new software tool.

Keywords: OpenSWAT, BASINS, watershed delineation, reclassification, overlay

1. Introduction

Although the Soil and Water Assessment Tool for ArcMap (ArcSWAT) has adequately proven watershed modeling records for past decades (Gassman et al., 2007), the necessity for an open source version of SWAT Geographic Information System (GIS) interface became inevitable among the international and local community due to licensing expenses of commercial software products. A centralized software system that can access many different geospatial databases may simplify the data retrieval needs of engineers and modelers as SWAT requires many watershed parameter inputs such as digital elevation model, soil dataset, land use dataset, slope data, crop data, weather dataset and management practices. The BASINS software tool was developed by the US Environment Protection Agency (EPA) (Battin et al., 1998) and is useful for retrieving different geographic and time series datasets from different Geo-databases.

The MapWindow GIS application was initially developed by Utah State University, but its further enhancements and maintenance are continued by Idaho State University (Ames et al., 2007). OpenSWAT is a free and open source SWAT GIS interface developed at Idaho State University to fulfill the international and local user needs (Veluppillai, 2008). OpenSWAT was developed as a plug-in for MapWindow GIS application for many reasons. One important reason is compatibility with BASINS 4.0. As MapWindow GIS application can accommodate any number of plug-ins as a component. BASINS, also developed as a plug-in for MapWindow GIS application, can work together with OpenSWAT in MapWindow to fulfill user needs. OpenSWAT plug-in uses SWAT Editor, which was developed by Texas A&M University (http://www.tamu.edu/) as a core application to perform further watershed modeling and analysis tasks. OpenSWAT is helpful for performing GIS related modeling activities (preprocessing, etc.) and saving the derived SWAT inputs in a database accessible to the SWAT Editor tool and SWAT model.

The OpenSWAT plug-in has components that input, edit, process and save geospatial and temporal datasets. Users provide a digital elevation model (DEM) as a topographic dataset and delineate watersheds with the aid of an automatic watershed delineator. Once users finish the delineation process, they can input soil, land use and slope data for reclassification. Based on sub-watersheds, land use, soil and slope, OpenSWAT creates unique modeling elements called hydrological response units (HRUs). These are the main building blocks of the SWAT model (Srinivasan et al., 1998). Once the software produces the HRU, users can filter HRUs based on the threshold values for “land use area over subbasin area”, “soil class area over land use area” and “slope class area over soil area”. Next, weather data is overlaid on the filtered HRUs and outputs are stored in the Microsoft Access project database. Finally, SWAT Editor is launched from the application to handle remaining watershed modeling processes (such as model run, sensitivity analysis, calibration, validation and prediction).

2. The Architecture of OpenSWAT

OpenSWAT functions as a middle tier for complete watershed modeling applications (Figure 1). Users can access GIS datasets from online data sources using the BASINS software tool. Once they acquire the required datasets, they can perform watershed modeling and analysis tasks using OpenSWAT. OpenSWAT produces several specific outputs including a project database (project.mdb), the routing path of streams (fig.fig), weather data outputs and GIS derived reports. SWAT Editor uses the outputs of OpenSWAT as inputs and is used to complete watershed modeling and analysis. The present version of OpenSWAT includes SWAT Editor as part of its core system. As previously noted, the current version of the BASINS software uses MapWindow GIS as its GIS platform. Because OpenSWAT also uses MapWindow GIS as its parent application, the next major release of BASINS will include OpenSWAT as one of its watershed modeling tools. OpenSWAT itself includes SWAT Editor as its major modeling component.

OpenSWAT was developed using Visual Studio.Net 2005, following an object oriented design and development strategy. OpenSWAT includes a total of 30 classes and 9 modules.

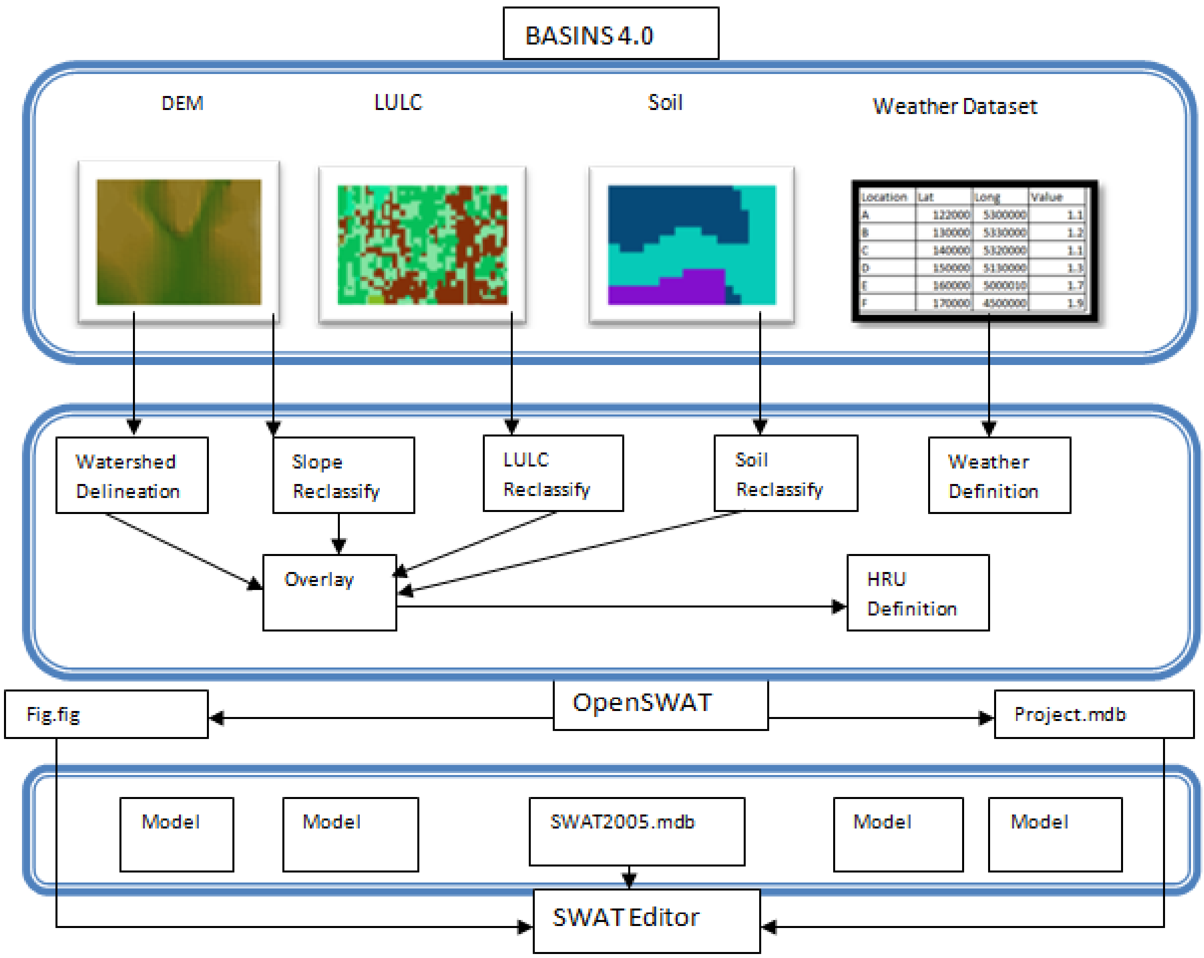

Figure 1. *The big picture of application interaction in OpenSWAT*

3. Methods

OpenSWAT life cycle development used the Rapid Application Development methodology (RAD) and Object Oriented Software Engineering (OOSE) to provide early functionality within a limited time period (Davis et al., 1988) and includes most of the recent development efforts in ArcSWAT (Arnold et al., 1998). The main phases of the OpenSWAT software development methodology are depicted in Figure 2.

Because Texas A&M University is heavily involved with SWAT development, initial planning and requirements for OpenSWAT were gathered from Texas A&M University (major client). In this phase, requirements were reviewed repeatedly to ensure fulfillment of the client's needs and expectations. Much communication was conducted between the client and the software development team at the Geospatial Software Laboratory, Idaho State University in the form of oral communication, questionnaires, specifications interchange and more. Based on this communication, a specification requirement document was designed and approved by the client.

Based on client requirements and software market trends, a combination of Object Oriented Software Engineering (OOSE) and Rapid Application Development (RAD) methodologies were chosen as the best choices for OpenSWAT development. Also, OOSE Unified Modeling Language (UML) was used to model the different software aspects including main processes, main actors, process flows, state changes, state collaborations, class definitions and physical processes. The purpose of UML is to provide a language and platform independent modeling notation. Table 2-1 describes the different UML models used for designing the OpenSWAT software tool.

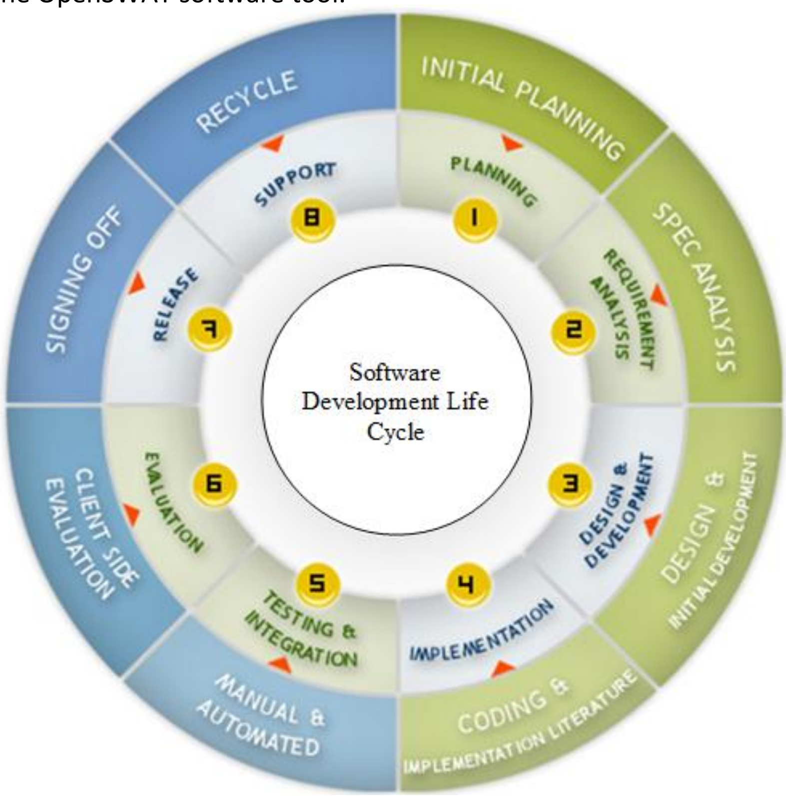

Figure 2. *Different phases of the software development lifecycle*

4. Results

The major result of this software development effort is the OpenSWAT tool, which (together with SWAT and SWAT Editor) is a complete watershed modeling software tool consisting of different sub-tools. OpenSWAT encompasses the Automatic Watershed Delineator (AWD), a separate plug-in developed at the Geospatial Software Laboratory at Idaho State University. This tool is used to extract stream networks from a Digital Elevation Model (DEM). AWD requires certain inputs from users such as DEM, stream network (National Hydrographic dataset–NHD), a mask, outlets/inlets and custom output locations.

The second major component of the OpenSWAT software tool is the land use (LU) reclassifying tool. This tool is used to reclassify different land uses based on user specified land use lookup tables. Users are able to specify their own custom lookup table, or they can choose different existing lookup tables such as USGS, NLCD 2001 and NLCD 1992.

The soil reclassifying tool is used to generate different soil classes. This tool requires users to input a soil grid and relevant lookup table to create new soil classifications. In the U.S., users may be able to use STATSGO or SURGO datasets for their soil needs.

OpenSWAT also contains another component called *Slope reclassifying tool*. This tool requires users to input a range of slope classification values and automatically takes a DEM, input by users at the watershed delineation step, and then calculates the slope values.

OpenSWAT contains another component called *Overlay tool*, which is used to overlay reclassified land use, soil and slope grids and to produce unique Hydrological Response Units (HRUs). By definition, HRUs are unique combinations of subbasin, land use, soil and slope. These are the basic building blocks of the SWAT watershed model.

The HRU definition tool is one of the filtering tools in OpenSWAT used to filter HRUs that are generated by the “overlay tool” because this tool usually produces copious amounts of HRUs. As most of the following steps depend on the number of HRUs, a large number of HRUs result in a big performance hit for the OpenSWAT software tool. The HRU definition tool is used to minimize the number of HRUs based on user requirements, which can reduce the performance hit drastically. The HRU definition tool requires users to input three threshold ration values--“land use area over subbasin area”, “soil area over land use area” and “slope area over soil area”. The “land use area over subbasin area” defines the minimum area of any land use over any subbasin area required to produce legitimate HRUs. The “soil area over land use area” defines the minimum area of any soil class over the area of any land use class required to produce legitimate HRUs. The “slope area over soil area” defines the minimum area of any slope class over the area of any soil class required to produce legitimate HRUs.

The *Weather data definition tool* is another major component of OpenSWAT. This tool is used to input different weather datasets such as weather generator data, rainfall, temperature, wind speed, solar radiation and relative humidity. In this step, users are able to input their own custom weather database, or they can input an existing U.S. weather database from the SWAT2005 parameter database for weather generator data. Users can input their own custom location table and relevant parameter table or use the simulation option for rainfall, temperature, wind speed, solar radiation and relative humidity data. If the users choose the simulation option for some parameters, then the software will generate those parameters.

The next important component in OpenSWAT (used for intercommunication between “SWAT Editor” and OpenSWAT) is the “Write output tables tool”. This tool is used convert GIS datasets into Microsoft Access table format. The converted tables are readable by SWAT Editor. Usually there are around 21 tables generated by this tool. This tool is also responsible for generating the model configuration file (fig.fig). This configuration file contains all model related parameters that are required to run the model successfully. This tool requires users to select different tables that they want to generate. If they run the model for the first time, it is appropriate to generate all tables.

The next important component used to intercommunicate with SWAT Editor is the Launch SWAT Editor tool. This tool is useful for launching another external application called "SWAT Editor". SWAT Editor encompasses the core SWAT engine, which does all remaining modeling tasks such as the model run, model calibration and sensitivity analysis. SWAT Editor requires users to specify the SWAT project database, SWAT2005 parameter database and SWAT executable folder. The advantage of accessing SWAT Editor from OpenSWAT is that usually required parameters are filled by OpenSWAT for the user.

OpenSWAT also has different reporting tools including two important reports produced at the end of the *reclassification & overlay* operation and *HRU definition* operation. These reports give a summary of different land uses, soils and slopes for each hydrological response unit as well as an area distribution of HRUs.

5. Conclusions

The OpenSWAT application was developed in Visual Studio 2005 to incorporate Microsoft's innovative technologies for producing a user friendly graphical user interface (GUI) with high speed inter/inner communication that would increase efficiency and improve performance. OpenSWAT is a free and open source software plug-in, so users world-wide can add or modify functions and tune the software as needed. This software tool is also a useful platform for different testing and analysis purposes. For example, students can use this software plug-in for research and development. Additionally, open source software developers can use the same idea to produce different free and open source software tools that can fulfill commercial software needs.

The object oriented software design, especially UML diagrams, are not only used to elucidate the current development effort but also so that future developers can use these diagrams to understand the process flows, activities, entities and deployment requirements. OpenSWAT can be used as a key component of a complete SWAT modeling system required for users to accomplish their watershed modeling needs. This research shows how component level development can be incorporated to achieve complex tasks by merging the disciplines of GIS, software engineering and hydrologic simulation.

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Facing issues of water and soil resource vulnerability:

A multi-model and multiscale, GIS-oriented Web framework approach based on the SWAT model

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Abstract

The latest advances in computer technology offer computing and storage resources that are distributed over a wide geographical domain and available from fast, secure networks. These resources provide important services, applications and advanced visualization tools. The new paradigm is based on an integrated and collaborative approach in which the complexity of technology is transparent to the end user, and interdisciplinary working groups and skills can be enhanced. On this basis, the development and use of enabling technologies (e.g., RDBMS with spatial extension, AJAX technologies, GRID/cloud computing, etc.) allows users to imagine new management approaches and exploit the data and physical resources available.

The BASHYT (Basin Scale hydrological Tool - http://www.eraprogetti.com/bashyt) is an innovative Web-based Collaborative Working Environment (CWE) able to quantify human and natural impacts on water body receptors that is based on the SWAT model. It permits the user to simulate and analyze the integrated water cycle (water balance and quality status of surface water bodies at different space and time scales) with a rigorous methodology (DPSIR framework) ultimately producing reports on environmental states by means of standardized procedures. The CWE framework can be thought of as an easy-to-use, open, interoperable, scalable and extensible development framework for constructing spatially enabled internet applications. The software supports a Web-based, live programming environment, making the programming features available to developers with almost no learning curve. This increases developer productivity by reducing scaffolding code when developing Web, GUI, database, GIS or other applications. We expect to improve model usability to aid in making management decisions based on watershed-scale (multi-scale) modeling that more realistically addresses the fate of multiple pollutants in multiple environmental media. In particular, we will discuss an application used to estimate an agricultural drought index and a distributed file system solution to run and store SWAT simulations for virtually unlimited basins for continental scale application.

Keywords: SQLite, GIS, WEB Portal, drought index, SWAT, water resources management, DSS

1. Introduction

The complexity of the interactions between land use, soil, climate, anthropogenic stresses and water quality requires the use of reliable problem solving models to evaluate water resource vulnerability. The correct characterization of rainfall, temperature, soil, land cover, anthropogenic stresses, etc. are strategic in representing the complex dynamics of surface and groundwater resources in order to design their sustainable use. The use of advanced ICT technologies, such as GIS, environmental models and Web-based applications, involves major investments both in terms of the acquisition of quality data and the development of an interdisciplinary approach to the study. Such technologies can provide a significant contribution to the description of the water cycle and phenomena related to it, simplifying the management, access, analysis of data and the report production mechanism.

Public and private environmental agencies are steadily moving towards the internet client-server paradigm, searching for ever more data, models and applications. Such institutes often interoperate little, even when solutions require an integrated, interdisciplinary approach. Nowadays, more than 3 million users can access INTERNET and their services, a number destined to increase enormously in the near future. Large-scale networking can contribute to moving from a local to a global scale, increasing the exchange of ideas and collaborations among scientific communities and citizens sharing the same motivations. Recent advances in distributed heterogeneous knowledge networks and experiences during many European projects led us to imagine that water and environmental management, disciplines largely based on GIS applications and numerical hydrological modeling, might draw huge benefits from the use of Web-based technologies and collaborative computing. The new paradigm is based on an integrated and collaborative approach in which the complexity of the technology is transparent to the end user, and interdisciplinary working groups and skills can be enhanced.

Based on these points, the BASHYT DSS aims to integrate tools and expertise in a live Web-based environment with the goal of organizing and providing an operational service for decision makers to wisely manage of water resources. The objective of this work is to present the latest developments in the BASHYT Web tool and to expose innovative environmental analysis and applications. In particular, we will show an application used to estimate an agricultural drought index and a distributed file system solution to run and store SWAT simulations for virtually unlimited basins. In this regard, BASHYT is moving from a single basin simulation scale to a larger continental or even world wide scale, becoming virtually a SWAT model production Web farm.

2. The BASHYT DSS

BASHYT aims to be a Collaborative Management Tool supporting adaptive strategies for water and soil resource vulnerability. The tools assist decision makers in the field of sustainable water resources management. Users access the main functions through a dedicated Portal. The software is based on an experimental Collaborative Working Environment (CWE) for environmental sciences that relies on hydrological models and DB-GIS technologies. This experimental CWE environment is used to set Web and grid services through which the system stores, manages and queries data collections, runs real-time applications and maps the results. Complex environmental models and pre/post processing GIS tools are used to model, analyze and visualize environmental dynamics.

BASHYT aims to:

- Analyze pressures on the environment and climate from natural and anthropogenic emissions and improve our understanding of the complex climate system;
- Identify critical areas (e.g., major contributors to nutrient loss or those affected by desertification) and prioritize critical sub-areas in order to develop a multi-year management analysis. This analysis can be essential, for instance, in reducing nutrient impacts from point and nonpoint sources on downstream water bodies;
- Design sub-regional and regional remediation strategies and evaluate their effectiveness using DPSIR as a standardized framework. DPSIR (Driving forces, Pressures, States, Impacts, Response) is a causal framework adopted by the European Environment Agency for describing interactions between society and the environment.
- Improve model usability to aid in making management decisions and watershed-scale (multi-scale) modeling to more realistically address the fate of multiple pollutants in multiple environmental media;
- Address subjects related to data archiving, distribution and interpretation through the use of interoperability standards and standardized procedures;
- Improve capabilities for coordinating, accessing, using and sharing environmental data, information and services;
- Improve public consciousness of environmental problems and strategic remediation strategies on local, regional and national scales;
- Deploy new applications exploiting Web Templating Technologies (e.g., Template Toolkit, Velocity Apache template, etc.);
- Manage contents and layout (Content Management System - CMS) in an easy fashion.

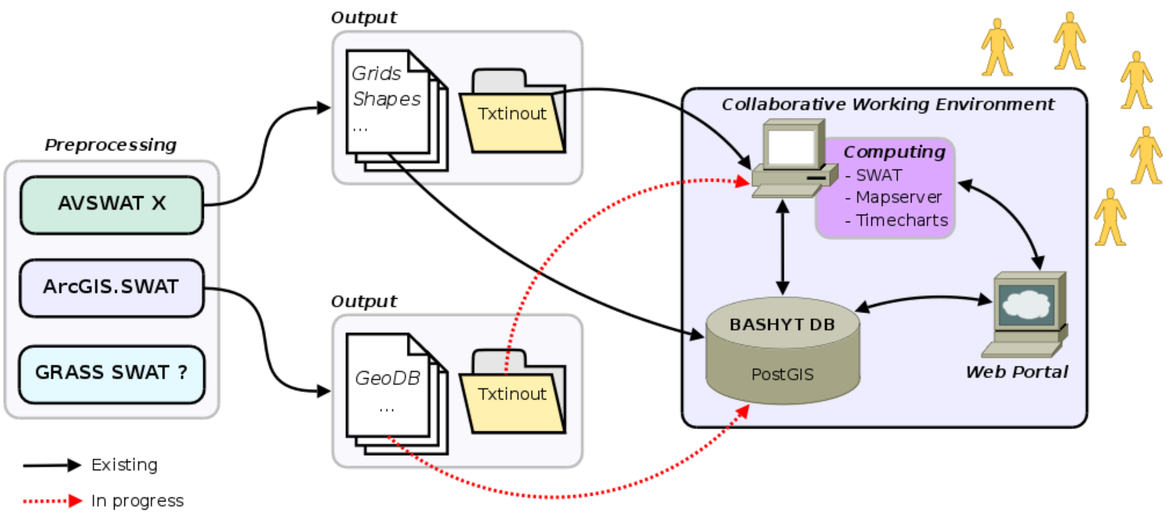

Figure 1. *Workflow AvsSWAT – BASHYT. Users can upload the input processed by AVSWAT as zip files (shape, grid, txtinout, etc.) into the BASHYT environment. The geographical feature sets are automatically inserted into a PostGIS geo-database. Bashyt commands the SWAT code to run using the txtinout input files then results are post processed and digested into the BASHYT DB. At this point, they are made available for the reporting production.*

BASHYT was developed using free software to transparently and automatically deploy the applications. Data objects are natively digested by the CWE environment, allowing Web services to be exposed for data mapping, querying and sharing, processing and output distribution all through secure connections on the Web interface. The CWE framework can be thought of as an easy-to-use, open, interoperable, scalable and extensible development framework for constructing spatially enabled internet applications.

The system was developed to be cross browsed by usual navigators, such as Internet Explorer, Mozilla Firefox, etc. No external program or plug-in is required. The complexity and functionality is supported entirely by the server side.

The CWE environment is based on technologies such as Web Templating, which is a fast, flexible and highly extensible processing system for Web content management and application development. One of the many differences between BASHYT and other tools, such as ArcGIS SWAT and AVSWAT X, is that the BASHYT framework allows the user to easily deploy innovative Web applications. The portal supports a Web-based, live programming environment, making the programming features available to developers with almost no learning curve. This increases developer productivity by reducing scaffolding code when developing Web, GUI, database, GIS or applications. This will allow Web designers and developers to concentrate on generating applications (e.g., constructing GIS, charts and graphs directly on the Web) without getting bogged down in programming matters, making the whole process of developing, updating and maintaining Web applications significantly easier.

GIS rendering is optimized using Open Source MapServer technologies. This is accomplished by exploiting the language scripting capabilities to access the MapServer CGI and OGC (WMS, WFS) interfaces. MapServer works as the map engine, providing spatial context where required. On the client side, AJAX (web 2.0) technologies, such as the msCross cross-browser interface developed by CRS4, are customized to allow users to dynamically display and browse the geographical information layers. In this way, the CWE inherits all the Geographic Information System (GIS) capabilities granted by these technologies.

3. DB Gridification: from a one basin scale scenario to virtually unlimited basins

We have designed a new prototype of a scalable, distributed geo-database file system that is based on SPATIALite (http://www.gaia-gis.it/) (simulations are stored in SPATIALite database files). The SPATIALite system is optimal for large, distributed, data-intensive applications like the SWAT model. Our choice guarantees high-performance accessibility to a large, virtually unlimited number of simulations/watersheds (run on a dedicated computing environment) stored in a distributed framework. BASHYT software accesses the system by acting as a work flow manager, posting requests and getting results. In this configuration, the computing and storage tasks are resolved outside the CWE framework.

Although our goals are similar to many other distributed file systems, our design was driven by observation of application workloads and the technological environment, both present and expected. This led us to reconsider the traditional choice of one Omni comprehensive PostGIS database (which still retains validity for a single basin situation) and explore radically different design points. Given the amount of spatial data required for continental application of our watershed scale model, we decided to try a solution based on the SQLite technology with spatial extension (SPATIALite). SQLite is an embedded database engine distributed as a common library. It is widely used in many popular applications like Mozilla Firefox, Apple Mac OS X, Google Apps and many more. SPATIALite is an SQLite extension that provides a large set of spatial functions and data structures (i.e., what PostGIS does for Postgres).

We have designed the SPATIALite distributed System to meet the rapidly growing demands of a GRID environment dedicated to SWAT model runs- data storage, access and query needs. For the purpose of this experiment, we are currently using in-house computing and storage resources on a cluster environment, but in the future, the system will be tested on a real GRID infrastructure.

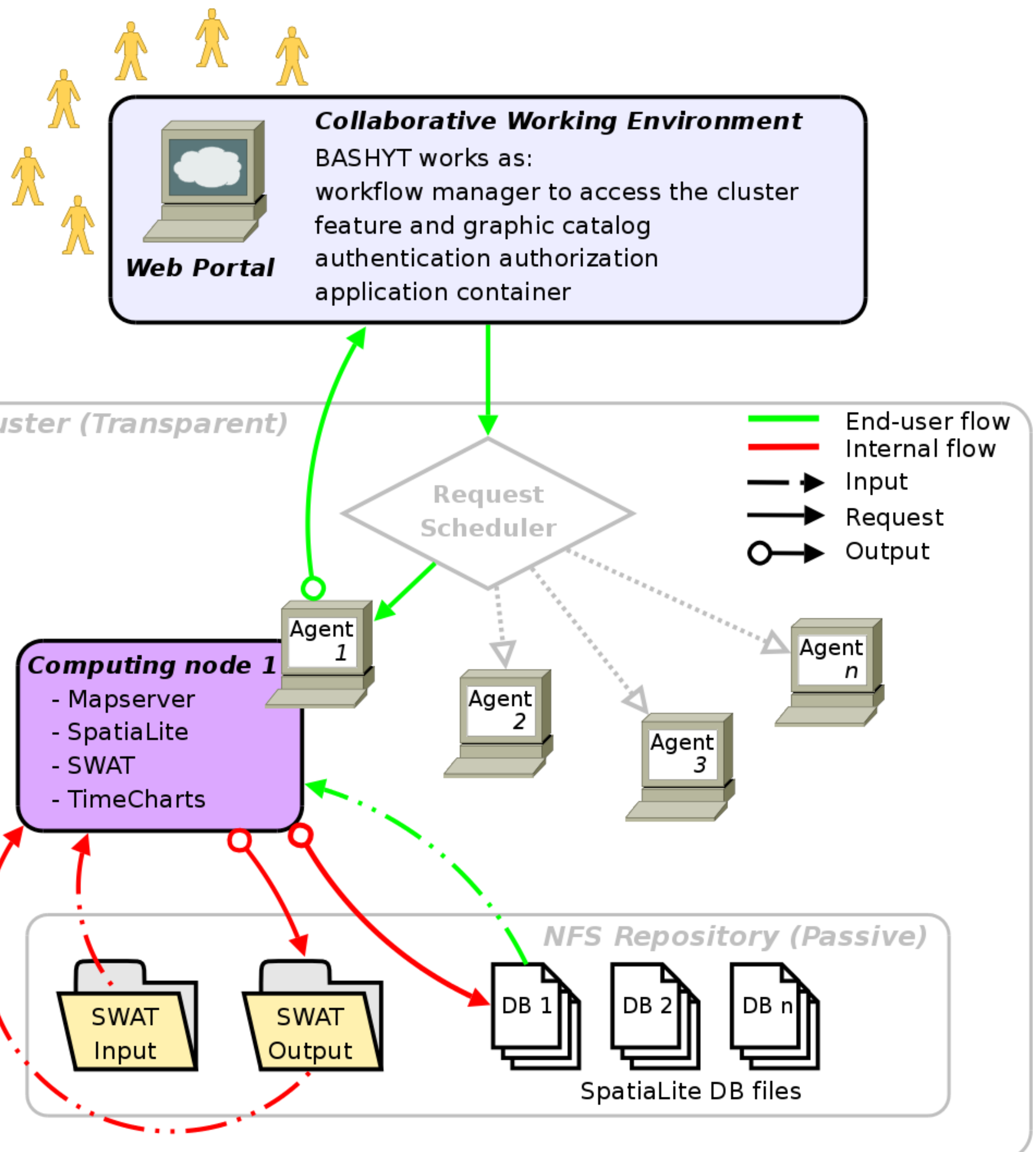

Figure 2. *The computing stage and storage is commanded by the Agent for virtually unlimited watersheds.*

The well known Postgres/PostGIS system is not flexible enough to meet scalability requirements in a regional or continental context where virtually hundreds of basins need to be simulated. The light weight library of SQLite (~300KB) also makes it a good choice for mobile devices. The serverless nature of this engine assures highly scalable scenarios, since all operations work as common read/write file system calls. This architecture does not need added configuration or administration charges. By linking our application to libsqlite, we acquired the power of a complete, transactional RDBMS without the need for an external server process to query but with useful portability freedom. SQLite offers the ability to load personal or third party extensions (shared libraries) written in C or other languages. This mechanism can be used to straighten the SQL functionalities of the engine or override its functions.

The core application of our system is an Agent, a background (daemon) process that listens to TCP and UDP protocols. The Agent accepts requests coming from the BASHYT portal and runs all needed tasks to compute the model and process its output. The Agent is replicated on every computing node to improve scalability and reliability and to provide a good level of fault-tolerance. It implements a slim protocol based on persistent direct connections with the portal. It does not pass through the Apache http server, and works via UDP, digesting fixed size requests. Load balancing is done by the cluster scheduler. This structure, combined with the absence of a dedicated DBMS process, reduces lags and resources needed by network communications. The Agent also commands the MapServer, rendering and other applications for the chart or report production mechanism. The application includes the libsqlite library for managing the whole database repository. When a SWAT simulation finishes, the Agent runs a batch procedure to format model output and import the data into one or more SQLite files (Internal flow). The SQLite architecture does not impose restrictions on distribution, size or number of files. Every single Agent instance is completely independent, and during write operation, it can handle all database files to optimize performances in the file system, database engine or portal. The main issue to consider when using SQLite is its strict dependence on the file system. SQLite will inherit any fault coming from the layer below without chance for recovery.

Often distributed network file systems suffer from file locking bugs. In general, this can cause SQLite data corruption or inconsistency in high traffic volume contexts. In SQLite, one reading operation locks all write requests on files and vice versa. When read/write actions alternate with high frequency in high concurrency conditions, this can represent a performance bottleneck. Although our system aims at working in high-volume data and traffic situations, the above issues are minor because end-user operations are read only operations. As a matter of fact, all write operations to import SWAT outputs are done by the Agent only. During this task, the simulation is not available to users for reading.

We tested SQLite carefully, mostly with regards to its SPATIALite extension. On one hand, this technology can still be considered young and does not have the reliability level or spatial functions of other engines like PostGIS. On the other hand, for limited controlled use, SPATIALite meets our needs; although, some Java changes on JDBC SQLite driver were required on our distributed system to make it work.

4. The soil moisture tool to quantify the agricultural drought

Drought is a temporary condition of relative scarcity in water resources as compared to normal resource values for a given time and place (Rossi, 2000). Regarding the elements of the hydrological cycle, we may distinguish between meteorological, agricultural, hydrological and operational drought. While meteorological drought is identified based on a precipitation deficit, agricultural drought depends on the soil moisture deficit, which is dependent on the precipitation regime and weather, soil characteristics and evapotranspiration rate. The persistence of agricultural drought conditions produces negative effects on both natural vegetation and agriculture. Drought periods have a significant impact on the water supply system, causing water shortages that negatively affect economic and social systems. Regional water authorities have organized operational systems to facilitate the collection, processing and dissemination of hydrometeorological data to monitor drought periods. Several indices and methods have been proposed since the Sixties to detect and monitor drought events. The most commonly used are the Standardized Precipitation Index – SPI (McKee et al., 1993), the Palmer index – PDSI (Palmer, 1965) and deciles method (Gibbs and Maher, 1967). However, some authors have highlighted several shortcomings in the implementation of such indices, especially if they are used for drought evaluation on a small spatial scale. To this end, agricultural drought indices that evaluate the water deficit on the basis of available water on the soil profile may be more accurate. The use of distributed hydrological models can provide reliable estimates of soil water content and help quantify moisture deficits by taking into account the distributed soil and land use characteristics.

SWAT's daily time step allows users to estimate the various components of the hydrological balance for each HRU (potential evapotranspiration, actual evapotranspiration, runoff, soil water content, etc.). The SMD (Soil Moisture Deficit) agricultural drought index, a variation of the approach proposed by Narasimhan (Narasimhan et al., 2002), was calculated on a monthly basis. For any given month, the index expresses the ratio between both the anomaly of the monthly value as compared to the average multi-annual data and the difference between the maximum and minimum values for the entire time series available (in our case 1995-2008). The index can be positive or negative, indicating either a monthly soil water content surplus or deficit, respectively. The above methodology was cast into the soil moisture tool in BASHYT, which automatically quantifies the anomaly magnitude observed in a given month and weighs it with respect to the variability of long-term estimated values to evaluate the SMD drought index.

4.1 Application to a case history: the San Sperate basin (Italy)

The Flumini Mannu of S. Sperate basin is found in the south central part of Sardinia (Italy). The main river is a tributary of Flumini Mannu of Cagliari River, which discharges its waters into the Santa Gilla humid area (among the largest wetlands in Europe) near the gulf of Cagliari. The area climate is Mediterranean with an average monthly temperature ranging from 8°C (January and February) to 25°C (July and August). The precipitation regime is characterized by peak rainfall in December (83 mm) and a minimum in July (8 mm). The S. Sperate River is characteristically fast flowing with a relatively important water volume in winter, reduced to a trickle during the summer. Land is primarily used to satisfy agricultural needs with large areas designed for crop cultivation (Cereal is predominant – 9091 ha). In the south we find vineyards (1709 ha), olive groves (2383 ha) and orchards 1709 ha) mainly. To the East woods and pastures are dominant. The soil properties of the S. Sperate basin were derived from a 1:250 000 soil vector map (Aru et al., 1991), where each cartographic unit was associated with one or two delineations that corresponded to subgroups of USDA soil taxonomy (Cadeddu et al., 2003). The CORINE (Cumer, 1999) Land Cover 1:100.000 vector map (Commissione Europea, Ministero dell'Ambiente, 1996) was used to describe the vegetation/land cover/land use layer. A 20 m digital elevation model was used to derive the geometrical features of the watershed. With this information, the S. Sperate was subdivided in 23 subbasins made up of 444 HRUs.

The model was then fed with daily air temperature and precipitation data for the period January 1995 – February 2008, recorded by the Regional Agricultural Service for Sardinia (S.A.R) monitoring network. The climatic stations used for this application are those located in the area or local surroundings: Decimomannu, Dolianova, Guasila, Siurgus-Donigala and Villasalto. The model calibration and validation process followed a regional scale approach and has already been described in a previous paper (Cau et al., 2005).

4.2 The environmental reporting

The hydrological cycle components that served as SWAT inputs were obtained on a daily time step for each elementary territorial unit (HRU). They were subsequently integrated and analyzed on a subbasin spatial scale and a monthly time step, by means of the BASHYT portal post-processing tools. The outputs are then produced and presented in time series and spatial representations by means of dedicated interactive Web pages within the portal.

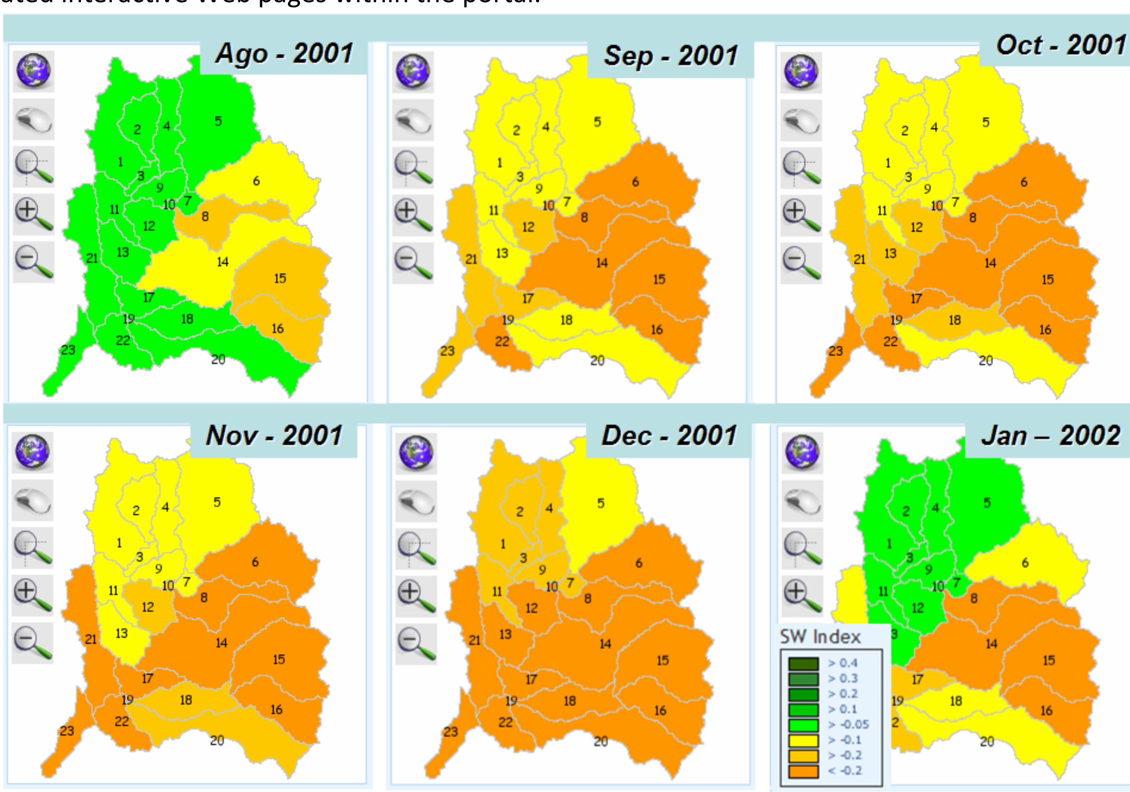

***Figure 3.** Spatial distribution of the monthly SMD index (period August 2001 - January 2002).*

Figure 3 shows the SMD index spatial distribution for the period August 2001 – January 2002. The Web application permits the user to interactively monitor the intensity of the deficit condition and the duration of the drought period. In particular, the period September - December 2001 is the longest drought period in the 15 year simulation while December 2007 is the month that showed the most severe intensity within the SMD index.

5. Conclusion

The proposed procedure for estimating the SMD drought index is based on the SWAT hydrological balance model which runs on a HRU spatial scale and on a daily time step. This approach has the advantage of examining the hydrological cycle at the correct scales of the hydrological phenomena involved. Subbasin monthly estimates are, as a matter of fact, derived from daily balances at the HRU scale. Water authorities need to have substantial scientific tools to analyze complex phenomena of interest. BASHYT can represent an important contribution in the field of environmental reporting systems. Such a decision support system is designed to meet the needs of administrations involved in integrating environmental reporting procedures (based primarily on GIS, tables, graphs) and analysis tools. The case history, although briefly presented and limited to the calculation of SMD on a complex Sardinian basin, allows to appreciate the potential of the proposed system. We have designed a prototype distributed System based on SPATIALite to meet the demands of data processing, storage and query needs of a continental application.

Acknowledgements
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A Web-Based Interface for SWAT Modeling on the TeraGrid

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Abstract

The Soil and Water Assessment Tool (SWAT) is a river basin scale model developed by the USDA Agricultural Research Service (ARS). It is widely used by researchers in various scientific domains to study the impact of land management practices on water quantity, water quality and sediment yield in large watersheds over long periods of time. Currently, most users run SWAT tests on their own desktop or laptop computers. While this is adequate for some, users who need to complete a large number of SWAT runs or calibration of the SWAT model for complex watersheds require more powerful computational and storage resources. In this paper we describe an effort to make the SWAT model widely useable and easily accessible through a web portal interface. The SWAT portal allows users to run SWAT simulations using the distributed resources provided by the TeraGrid--a national cyberinfrastructure for high end computing funded by the National Science Foundation. This portal supports three types of SWAT simulations: regular simulation, auto-calibration and sensitivity analysis. It provides an intuitive interface for users to configure one or multiple SWAT cases, submit these runs as computation jobs to the TeraGrid, monitor job status, visualize results and download output. This TeraGrid based SWAT portal uses a shared community account to submit jobs to the TeraGrid resource, thus eliminating the need for users to know the details of TeraGrid allocation requests and usage. Any user with a browser can connect to this portal over the Internet and benefit from the resources on the TeraGrid. This paper describes the design and implementation of the SWAT portal as well as several case studies by our early users and our future plans to improve the SWAT portal.

Keywords: SWAT model, portal, web interface, TeraGrid, community account, cyberinfrastructure

1. Introduction

The SWAT (Soil and Water Assessment Tool) model was developed by USDA Agricultural Research Service (ARS) (Arnold, 1998). It is widely used to study the long term impacts of agricultural and land management practices on water quantity, sediment yield and water quality in large complex watersheds over long periods of time (Neitsch, 2002; Gassman et al., 2007). Currently, the SWAT model is typically run as an application on a personal computer. While the model is computationally efficient and easy to use for large watershed simulations, it has a few limitations: (1) larger storage and more powerful computational resources are required for those who need to calibrate the model for large watersheds using all available parameters or to perform sensitivity analysis. To run such computations on a personal computer, the SWAT model often needs to run for multiple days. The user may need to restart the simulation if there is a power outage during that period. Furthermore, it may take months to run a set of experiments with slightly different parameter settings using this conventional approach. (2) Even for regular simulations that take far less time, a user sometimes needs to run hundreds of cases with different configuration files and input files. To run these cases using the desktop application is error prone and time consuming.

To address the above challenges, we have developed a SWAT web interface that allows users to easily configure and run the SWAT model using the distributed resources provided by the TeraGrid—an NSF funded national cyberinfrastructure of high-end computing and storage resources for researchers in the U.S. Our overarching goal is to provide a "one-stop shop" for running SWAT simulations. We began by building an online SWAT simulation portal that allows users to easily run long simulation cases by utilizing the TeraGrid resources and to automate the process of running a large number of SWAT simulations to test multiple scenarios. Depending on the type of SWAT simulation requested, different TeraGrid resources are utilized. While it is important for the TeraGrid to provide a user-friendly portal interface to run SWAT simulations on, managing large amounts of data efficiently for post-processing and analysis are critical to scientific discovery and user productivity. Traditionally, users must download simulation results, which can be abundant, to a local workstation in order to run post-processing scripts and generate graphs or other visualizations. The SWAT portal integrates simulation execution along with data management, post-processing and visualization, aiming to significantly increase research productivity by housing all these features in one place. The development of the SWAT portal is part of an NSF funded project called C4E4 (CyberInfrastructure for End-to-End Environmental Exploration) (Zhao, 2007). It has been used in several research groups at Purdue University and is making direct impacts.

In recent years, web-based simulation interfaces such as the nanoHUB, LEAD and web-based GIS along with decision support systems have become popular platforms for bringing scientific applications to a broad user community (nanoHUB, LEAD, Watergen). We envision that the SWAT portal will similarly improve and broaden the use of SWAT and the TeraGrid for hydrological research. The SWAT portal helps by eliminating technological barriers related to advanced knowledge of TeraGrid systems. Any user with a web browser can connect to this SWAT portal and benefit from TeraGrid resources.

In the following sections, we first present the overall system design and workflow. We then describe in detail the user interface, job management, data access and post processing components.

Afterward, two case studies are discussed that demonstrate the benefit of the portal. The final section discusses future work and concludes the paper.

2. Overview of SWAT Portal Design

In this section, we give a brief overview of the SWAT model and the workflow associated with a typical run. We then describe the setup of the SWAT portal and how it submits SWAT jobs to TeraGrid resources.

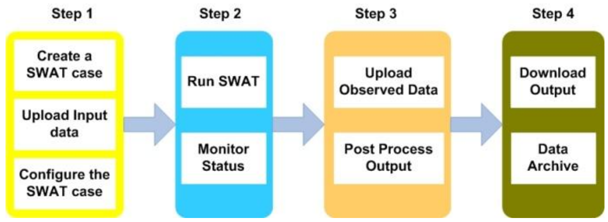

Figure 1. *SWAT portal workflow*

2.1 SWAT Model Workflow

A typical SWAT simulation run from the portal consists of four steps as shown in Figure 1. A user first creates a new simulation case and uploads the corresponding input file. The user then specifies the type of simulation. The portal supports three types of SWAT simulations: regular simulation, auto-calibration and sensitivity analysis. A user can run multiple simulations at the same time. In the second step, the portal submits the SWAT simulation(s) to the appropriate TeraGrid computation resources depending on the type of simulation. A shared community account is used to submit jobs, eliminating the need for users to know how to obtain TeraGrid allocations and configure TeraGrid systems. The user can track the status of submitted runs from the portal. Once the job is complete, the user may process the output to generate plots to be included in possible future publications. In the final step, the user can download the output data of interest from the portal. Old data will automatically be archived and can be accessed when needed.

2.2 System Architecture

The setup of the SWAT portal matches the workflow described in the previous section (Figure 2). Each workflow step is a functional unit with a corresponding user interface provided by the portal. Behind the scene, the portal uses a MySQL database to manage the information about the users and their simulations. To make the portal scalable for a large number of users, the simulation jobs are submitted to a remote TeraGrid computation resource using the Globus middleware (Globus).

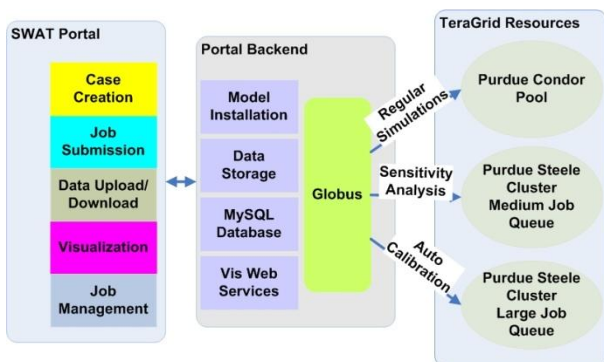

Figure 2. *SWAT portal architecture*

There are 11 resource providers on TeraGrid. We chose to use the Condor pool and Steele Linux cluster at Purdue University (Condor, Steele). The Condor pool consists of over 20,000 processors of mixed architecture types and configurations. The Steele cluster consists of 893 8-core Dell 1950 systems with various combinations of 16-32 GB RAM and Gigabit Ethernet and Infiniband. These two resources were selected because (1) the vast number of Condor nodes makes it readily available to run normal SWAT simulations. Most of the time, the user can access the cycles through Condor within minutes. (2) The Steele cluster provides several queues with different maximum wall clock limits. It is the only

TeraGrid Linux cluster that allows a maximum wall clock limit of 720 hours, which is long enough to run auto-calibration cases.

The SWAT model developed by USDA is currently only available for the MS Windows platform. In order to run SWAT on TeraGrid Linux systems, we first ported the source code of SWAT 2005 to Linux, using the Intel FORTRAN 90 compiler. This executable is then used by the portal to run SWAT simulations on Steele and Condor. For the backend system, we installed the Linux version of SWAT executable in a TeraGrid "community software area" on Steele. There are also several shell scripts invoked by the portal to create user directories, launch SWAT on a compute node and archive the output. In order to support multiple users from the portal, separate directories are created for each user to hold their model input, model output and observed data for post-processing.

3. SWAT Portal Implementation

In this section we describe the design and implementation of the main components of the SWAT portal.

3.1 User Interface

The SWAT portal interface is implemented using the Gridsphere portal development framework (GS). The Gridsphere framework provides an open source portlet API that is JSR 168 compliant (JSR), a simple architecture for portlet integration and a tag library for user interface design. Each functional unit of the portal is implemented as a *portlet*, which dynamically generates the user interface and invokes the services on the backend.

3.2 SWAT Execution

In the first step, the user needs to upload an input data archive using the data upload interface. On the job configuration page, the user specifies a set of configuration settings including the type of simulation, the name of the experiment, description, keywords and an email address to send notification when the simulation completes. The user can then click on the submit button to send the simulation job to the TeraGrid. Internally, the portal uses Java CoG kit and GRAM API to interact with the TeraGrid resource (Cog, GRAM). A shared community account and GSI authentication is used when submitting jobs to the GRAM server. There are three types of jobs, and they are submitted to different computation resources based on their characteristics: normal simulations are dispatched to the Purdue Condor Pool; sensitivity analysis jobs are sent to the medium size PBS job queue of the Steele cluster; and auto-calibrations go to the large size PBS job queue of the Steele cluster. All of these operations are transparent to the user.

3.3 Job Management

The job management component allows users to track the status of their simulation runs. The jobs are listed in a table that can be sorted based on various attributes, making it

Figure 3. *Job management interface*

easy to find the one of interest. There are five possible job states: *submitted*, *pending*, *active*, *done*, and *error*. The portal uses a custom implementation of GRAM JobListener to get real time updates on the status of a submitted job. It also provides links to the log files for debugging purposes. Users can also delete unwanted cases from this interface.

3.4 Visualization

SWAT output files can be voluminous. As a result, users find it difficult to download the data and extract the variables for a particular subbasin/reach/HRU. The visualization component addresses this need and provides interactive web–based plotting services. It asynchronously invokes a visualization web service that parses and plots selected variables in STD, SUB, RCH and HRU files. Four types of plots can be generated using gnuplot (gnuplot): a simulation plot on a specific variable, a comparison plot using the observed data, a multi-variable plot of two different variables using Y1 and Y2 axes, and finally, an all-in-one plot. For each plot generated, the user can download both the plot and the raw data from the portal.

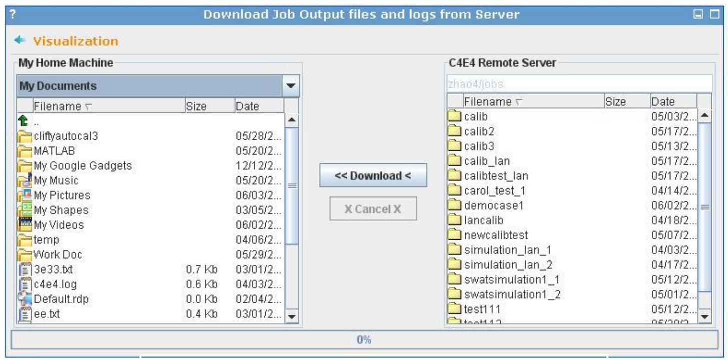

Figure 4. *Data access interface*

3.5 Data Access

The portal provides easy-to-use interfaces for uploading input/observed data and downloading output data. Each interface is implemented as a portlet with an embedded Java applet. The data access applet is a client-side Java component that supports uploading and downloading files and folders to any web server. The applet is designed for cross-browser support. Java Server Pages deployed on the server side act as the backend and handle the file streams over HTTP and HTTPS. All file operations are processed in the context of the user account and access is restricted and secure.

4. Use Cases

In this section we describe two usage cases involving real users. In both cases, the capabilities provided by the SWAT portal significantly increased the researchers' productivity, enabling large scale studies that are not practical using the conventional approach.

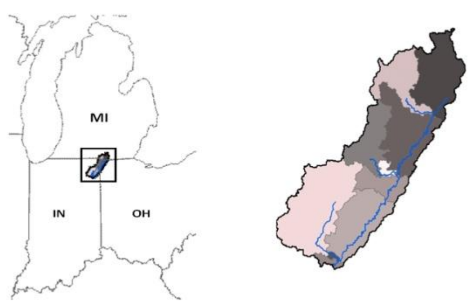

Figure 5*. St. Joseph River Watershed and its sub-watersheds*

4.1 Effect of the non-linear optimization technique on stability of auto-calibration

Shuffled Complex Evolution algorithm (SCE-UA; Duan et al., 1992) is a widely used global optimization technique in watershed modeling (Eckhardt and Arnold, 2001; van Griensven and Bauwens, 2003; Kannan et al., 2008). The probabilistic approach followed in the SCE-UA technique (evaluation of objective function at randomly selected parameter set from specified parameter space) raises question about the stability of the auto-calibration results, particularly when large parameters are used. For example, a modeler cannot confirm whether the auto-calibration routine would give same results if repeated multiple times using the same inputs. Investigation of this issue is hindered by the high computational demand of the SCE-UA implementation in hydrologic models. In this study, SCE-UA implementation in SWAT auto-calibration is evaluated by using the SWAT portal. Such an investigation would be impossible using a personal computer.

SWAT was used to create a watershed model for the St. Joseph River Watershed (SJRW) in Northern Indiana (Figure 5). SJRW (total area: 2800 km^2) was divided into 10 sub-watersheds and 97 hydrologic response units (HRUs). The SJRW model was calibrated for 7 years of daily streamflow data (1993-1999) at the watershed outlet using SCE-UA algorithm through an auto-calibration routine in ArcSWAT (version 1.0.5). Fourteen model parameters were included in model calibration based on sensitivity analysis results and available literature (see Kumar and Merwade, 2009 for detail). Calibration results were validated using 4 additional years of streamflow data (2000-2003) and results were found to be satisfactory (Table 1, Figure 6). The calibration runs were repeated 50 times using the same set of inputs. Results were compared with respect to model performance during calibration and validation and the range of values associated with each parameter. All 50 simulations were submitted in parallel through the SWAT portal and completed within 72 hours using the Steele cluster at Purdue.

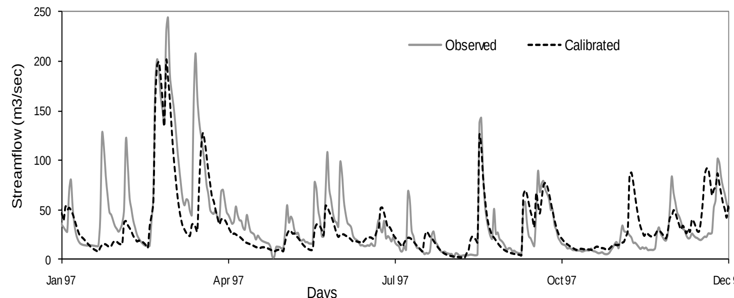

Figure 6. *streamflow hydrograph (Group2) for a calibration year 1997*

Results from the 50 calibration runs were divided into three groups such that the results are the same in each group. Group 1 includes the calibration runs from 1-30; Group 2 includes runs from 31-40; and Group 3 includes runs from 41-50. The calibration and validation results from each group are presented in Table 1. Results from Group 1 are somewhat poor in comparison to Groups 2 and 3. In addition, fewer good parameter sets (<20) were obtained in Group 1 compared to the other two groups, which produced more than 1700 good parameter sets. Therefore, Group 1 results are not included in parameter uncertainty analysis. Uncertainty ranges associated with selected parameters for Groups 2 and 3 are shown in Figure 7. The first row of parameters in Figure 7 show similar uncertainty ranges (except for *Alpha_bf*) between Groups 2 and 3 while the opposite is true for the second row of parameters. Kumar and Merwade (2009) have classified the first row of parameters as significant and second row of parameters as insignificant.

Table 1. *Model calibration and validation results for daily streamflow output*

Model	Calibration (1993-1999)		Validation (2000-2003)	
	R2NS	Mbias (%)	R2NS	Mbias (%)
Group1	0.54	0.4	0.55	21.8
Group2	0.58	-2.9	0.57	18.3
Group3	0.57	-8.8	0.57	11.0

The Fifty auto-calibration runs performed in this study using same set of inputs resulted in 3 different groups of optimized parameters. In terms of final model output (streamflow), the results produced by different calibration runs are not significantly different. The probabilistic nature of the optimization technique does introduce sources of uncertainty in auto-calibration results. However, uncertainty introduced by the model structure (significant vs. insignificant parameters) seems to play a larger role. The issue of model structure can be investigated by using a simpler model (fewer model parameters) or including only significant parameters in model calibration.

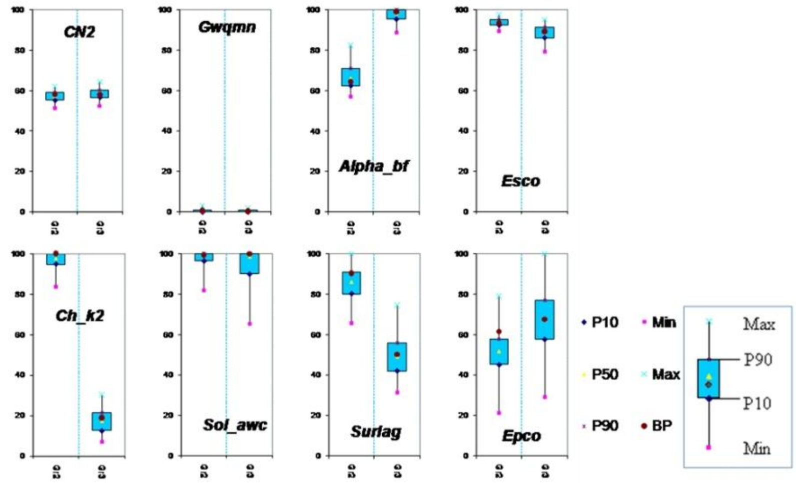

Figure 7. *Uncertainty plots for good parameter sets from Group2 (Gr2) and Group3 (Gr3), Y axis represents normalized value of parameter uncertainty range (P10, P50 and P90 are 10th, 50th and 90th percentile; Min: Minimum and Max: Maximum of good parameter sets; BP: Best Parameter set)*

2.2 Clifty creek watershed initiative project

Clifty creek watershed, located in southeastern Indiana, has an area of 522 km^2. The land use in this watershed is predominately agricultural with corn and soybean occupying 84% of the total area. Close to 4% of the watershed is urban and 10% forest. The water quality in Columbus, a city located downstream, is of concern due to nonpoint source (NPS) pollutants that have been degrading the watershed. Nonpoint source pollutants generated from surface runoff include nutrients, sediment and pesticides that are often the result of a desire to achieve higher yields through intensive fertilizer and pesticide application in agricultural regions. The goal of this project is to reduce NPS pollution by implementing both rural and urban Best Management Practices (BMPs) in the Clifty creek watershed.

The model for this project was developed using the ArcSWAT interface available in ArcGIS 9.2. The watershed was delineated from a 30 m Digital Elevation Model (DEM) obtained from United States Geological Survey (USGS). The watershed was then divided into sub-watersheds based on user-defined watershed outlets for which detailed outputs were required. These outlets consist of observed streamflow and water quality monitoring stations located in the watershed. The sub-watersheds were further divided into Hydrologic Response Units (HRUs) based on common land use and soil type. HRUs form the unit at which SWAT model calculations are performed. The land use data was obtained in a gridded form from National Land Cover Database (NLCD) 2001, and the soil data was obtained from STATSGO.

The watershed model was calibrated for streamflow using the SWAT web portal. Table 2 provides details about various parameters used in calibration that were observed to be sensitive in literature that used SWAT to simulate streamflow. The auto-calibration method available in SWAT uses a shuffled complex algorithm to perform the optimization of the objective function (which was sum squared errors in the simulation) by obtaining optimal parameter values. The total execution time of the model calibration was 12 hours using the Steele cluster compared to 41 hours when run on a personal computer. The optimal parameter values obtained are shown in Table 2.

Table 2. *Streamflow calibration of the SWAT model for Clifty Creek watershed*

Parameter	Usle_P	Slsubbsn	Slope	Esco	Ch_K2	Timp	Surlag	Cn2	Usle_C	Epco	Ch_N	Smfmx
Low	0.1	-25	0	0	-25	0.01	0	-10	0.001	0	0.01	0
high	1	25	0.6	1	25	1	10	10	0.5	1	0.5	10
optimal	0.247	7.466	0.10	0.829	-6.153	0.08	8.627	-5.874	0.165	0.081	0.245	4.573

5. Future Work

In the future, we plan to develop services that dynamically submit SWAT jobs to other TeraGrid sites primarily based on the availability of computation resources. This will significantly reduce the average waiting time before jobs are actually run on a cluster. We would also like to work closely with the SWAT user community to get feedback on the portal design and add new features based on their needs. For example, we are currently working with a research group in the Agricultural and Biological Engineering Department at Purdue University to implement an interface that enables batch configuration and submission of a large number of jobs with slightly different parameter settings. Finally, we are in the process of making the portal available for instructional use.

6. Conclusion

In this paper we describe the design and implementation of a web portal that makes it easy to run different types of SWAT simulations using TeraGrid resources. The portal integrates a comprehensive set of services for end-to-end scientific exploration including data upload/download, simulation composition, execution, status tracking and visualization. The main purpose of this work is to enable users to model long running watershed calibration cases as well as a large number of SWAT simulations using TeraGrid resources, thus significantly reducing the total amount of time required. We believe this web interface addresses an important demand in the SWAT community and will prove to be a convenient and efficient tool for research and educational users.

Acknowledgements

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SWAT Application Tool Development for Water Resources Management at County-Level in Beijing, China

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Abstract

In order to provide a technical tool for the Integrated Water and Environment Management Project (IWEMP) supported by GEF in Beijing, China, we developed a SWAT application tool at the county-level that is based on the SWAT core operation file SWAT2005.exe. Predefined stream networks and subbasins were integrated with the tool for solving problems related to the delineation of plains regions. Water balance simulation results agreed well with evapotranspiration, groundwater levels and runoff in early studies. These results demonstrate that SWAT is adaptable for plain areas, and can be used as an effective tool for agricultural water resources management.

Keywords: SWAT, water resources, plain areas

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1. Introduction

Tongzhou District is located to the southeast of Beijing, between 116°32'E and 116°56'E longitude and 39°36'N and 40°02'N latitude, and covers an area of 907 km^2. The area's elevation ranges from 8 to 32 m, and most parts of the district are covered by agricultural farmland. Average annual precipitation within the district is 526 mm. Water resources per capita are about 410 m^3, and 75% of water resources are used for irrigation (BNU, 2009).

Evapotranspiration (ET) is an important factor in the water cycle and can be used for monitoring agricultural water consumption. The traditional method of ET monitoring is usually costly and can only be used at certain points for specific crop types, which is insufficient for estimating areal ET. However, a distributed hydrological model provides an adequate tool for simulating the ET, as it utilizes observed climate data, such as precipitation and air temperature, to simulate the ET at various spatial scales. Many kinds of distributed hydrological models exist. Of those, the SWAT model has been found to suitably simulate ET in areas where there is very limited observational data. However, when SWAT is applied to plains regions, it is difficult to delineate subbasins using only the digital elevation model (DEM) data because of the flat terrain. Furthermore, SWAT does not support the graphic output; all the calculated results are exported to text files. Therefore, it is necessary for users to do the post-processing using other geographical information system (GIS) software.

With the support of the Global Environmental Facility (GEF), the Tongzhou District is undertaking the Integrated Water and Environmental Management Project (BNU, 2009). An important component of the project is estimating future changes in ET and regulating the water consumption plan based on those calculations.

Through our research, a SWAT Application Tool was developed using Visual Basic 6.0, ACCESS database and MapX OCX control to simplify the processes of inputting data, parameter calibration, scenario analysis, and supplying graphical interfaces for display of simulated results. Then, the tool was applied to the IWEMP to calculate monthly variations in regional evapotranspiration.

2. Structure Design of the SWAT Application Tool

As shown in Figure 1, the application tool designed in this research has a three-layer structure including a data layer, model layer and application layer.

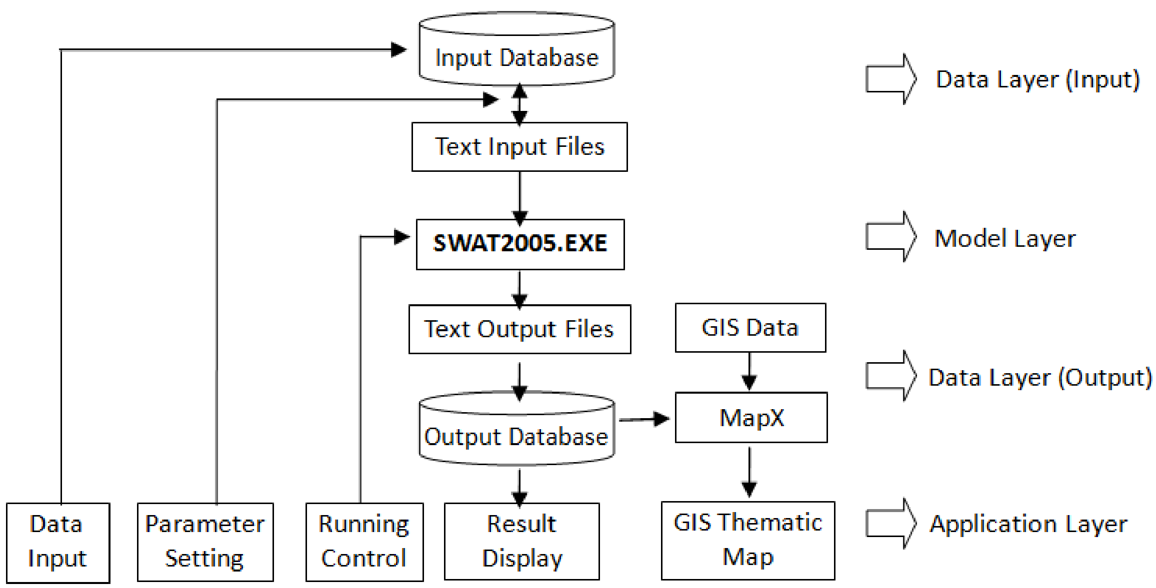

Figure 1. *Structural design of the SWAT Application Tool*

The data layer includes an input and output database, which has the same data formats as those of ArcSWAT and can exchange data with SWAT in the form of original input and output text files. The model layer uses SWAT2005.exe file, which is the same as the original SWAT core operation file. The application layer is linked with the data layer to operate the data input, parameter calibration, result output and thematic map generation. Meanwhile, it is also linked with the model layer to control the model operation.

The SWAT Application Tool was developed using VB6.0 with the ACCESS database, and the MapX 4.5 OCX control was used to support GIS operations. The calculated results of each subbasin are linked to GIS layers using the index information, which enables the SWAT Application Tool to generate GIS thematic maps quickly.

3. Functions of the SWAT Application Tool

As shown in Figure 2, the SWAT Application Tool contains seven modules: GIS control, system settings, result display, data input, running operation, scenario analysis and parameter calibration.

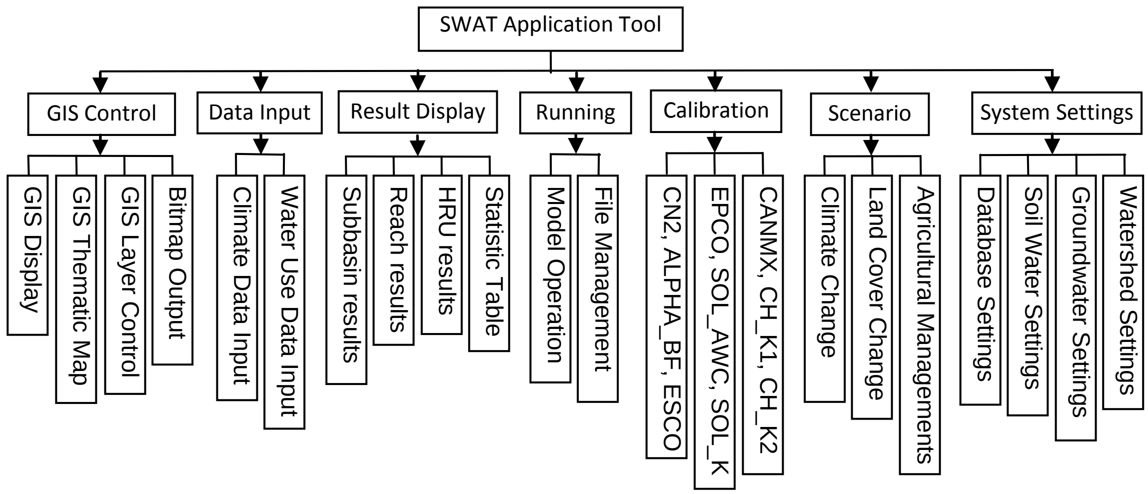

Figure 2. *Functional design of the SWAT Application Tool*

3.1 GIS Display

The main function of this module is to display the GIS information of both subbasin and river networks and to generate thematic maps of the simulation results. Meanwhile, users can perform the general operations of GIS software, such as zoom in/out, panning, distance measuring, adding GIS layers, etc.

3.2 Data Input

- *Climate data input*: meteorological data, such as precipitation and air temperature, can be processed into files by using the data input function of the Tool. Before import, the original data needs to be transferred into CSV format.
- *Water uses*: this module also considers the industrial and domestic water uses, which are subtracted from the river channel, groundwater or pond.

3.3 Result Display

- *Subbasin data display*: This function displays the simulated monthly or yearly results of the whole watershed or each individual subbasin.
- *Reach data display*: This function displays the monthly or yearly variations in channel inflow and outflow, evaporation at the water surface and transmission losses through the streambed.
- *HRU data display*: This function displays the simulated monthly or yearly results of the whole watershed or each HRU. It also shows the monthly or yearly changes in the water balance. In addition, the observed data can be imported to show correlations between the simulated and observed results.
- *Statistic table display*: This function displays the statistical results of each simulated item according to the land cover types.

Meanwhile, all of the outputs listed above can also be exported to CSV files.

3.4 Parameter Calibration

The SWAT Application Tool includes nine parameters that are closely related to the water balance calculation. Settings for those parameters correspond to subbasins, land cover types and soil types.

3.5 Scenario Analysis

- *Climate changes*: This function allows for changes in precipitation and air temperature data.
- *Land cover changes*: This function allows for changes in land cover type and ratio in any subbasin.
- *Agricultural management*: This function simplifies the complex data input for the original MGT files, allowing users to input cultivation, irrigation and fertilization data conveniently.

3.6 System Settings

- *Database settings*: The module allows the user to adjust settings for weather generator input data, land cover data and soil data. Users can also change parameters or add new types.
- *Soil water settings*: Evapotranspiration is usually the biggest contributor in the water cycle, and simulated ET is sensitive to both soil evaporation compensation factor (ESCO) and plant uptake compensation factor (EPCO) parameters. Thus, this module sets the soil water related parameters independently.
- *Groundwater settings*: Groundwater recharge is an important part of the water cycle in the plains region. In groundwater settings, an open dialog window is supplied that allows users to change groundwater related parameters, such as initial groundwater height, initial depth of water in the shallow aquifer and threshold depth of water in the shallow aquifer required for return flow to occur, etc.
- *Watershed settings*: This module includes inlet, reservoir and point source settings.

4. Application of the Tool

4.1 Data Preparation

The stream networks and subbasins were first generated using DEM data with reference to the digital map of the Tongzhou District, processed using the 'Burn in' function of ArcSWAT. After the extracted stream networks and subbasins were exported and rectified manually in ArcGIS, the rectified layers were re-imported as predefined watershed and stream datasets for calculating subbasin parameters in ArcSWAT. Finally, the Tongzhou District was delineated, giving a total of 89 subbasins and 171 HRUs, and all of the delineation results were transferred to the SWAT Application Tool for model operation. Observed climate and water use data collected from 2000 to 2005 were used to perform the hydrological calculations.

4.2 Results and Discussion

The ET simulation results were calibrated using 2002 to 2003 RS-ET data (BNU, 2009) from a previous study. As shown in Figure 3, the results calculated during that period show a correlation with the RS-ET data represented by an R^2 of 0.619. The SWAT model was validated using the RS-ET data from 2004-2005 (as shown in Figure 4). The results show a correlation with the RS-ET data with an R^2 of 0.674. Since the RS-ET data is generally believed to be 10%-20% higher than the actual values (Luo et al., 2008; NBU, 2009), the simulated ET values are within the acceptable level of accuracy.

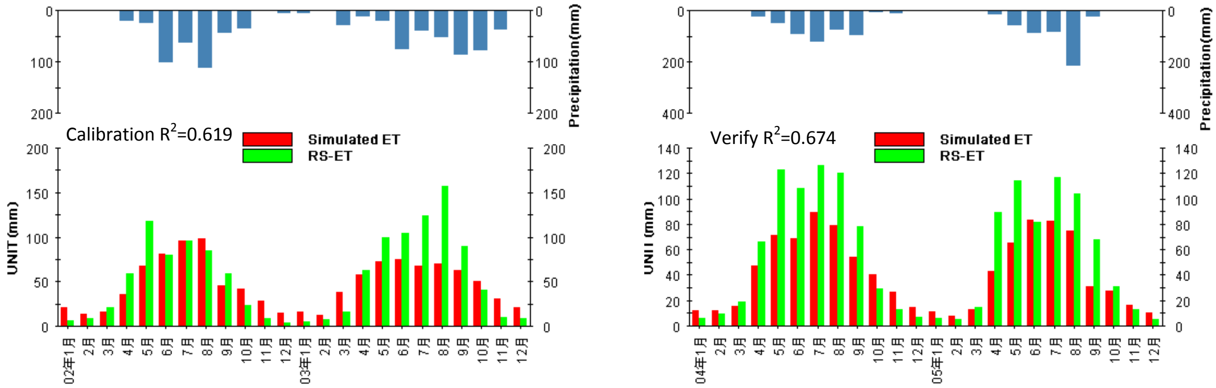

Figure 3. *Results of calibration and verification for ET from January 2002 to December 2005*

The simulated evapotranspiration results were also validated by comparing calculated groundwater levels with observed monthly data (as shown in Figure 4). The groundwater levels calculated during the period of 2003-2005 were found to be in good accordance with the observed data.

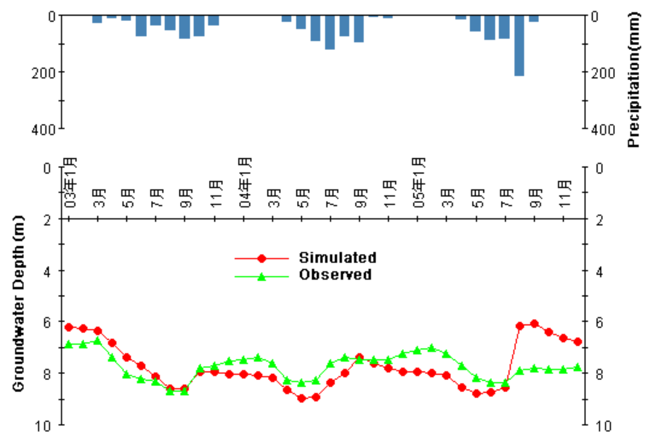

Figure 4. *Simulated results of groundwater depth during January 2003 to December 2005*

In Figure 5, the computed results of the water balance calculations show that the average annual runoff from 2003 to 2005 varies between 20-60 mm for the District. The average annual runoff from 1980 to 2005 is reported to be about 58 mm (BNU, 2009). Compared with the previous study, the results of the runoff simulation were acceptable, considering the decreasing trend of precipitation in the area.

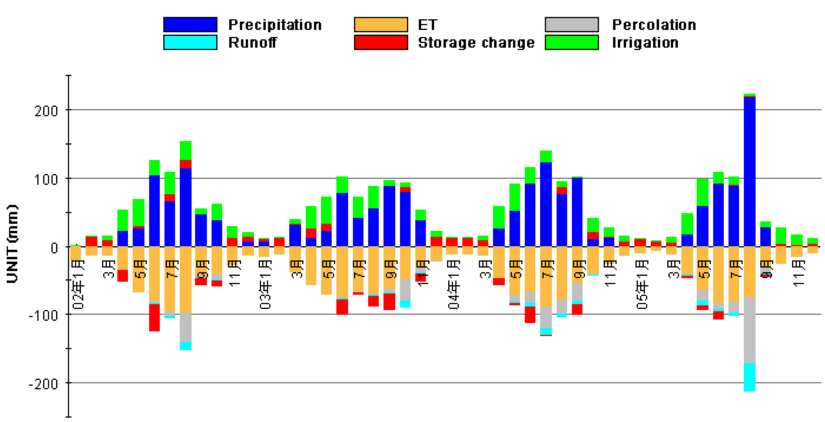

Figure 5. *Water balance simulation results from January 2002 to December 2005*

5. Conclusion

ET is an important factor in managing water resources. In order to determine the exact ET values for the agricultural lands of the Tongzhou District of Beijing, a SWAT Application Tool was developed and used to simulate monthly changes in ET. Through the calibration and validation of the model, groundwater depth and runoff generation simulation results demonstrated that the Tool can perform reasonably well and that SWAT can be adapted for the plains regions, making the model an effective tool for agricultural water resources management. In this research, we found that runoff was relatively low compared to ET and groundwater recharge. Therefore, the influence of overland flow was neglected. However, under extreme climate conditions, heavy rainfall may bring about high levels of overland flow and cause obvious errors in the simulated results; therefore, it should be considered.

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Effects of climate change on low-flow conditions in Ruscom River watershed, Ontario

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Abstract

Climate changes in recent decades indicate that there are going to be extreme weather conditions in the future including an extended periods of dry days. These climate conditions are likely to affect streamflow. The objective of the present study is to understand and predict the effect of climate change on low-flows from the Ruscom River watershed. This watershed is one of the sub-watersheds draining into Lake St. Clair on the Canadian side.

The Soil and Water Assessment Tool (SWAT) model was implemented to simulate the watershed hydrologic regime. The model was calibrated and validated for streamflow from the Ruscom River watershed using observed monthly flow data. LARS-WG weather generator used Canadian Regional Climate Model (CRCM) outputs under the SRES A2 scenario for the period, 2041-2070 for the generation of daily, future weather data on a local scale.

The Nash-Suttcliffe efficiency and r^2 for streamflow predictions were found to be greater than 0.74 during calibration and validation periods. Under the projected climate scenario, the future mean monthly minimum and maximum temperatures may increase by 3.2 ^{o}C and 3.6 ^{o}C, respectively, compared to temperatures in the base period, 1961-1990. Average annual precipitation would also increase by 8%. Flow duration curves generated from SWAT simulated streamflow indicated that low-flows in the Ruscom River would be increased in winter and summer but decreased in fall due to possible climate change. Based on frequency analysis, annual minimum monthly flow of the 5-yr return period could be reduced by about 50%.

Keywords: SWAT, climate change, low-flow, watershed, model, streamflow

1. Introduction

Climatic warming observed over the past several decades is consistently associated with changes in the hydrologic cycle and hydrologic systems (Bates et al., 2008). Increases in temperature and changes in precipitation have been observed across most of Canada during the past century. Over the last half of the twentieth century, annual average temperatures across Ontario have increased between 0 and 1.4°C, and annual precipitation in southern Canada has increased approximately 5 to 35% since 1900 (Chiotti and Lavender, 2008). Climate projections for the present century indicate that Canada will likely experience greater rates of warming than most other regions of the world with a varied magnitude of changes in climate across the country (Lemmen and Warren, 2008). Future climate changes will affect regional hydrologic conditions thereby impacting available water resources (Jyrkama and Sykes, 2007; Gleick, 1989) as well as the frequency of flooding and ecologically damaging low-flows (Fowler and Kilsby, 2007).

Climate change poses a major challenge for water managers, stakeholders and policy makers due to uncertainty surrounding future climatic and hydrologic conditions. Understating low-flow process and reliable low-flow information are required for integrated and environmentally sustainable watershed management (Smakhtin, 2001). The Ruscom River within the Essex County, Ontario sometimes experiences very low-flow conditions during dry season, as indicated by past streamflow records. Therefore, it is necessary to study watershed low-flow conditions and integrate these studies into sustainable planning, management of water resources and maintenance of the watershed ecosystem considering the likelihood of future climate change impacts.

Continuous simulation watershed models are useful for predicting the long-term effects of hydrologic changes and watershed management practices (Borah and Bera, 2004). The Soil and Water Assessment Tool (SWAT) is a widely used model for long-term, continuous simulation in predominantly agricultural watersheds. This comprehensive model has been successfully applied in many countries all over the world for continuous simulation of flow, sediment and nutrient studies, evaluation of best management practices and climate change impact studies (Gassman et al., 2005). In this study, ArcSWAT was applied for the watershed modeling, and the Canadian Regional Climate Model (CRCM) simulated output was used to determine the future climate change scenario and SWAT input. The objective of this study is to simulate streamflow and to predict the impact of future climate change on low-flow conditions in the Ruscom River watershed.

2. Study Area

The Ruscom River watershed is the second largest watershed within Essex County. It is located in the southernmost part of Ontario on a peninsula of land in the Great Lakes Basin (Figure 1). The Essex Region has a humid continental climate with four distinct seasons. The area's annual average precipitation is about 920 mm, and monthly mean temperature ranges between -4.5 and 22.7 °C. The watershed has an area of about 175 km^2 all draining into Lake St. Clair. The soils of this area are mainly clayey in texture, and the topography is level to slightly undulating. It is predominantly an agricultural watershed, and the major crops grown are soybeans, corn and wheat.

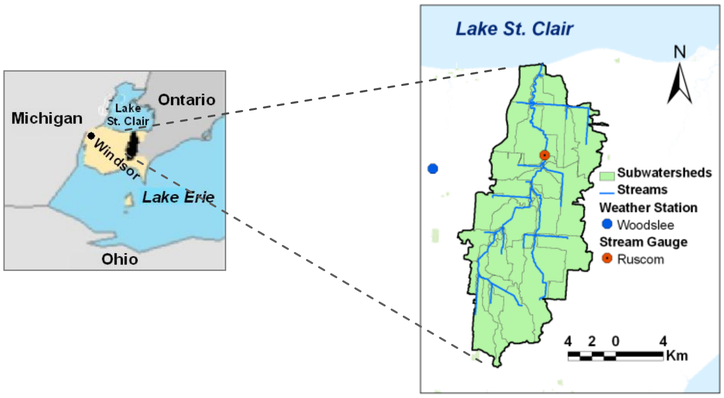

Figure 1. *Map of the Ruscom River watershed*

3. Methodology

3.1 Data acquisition

For SWAT modeling, required GIS data layers of the Ruscom River watershed including soil and land use data, a watershed map and Digital Elevation Model (DEM) were obtained from the Essex Region Conservation Authority (ERCA). The closest weather station to the watershed, Woodslee, was selected for weather data. The necessary weather data for running the model were obtained from Environment Canada's website. The CRCM simulated weather data for the observed period (1961-1990) and the SRES A2 scenario for the future period (2041-2070) were obtained from the Data Access Integration's (DAI's) website. Soil information was taken from the Essex County Soil Report (Richards et al., 1949). Soil properties, such as bulk density, available water content and saturated hydraulic conductivity of soils were calculated using the Soil Water Characteristic - Hydraulic Properties Calculator developed by Saxton (2006). Crop and management data were obtained from ERCA and the website of Ontario Ministry of Agriculture, Food and Rural Affairs (OMAFRA).

3.2 Model setup

Processing of the Ruscom River watershed DEM resulted in 31 sub-watersheds. The heat unit scheduling option was selected for model simulations because it allows the model to adjust the timing of operation to the variable weather conditions for each year (Neitsch et al., 2002). Other selected key options included the Curve Number (CN) method for generating surface runoff from precipitation, the Penman-Monteith method for computing potential evapotranspiration and the Muskingum method for simulating channel routing. The model was set up with the first three years as model initialization period used to stabilize the model.

3.3 SWAT calibration and validation

The calibration and validation periods were chosen by considering the availability and completeness of continuous streamflow and weather data. The model was calibrated for a five year period from 1990 to 1994 and validated for another five year period from 1980 to 1984 using observed streamflow data recorded within the Ruscom River near Ruscom station. Three commonly used model efficiency criteria were used to evaluate the performance of the model, including the Coefficient of determination (r^2), Nash-Sutcliffe efficiency (*NSE*) and Index of agreement (*IA*).

3.4 Weather data generation

LARS-WG, a stochastic weather generator (Semenov, 2008), was used for the simulation of future weather data. In this process, site analysis was performed for observed historical weather data over the period 1961 to 1990 to derive the statistical parameters. Changes in mean precipitation, mean wet and dry series lengths, mean temperature and its standard deviation and mean solar radiation for each month were calculated from the CRCM outputs for the base and future periods. Daily future weather data were generated from the obtained climate change scenario.

3.5 Model simulation and output analysis

The calibrated and validated SWAT model was applied to simulate streamflow from the Ruscom River watershed for the base (1961-1990) and future (2041-2070) periods. The simulated monthly streamflows at the outlet of the watershed were analyzed using statistical software, HEC-SSP (USACE, 2009), to predict the impact of possible future climate change scenario on low-flow conditions.

4. Results and Discussions

4.1 Calibration and validation

A plot of observed versus simulated streamflow and corresponding monthly precipitation during the calibration period is shown in Figure 2a. The figure illustrates that there is fairly good agreement between observed and simulated flow with the exception of a few months. Simulated flows are lower for some winter season months. The r^2, *NSE* and *IA* values of the model during the calibration period were 0.80, 0.81 and 0.94, respectively, indicating good model performance. The observed versus simulated streamflow and monthly precipitation plot for the validation period is presented in Figure 2b. It appears from the figure that model predicted flows adequately match observed flows except in regard to a few cases. Particularly, simulated flow for the month of March 1982 is considerably lower than observed flow. The r^2, *NSE* and *IA* values for the validation period were 0.74, 0.76 and 0.92, respectively, which confirm a good performance of the SWAT model for the Ruscom River watershed.

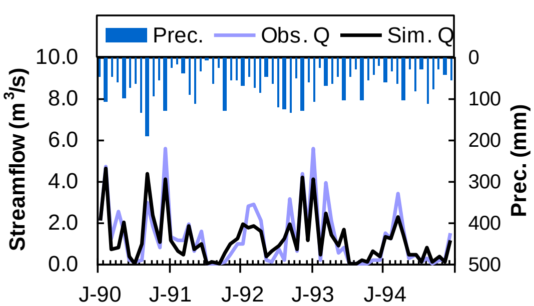

Figure 2a. *Monthly calibration*

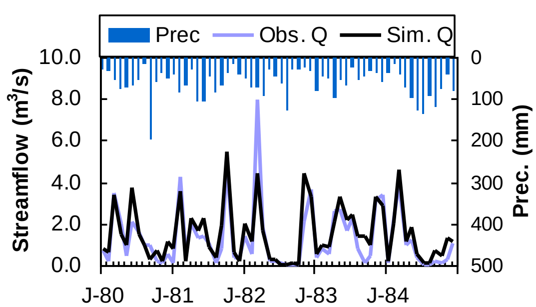

Figure 2b. *Monthly validation*

4.2 Climate change

Under the SRES A2 emission scenario, monthly minimum and maximum future temperature could, on average, be increased by 3.2°C and 3.6°C, respectively. Average monthly precipitation over the base period (1961-1990) and the future period (2041-2070) are presented in Figure 3. CRCM simulated precipitation for the observed period differs significantly from observed precipitation recorded at the Woodslee weather station for May, August and September. The LARS-WG was used to generate weather data for the future period based on relative changes in CRCM outputs. The generated average annual precipitation of 945 mm for the future period was found to be 8% higher than the observed precipitation of 871mm for the base period.

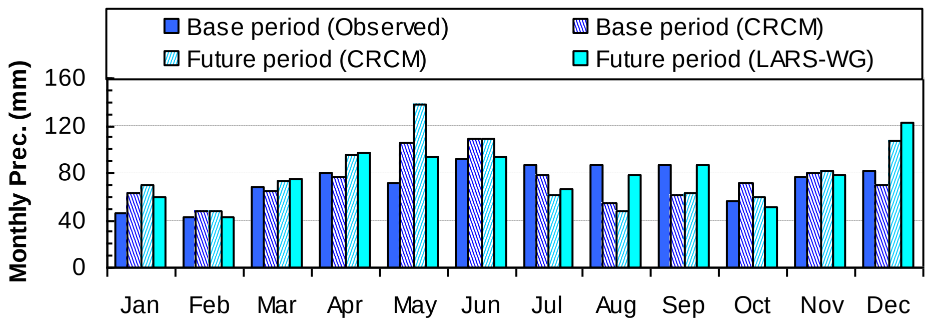

***Figure 3**. Average monthly precipitation over base and future periods*

4.3 Impact of climate change

Table 1 displays the results from the frequency analysis using lognormal and log Pearson Type III distribution based on annual minimum monthly flow over the base and future periods. The analysis showed that the 2-year return period of annual, minimum monthly flow could be about 23% lower than that of the base period in the future. Also, the future 5-year low-flow return period would be reduced, which is found to be about 0.001 m^3/s.

***Table 1.** Changes in annual minimum monthly streamflow*

Distribution	Return Period	Base Period Flow (m^3/s)	Future Period Flow (m^3/s)	Relative Change
Lognormal	2	0.013	0.010	-23%
	5	0.002	0.001	-50%
Log Pearson III	2	0.015	0.012	-20%
	5	0.002	0.001	-50%

The Flow Duration Curves (FDCs) generated from monthly simulated streamflow are depicted in Figure 4. The curves were developed by taking monthly flow data from a specific season for both the base period (1961-1990) and future period (2041-2070). The FDCs provide information on low-flow conditions in different seasons based on the portion of FDCs with streamflows below the median flow. The median streamflow (Q50) is the flow that is equaled or exceeded 50% of the time.

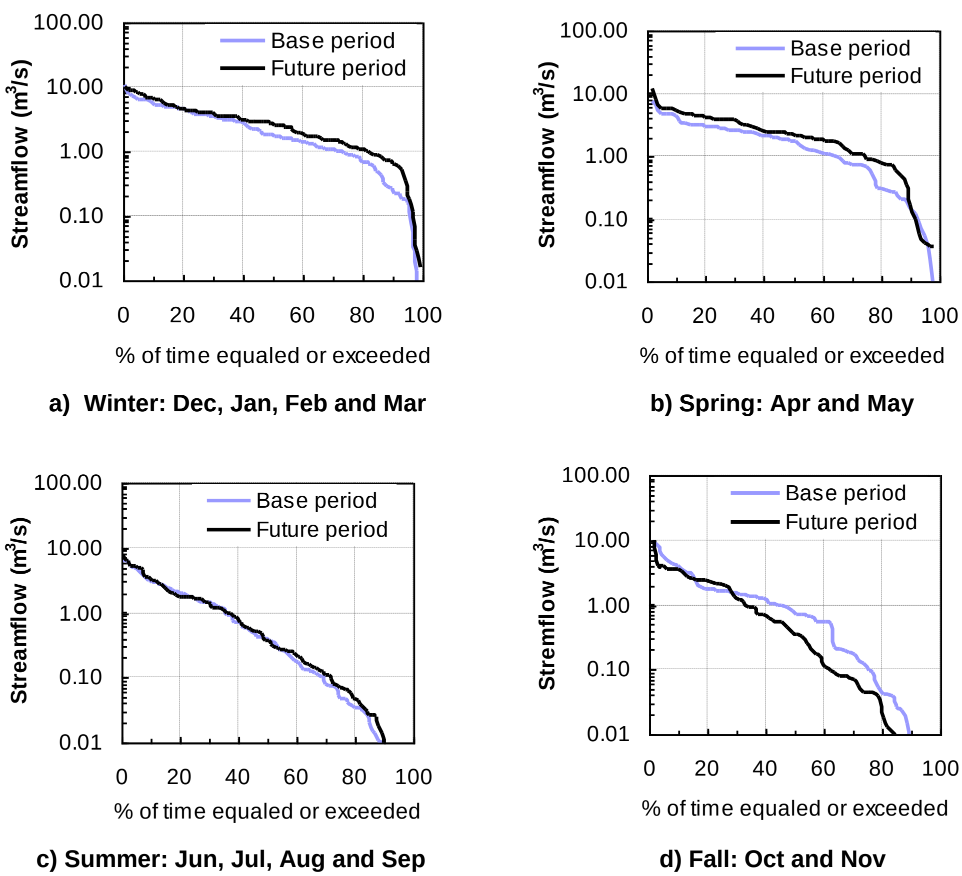

***Figure 4**. Seasonal flow duration curves based on monthly streamflow*

The figure shows that low-flows during the winter and spring seasons could increase due to future climate change. The change is substantial for flows within the range of Q90 to Q80 during these seasons. It is also evident from the figure that climate change could cause decreased rates of low-flow in the future fall seasons. The Q95 for this season could be as low as 0.01m^3/s

The results of the flow frequency analysis for individual months using Log Pearson Type III distribution are presented graphically in Figures 5. The figures depict that monthly low-flows (Q95 and Q90) would increase during the months of January, May, August, September and December due to the projected climate change scenario. Conversely, decreased low-flows are likely to occur during the months of March, April, July and November. The changes in low-flows are mainly due to changes in monthly precipitation, wet and dry spells and temperature as predicted by the CRCM. The lowest streamflow value of 0.001m^3/s that would be equaled or exceeded 95% of the time (Q95) was found during the month of October in the future climate change scenario.

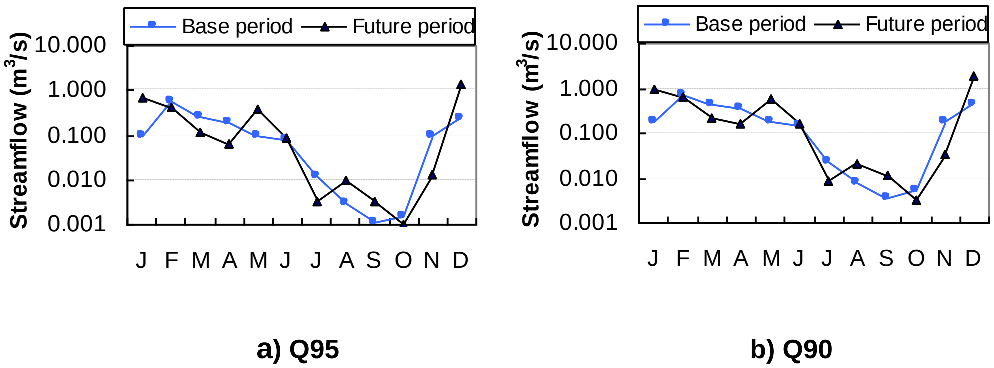

Figure 5. *Monthly streamflow equaled or exceeded 95% and 90% of the time*

5. Conclusions and Recommendations

The model performance for the calibration and validation periods shows that SWAT can reasonably predict monthly streamflow for the Ruscom River watershed. The study reveals that low-flow conditions in the watershed could change significantly due to possible future climate change. In particular, winter and spring low-flows would be increased while low-flows during the fall season would be decreased. The flow frequency analysis indicates that the 2-yr return period of annual, minimum monthly streamflow can be reduced by more than 20%, and the conditions would be worse for higher return periods.

In this study, only the climatic conditions under the SRES A2 scenario were considered for predicting future low-flow conditions. Since there are uncertainties associated with future climate predictions, further studies should be performed with multiple future climate scenarios in order to understand the full range of climate change impacts on low-flow conditions in the Ruscom River watershed.

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Changes in plant phenology and physiology under climate change and the related impacts on regional water resources

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Abstract

Vegetation patterns and processes play a major role in the regional water balance of most semi-humid and semi-arid regions worldwide. When enough water is available, climate change stimulates net primary production via temperature increases and CO_2 fertilization. Plants are located at the interface between the soil and atmosphere and connect deeper horizons with the surface. Changes in land use and plant phenology and physiology will therefore have a strong impact on regional water resources. However, there is an ongoing discussion about the possible extent of these impacts, especially about the impacts of changes in plant physiology on runoff generation. Plant stomata open less widely under increased carbon dioxide concentration. This reduces transpiration, thus increasing runoff. On the other hand, plants start growing earlier in spring, and the landscape is covered by green vegetation longer into fall, decreasing runoff. Finally, the intensity of agricultural production is increasing due to rising demand for food and bio-fuels, which may also affect runoff.

The aim of this study is to investigate the possible response of the regional water balance to changes in land use and plant phenology and physiology under climate change scenarios and to quantify the inherent uncertainty.

Keywords: vegetation processes, climate change, plant phenology, plant physiology, land use change, water resources

1. Introduction

The basic water balance equation reads "precipitation equals evapotranspiration plus runoff". In the majority of Central European river basins, most precipitation falling within a catchment is subject to evapotranspiration, and only a small part is effective precipitation that generates runoff. Small changes in evapotranspiration will therefore result in large changes in runoff (Betts et al., 2007; Hattermann et al., 2008). The most important driver for the evapotranspiration regime is temperature, and the most important water user is vegetation. This becomes visible when analyzing the flow regime of the largest Central European rivers (i.e., Rhine, Elbe, Oder). Precipitation has a small maximum in summer, but the flow regime has a pronounced flow maximum in winter (see Figure 1). Plant phenology and physiology are driven by temperature and available CO^2. Therefore, the strong correlation among evapotranspiration, temperature and vegetation dynamics (which is, again, a function of temperature) makes it very important to consider vegetation processes as dynamic with climate change scenarios. The aim of the study is to investigate three topics that are related to climate change, vegetation patterns and processes and the water cycle:

- Changes in land use intensity
- Changes in plant phenology
- Changes in plant physiology

The investigations were carried out using the model SWIM (Soil and Water Integrated Model) (Krysanova et al., 1998). The model was intensively validated for hydrological and plant processes using plot and catchment data for comparison (Krysanova and Wechsung, 2002; Hattermann et al., 2005 and 2008; Post et al., 2008). The climate scenarios are a result of a PIK (Potsdam Institute for Climate Impact Research) internal study to investigate climate change impacts on water resources, crop yields and forest growth.

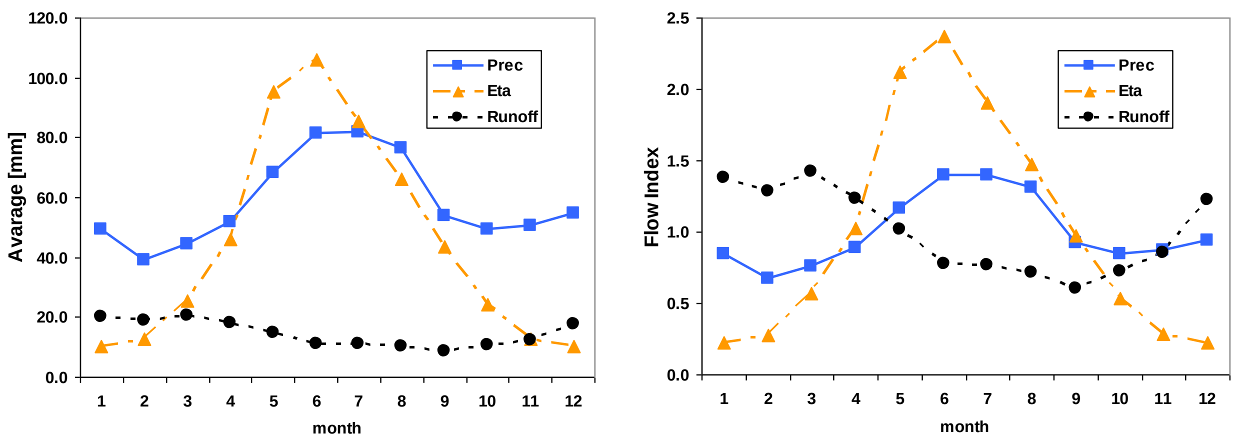

Figure 3. *Observed daily precipitation, evapotranspiration and river discharge in the Elbe basin (average values 1961-90). Left: basin wide average values in mm. Right: basin wide average normalized by the annual values.*

2. Methodology

The ecohydrological watershed model SWIM was derived from the SWAT (Soil and Water Assessment Tool) model, consult Arnold et al. (1994) and Krysanova et al. (1998).

SWIM integrates hydrological processes, vegetation, erosion and nutrient dynamics at the basin scale. A three-level scheme of spatial disaggregation from basin to subbasins and to hydrotopes is used. A hydrotope is a set of elementary units in the subbasin that have the same geographical features such as land use, soil type and average water table depth. Therefore, it can be assumed that they behave in a hydrologically uniform way (Krysanova and Becker, 2000). Water fluxes, plant growth and nitrogen dynamics are calculated for every hydrotope, where up to 60 vertical soil layers can be considered. The hydrotope outputs are aggregated at the subbasin scale. Mean resistance time and potential retention of water and nutrient fluxes can be calculated using spatial features of the hydrotopes like distance to the next river, gradient of the groundwater table and permeability of the aquifer (Hattermann et al., 2006). This approach allows for consideration and investigation of the spatial pattern of land use and land use changes. Lateral fluxes are routed over the river network, taking transmission losses into account. A full description of the model can be found in Krysanova et al. (1998) and Krysanova and Becker (2000). An extensive hydrological validation of the model in the Elbe basin including sensitivity and uncertainty analyses is described in Hattermann et al. (2005).

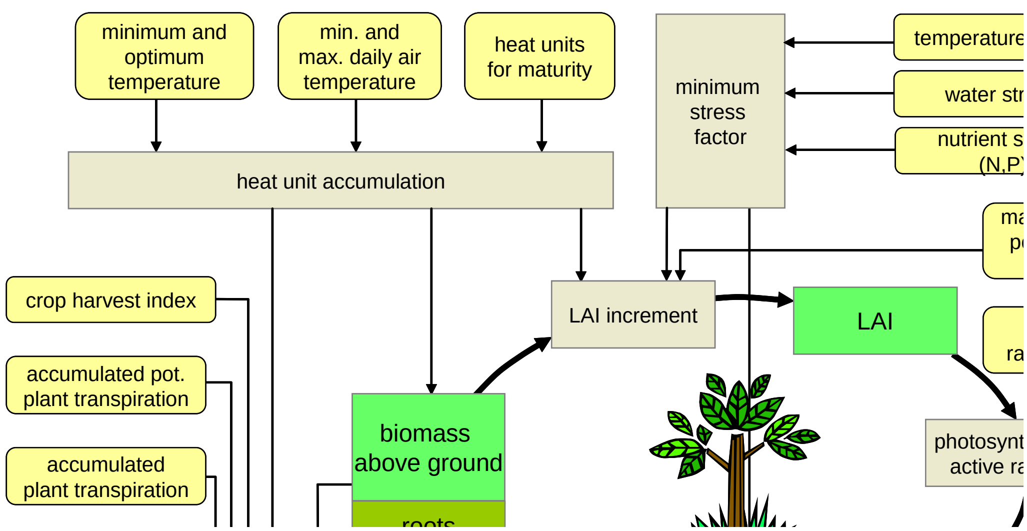

Figure 2. *Plant processes in SWIM*

Plant growth is calculated based on a simplified EPIC approach as shown in Figure 2 (Williams et al., 1984). For this purpose, a special agricultural database parameterized for the region was put into use. With the aid of the database, various cultivars (wheat, barley, maize, potatoes, rapeseed, etc.) as well as natural vegetation populations (forest, grassland) can be dynamically modeled on a day by day basis. SWIM computes the impact of climate and land use changes (i.e., type of cultivar, soil processing technology) on evapotranspiration, runoff and ground water recharge as well as nutrient balances and nutrient deposition into water bodies (Krysanova et al., 1998).

Potential evapotranspiration is calculated using the method of Turc-Ivanov (DVWK, 1996). The method distinguishes processes below and above 5 °C:

$$ET_p = \begin{cases} a\Omega(G+b)\dfrac{T}{T+15} & \text{for } T \geq 5°\text{C} \\ 0{,}000036(25+T)^2(100-RF) & \text{for } T < 5°\text{C} \end{cases}$$

G global radiation [J/cm²]

a, b parameters; a = 0,0031 and b = 209,4 for Δt = 1 d

Ω monthly correction following GLUGLA (1989) (Jan 0,70; Feb 0,85; Mar 0,95; Apr 1,05; May 1,25; Jun 1,15; Jul 1,05; Aug 0,95; Sep 0,90; Oct 0,80; Nov 0,75; Dec 0,70)

RF humidity [%]

T mean temperature [°C]

SWIM varies the resulting potential evapotranspiration, taking into account land use, soil water availability and plant water demand.

A new semi-mechanistic approach derived from a mechanistic model for net leaf assimilation (Harley et al., 1992) that takes into account the interaction between CO_2 and temperature, was used to adjust plant growth to changing CO_2 concentrations (see also Krysanova and Wechsung, 2002):

In this method, a temperature-dependent enhancement factor α was derived for cotton

$$\alpha_{cot} = \exp\left(a_2\left(CO_2^{i^*} - CO_2^{i^0}\right) - b_2\left[\left(CO_2^{i^*}\right)^2 - \left(CO_2^{i^0}\right)^2\right] + c_2 \cdot \left(CO_2^{i^*} - CO_2^{i^0}\right) \cdot T\right),$$

$$CO_2^i = 0.7 \cdot CO_2^a,$$

where T denotes the leaf temperature (°C), CO_2^i is the carbon dioxide concentration inside leaves (μmol mol^{-1}), ° and * are indices for current and future CO_2 concentrations, and coefficients $a_2 = 0.3898 \cdot 10^{-2}$, $b_2 = 0.3769 \cdot 10^{-5}$ and $c_2 = 0.3697 \cdot 10^{-4}$. The cotton-specific factor α was adjusted for wheat, barley and maize according to the latest crop-specific results reported in the literature (Krysanova and Wechsung, 2002):

$$\alpha_{wheat} = \alpha_{cot}^{0.6}, \alpha_{barley} = \alpha_{cot}^{0.6}, \alpha_{maize} = \alpha_{cot}^{0.36},$$

implying an increase in leaf net photosynthesis of 31%, 31% and 10% for wheat, barley and maize, respectively, if atmospheric CO_2 increases from 360 to 720 ppm at 20°C.

Additionally, a possible reduction of potential leaf transpiration due to higher CO_2 (factor β) derived directly from the enhancement of photosynthesis (factor α) was taken into account in combination with both methods as:

$$\beta = \alpha \cdot \frac{CO_2^0}{CO_2^*}, \text{ where } \alpha = \frac{A^*}{A^0} \text{ and } \beta = \frac{E_{pot}^*}{E_{pot}^0},$$

resulting from

$$\left(\frac{A}{E}\right)^{*} \Big/ \left(\frac{A}{E}\right)^{0}, \text{and } \frac{A}{E} = \frac{CO_2^a - CO_2^i}{VPD} \cdot \frac{r_t^W}{r_t^C}$$

under assumption that for a given plant

$$\frac{r_t^{W0}}{r_t^{C0}} \approx \frac{r_t^{W*}}{r_t^{C*}}, VPD^0 \approx VPD^*, \text{and } \frac{CO_2^i}{CO_2^a} = \text{const},$$

where A denotes net leaf assimilation (µmol m^{-2} s^{-1}), $E_{(pot)}$ the (potential) leaf transpiration (mol m^{-2} s^{-1}), VPD the vapor pressure deficit (kPa), r_t^C the total leaf resistance to CO_2 transfer (m^2 s mol^{-1}) and r_t^W the total leaf resistance to water vapor transfer (m^2 s mol^{-1}).

3. Selected results

3.1 Land use changes

Changes in the landscape water balance due to changes in agriculture have been simulated in the Elbe basin using SWIM after transferring results provided by the agro-economic model RAUMIS (Henrichsmeyer et al., 1996) to the hydrotope scale of SWIM. A liberalization scenario was applied in which large areas having low precipitation and soils with low water holding capacity became fallow land. Also important is the further treatment of these areas. For example, keeping them as extensive grassland would result in a decrease in overall evapotranspiration (basin wide total decrease ~4 %) and an increase in overall groundwater recharge (basin wide total increase ~10 %) while development of forest would lead to an increase of evapotranspiration, pending on tree composition and age structure (for results see Wattenbach et al., 2005). Monthly changes are highest during the summer months, but seasonality is more pronounced for evapotranspiration than groundwater recharge due to the fact that groundwater recharge is buffered by soil percolation (see Figure 3).

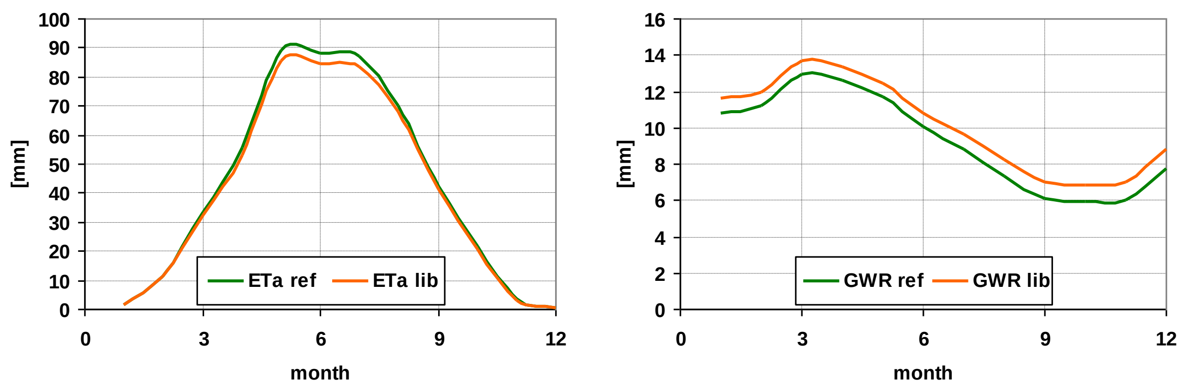

Figure 3. *Simulated changes in monthly actual evapotranspiration (left) and groundwater recharge (right) as a basin wide integral for the German part of the Elbe catchment (ten year average, induced only by changes in crop rotations as defined by RAUMIS) (Hattermann et al., 2007)*

3.2 Plant phenology

In 2008, for the first time in history, two grain harvests per year have been recorded in Germany. Our study indicates that this event is not an outlier; rather, this phenomenon could become a regular pattern under climate change (Figure 4). The remaining questions are: (1) how much additional biomass production is possible considering both an increase in temperature and a change in water availability under climate and land use change; (2) what are the consequences for the entire regional water balance, and (3) at which point is a successful second harvest reliable enough to compensate farmers for possible losses due to a sudden onset of winter. Figure 4 shows a typical crop rotation under climate scenario conditions for the period 2051-55 in which winter wheat is followed by summer barley. In nearly each of the simulated years, two grain harvests are possible. In addition, when using the second plant as biofuel, whether this plant (barley, maize) reaches maturity becomes less important, and cultivating a second plant is less risky for farmers as they can make use of the biomass in any case. However, the more intense cultivation of summer crops leads to a more pronounced water deficit, especially at the end of the summer and early spring. The feedback between vegetation and water resources has to be investigated and quantified to guarantee sustainable water use in the different regions.

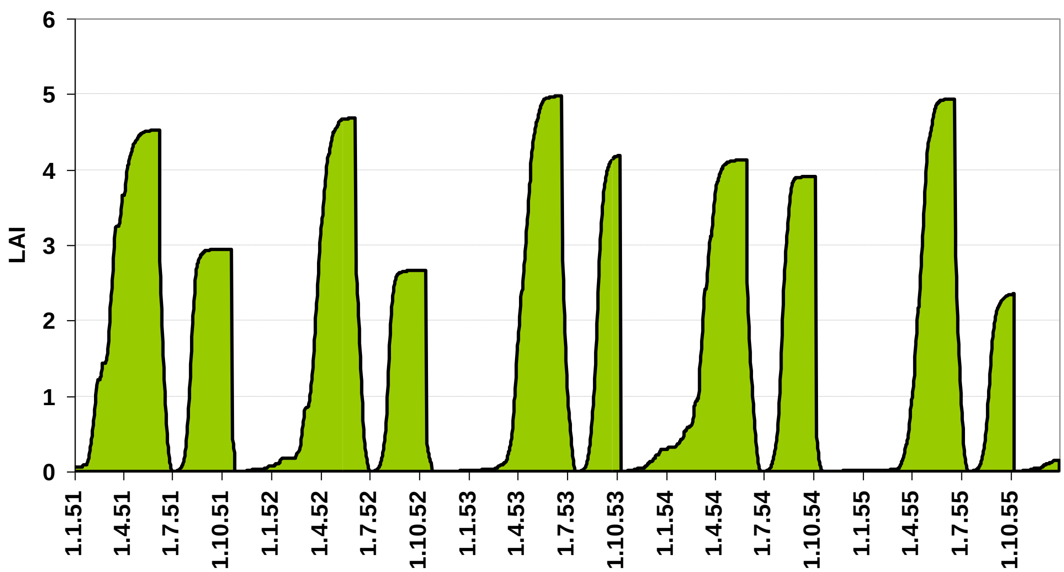

Figure 4. *LAI development under scenario conditions in the period 2051-55 as simulated in a hydrotope having a crop rotation of winter wheat and summer barley.*

3.3 Plant physiology

Table 1 shows the water fluxes under cropland (winter wheat) and climate change (temperature increases of 1.5 K and 3.0 K) scenarios in the State of Brandenburg. In comparing the simulated results, we took the effects of CO_2 fertilization into account (an increase in CO_2 concentration to 446 ppm until 2050), see Krysanova and Wechsung, 2002. The scenarios were produced using the statistical climate model STAR (Gerstengarbe and Werner, 1997).

Table 1. *Change in hydrological processes for cropland in Brandenburg, climate change only is referred to as "CC only" and climate change + factors alpha and beta is "CC + α + β" (after Krysanova and Wechsung, 2002, changed)*

Hydrological flow	**CC only**		**CC + α + β**	
	2020-2030	2040-2050	2020-2030	2040-2050
Scenario ST15				
Precipitation	-5.2	-13.4	-5.2	-13.4
Evapotranspiration	1.9	-2.0	0.0	-3.8
Runoff	-8.0	-37.7	3.3	-29.2
Groundwater recharge	-41.4	-63.7	-33.4	-55.3
Scenario ST30				
Precipitation	-2.4	-12.1	-2.4	-12.1
Evapotranspiration	4.5	-0.9	2.4	-3.0
Runoff	-6.1	-47.7	6.1	-37.7
Groundwater recharge	-36.2	-61.7	-27.1	-52.1

The results illustrate the adaptive capability of crops when stomata processes and the fertilization effect of CO_2 are considered. Crop yields increase under such conditions (not shown here), and the decrease in groundwater recharge is less pronounced when the stimulating effect of CO_2 is considered ("*CC + α + β*" in Table 1). These effects are extremely important, especially under semi-humid conditions in Central Europe where climate scenarios suggest a further decrease in precipitation, and the demand for biofuel production is increasing.

4. Conclusions

Vegetation plays a key role in the water cycle of most semi-humid to semi-arid landscapes where transpiration is much higher than evaporation due to large tracts of vegetative cover. However, the role of vegetation patterns and plant processes under climate change conditions is still under discussion, and considering different and often antagonistic processes can result in a change in the trend direction. For example, adapted land use management can help to counteract the undesirable effects of climate change by improving agricultural water use. However, the trend in agriculture is towards more intense water use because of the increased demand for food and biofuel. At the same time, the phonological phases of plants are changing due to the increase in annual mean temperature. In Central Europe, it is likely that a second harvest will be possible under climate change conditions, again increasing the pressure on available water resources. Results from this study show that water use efficiency can increase because of the plant's potential to adapt stomata processes to higher CO_2 concentrations. In sum, investigation of plant processes is still a challenge, but it is crucial to understanding the feedbacks of hydrology to vegetation, especially under climate change conditions.

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Setting up SWAT to quantify water-related ecosystem services in a large data-scarce watershed in East Africa

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Abstract

The SWAT model was set up and calibrated to quantify water-related ecosystem services in the 43,000 km^2 Pangani Basin in Tanzania/Kenya. An ecosystem service is realized when resource availability matches stakeholder demand; this starting assumption requires modeling at fine spatial detail and compatibility of model outputs with socio-economic data. Uncertainty assessment is imperative due to the limited data available and the quality of existing data. A model of the basin that produces spatially detailed outputs compatible with socio-economic information and planning units could be set up by a) improving input data through a combination of datasets from different sources, b) using the modified model version SWAT-P, c) developing a more flexible subbasin delineation process and d) using the SUFI-2 algorithm for calibration and uncertainty assessment and including uncertainty in time-series inputs. Calibration of monthly discharge in the upper basin yields satisfactory preliminary results with Nash-Sutcliffe coefficients of ≥ 0.5 at most gauges. On average, 68% of measured data bracketed in the 95% prediction uncertainty, the average width of this uncertainty range was about 0.7 standard deviations of measured data.

Keywords: Ecosystem services, hydrological modeling, SWAT, East Africa, SUFI-2

1. Introduction

The East African Pangani Basin offers a wide range of water-related ecosystem services to people living within and outside its boundaries. It provides services for domestic use, agriculture, and hydropower production and supporting services like flow regulation and purification. Water provisions also serve a cultural purpose at sacred sites and for recreation. Demand for these services is rapidly increasing with economic and demographic growth, but at the same time, water availability threatens to become less reliable with ongoing climate and land use change. Thus, the Pangani Basin represents an example of challenges faced in many dry, tropical watersheds.

The concept of "ecosystem services" is increasingly being regarded as a promising approach to mitigate problems of unsustainable resource use, including water. Ecosystem services are broadly defined as "the benefits people receive from ecosystems" (MA 2005). It is believed that sustainable resource use can be promoted by explicitly stating these benefits and their value.

This study's objective is to set up and calibrate the SWAT model in order to quantify water-related ecosystem services in Pangani Basin. We started from the assumption that an ecosystem service is realized if the availability of a resource (like water) matches a demand by any stakeholder in terms of quantity, quality, timing and location (Notter et al. [submitted]). In modeling terms, this implies that water availability and demand should be made explicit for spatial and temporal units within which the ecosystem services of interest are transferrable. In the case of the Pangani Basin, it was necessary to use a monthly temporal resolution and spatial units corresponding to the intersection of climatic and land use zones with the smallest units at which stakeholder data are available (i.e., the administrative level of the Ward). An additional challenge was the lack of high quality data on climate, discharge and water use, which introduces much uncertainty and therefore makes uncertainty assessment an imperative.
We attempted to meet these challenges with a combination of four strategies:

a) Reducing data limitations by combining datasets from different sources and using GIS tools to determine and implement the most appropriate technique for pre-processing climatic data;
b) Implementing minor modifications to the SWAT2005 model code;
c) Developing a subbasin configuration procedure that takes into account administrative units and elevation zones while minimizing the number of subbasins created;
d) Applying the SUFI-2 algorithm for model calibration and uncertainty assessment and including time-series inputs such as rainfall, temperature, point sources and maximum diversions in the uncertainty analysis.

2. The study area

Pangani basin stretches over 43,000 km^2 between Kilimanjaro and the Indian Ocean (Fig. 1). The majority of its area (95%) is located in Tanzania, and the remaining 5% is in Kenya. Most of the discharge in perennial rivers originates from the humid mountain ranges while the surrounding lowlands have a semi-arid climate (Ngana, 2001). Crops (coffee, bananas, maize, flowers, sugarcane and rice) are grown mostly on the mountain slopes and foot zones or in irrigated areas in the river plains. The upper basin includes some of the most economically productive areas in Tanzania, with growing international investments in large-scale agriculture and industries. Hydropower generation along the Pangani River satisfies a significant share of Tanzania's electricity demand. However, growing water demand is increasingly leading to conflicts between water users.

3. Materials and methods

3.1 Data collection and quality control

Three types of data were required for the study:

- ***Hydro-meteorological data:*** daily rainfall, minimum/maximum temperatures and river discharge data were obtained from the University of Dar es Salaam and the Tanzania Ministry of Water. The data were quality-controlled using methods described by Feng et al. (2004). Information on point source inputs (i.e., large springs and boreholes) and granted diversion amounts were available from catchment authorities and case studies (Ngana, 2001; Ngana, 2002; United Republic of Tanzania, 1977; Jalon and Mezer, 1971).
- ***Spatial data:*** For the Digital Elevation Model (DEM), the 90 m resolution dataset by the Shuttle Radar Topography Mission (SRTM) done by NASA (Farr et al., 2007) was used. A soil map was combined from the FAO maps for Southern Africa (source scale 1:2,000,000) and Northeastern Africa (source scale 1:1,000,000) (Dijkshoorn, 2003; FAO, 1997). The FAO Africover map from 1997 (FAO 2002) served as land cover input. Boundaries of administrative units at sub-district (Ward in Tanzania, Division in Kenya) level were obtained from the National Statistics Offices. River and infrastructure networks, settlements and protected area boundaries digitized from 1:250,000 topographic map sheets were obtained from the University of Dar es Salaam. The GeoCover 2000 satellite image at 14.25 m resolution was used as spatial reference with an absolute positional accuracy of ±75 m (Earth Satellite Corporation, 2004) to which all other spatial input layers were aligned.
- ***Data related to stakeholder demand for water-related ecosystem services:*** Census data from around the years 1990 and 2000 were obtained from the National Statistics Offices. In addition to the population figures, the data for the 2000 time period contain information on household size and the type of water source for domestic use. The 2000/01 Household Budget Survey and 2002/03 Agricultural Sample Census data allowed us to estimate livestock numbers and fertilizer inputs.

3.2 Pre-processing of input data

3.2.1 Time-series data

Meteorological time-series inputs, especially precipitation data, have been repeatedly identified as one of the main limiting factors in hydrologic modeling due to spatial patterns not being captured by wide-meshed monitoring networks (e.g., Notter et al., 2007). Depending on the chosen interpolation technique, better or poorer spatial representations of meteorological variables can be achieved (e.g., Goovaerts, 2000). The SWAT model itself uses no internal interpolation algorithm (Neitsch et al., 2005). However, it is possible to carry out interpolation on subbasin areas outside the model then use the calculated rainfall amount as "pseudo-gauge" inputs (Zhang, 2006).

For the purpose of testing the performance of different interpolation techniques and pre-processing the meteorological inputs for SWAT, a time-series interpolation tool was developed using ArcGIS and ArcObjects (© ESRI Inc.). This tool interpolates the time-series data of meteorological variables to raster or polygon geometries by using the interpolation techniques available in ArcGIS (Inverse Distance Weighting (IDW), Spline and Kriging). Additionally, a secondary variable like elevation can be included in the interpolation.

The performance of the different interpolation techniques was assessed by cross-validation. First, the univariate algorithms (IDW, Kriging and Spline) were tested against each other with varying parameter settings that used samples of precipitation and temperature on a daily, monthly and annual time step between 1980 and 2000. The technique obtaining the lowest Root Mean Square Error (RMSE) between interpolated and measured values was then combined with elevation as a secondary variable and again tested using cross-validation. The resulting best technique was used to pre-process SWAT climate inputs.

3.2.2 Spatial data

Given the requirement of high spatial detail, efforts were made to improve the river network and the soil input data.

The available digital river network for the basin, at a source scale of 1:250,000, showed deviations of >1 km. On the other hand, the DEM derived from SRTM data was spatially accurate, but it cannot determine river directions reliably in flat areas. Therefore, a combined approach based on the GeoCover satellite image and the DEM was chosen. In flat areas, where water courses are distinguishable, they were classified from the satellite image using the maximum likelihood classification method. The stream lines obtained by this method were then used to "burn in" the DEM using the "Agree" algorithm (Hellweger, 1997). In more mountainous areas, the stream delineation was done based on the DEM. This method left only a few streams to be corrected manually that were neither captured by the satellite image classification nor accurately delineated based on the DEM.

For soil data, the depth parameter was spatially disaggregated based on slope (derived from the DEM). Plotting soil depth against slope for the 4,965 samples contained in the SOTER database for Southern Africa (Dijkshoorn, 2003) revealed that soil depth varied at all slopes, but the maximum depth among samples diminished with increasing slope. Therefore, soil depth was assigned to each soil type based on its average depth according to the SOTER database, but an upper limit was set based on slope. Where slope exceeded 8%, soil depth was not allowed to exceed 1 m, and where slope was over 30%, the maximum soil depth assigned was 50 cm. All other soil parameters required by SWAT were not spatially disaggregated but were determined based on soil types given in the original maps using the Rosetta.exe tool (Schaap, 1999).

3.3 The hydrological model: from SWAT2005 to SWAT-P

In order to quantify water-related ecosystem services in Pangani Basin, a few modifications to the source code of SWAT2005 became necessary:

- When using the auto-irrigation routine to simulate irrigation, an error in the code caused all flow in a river to be set to zero, even if only a part of it was removed for irrigation. This detected flaw was corrected and reported to the SWAT developers and has since been corrected in the SWAT2005 source code downloadable from the SWAT website.

- The dormancy threshold for tropical latitudes (20°N – 20°S) was decreased from 0 to -1 in order to avoid unintended dormancy of plants, which can occur due to differences between the latitudes of the closest weather station and the subbasin center.
- The floodplain routine in SWAT2005 does not simulate the spilling of water over into adjacent HRUs. Since the flooding of Kirua swamp along the middle reaches of Pangani River is a relevant process for both water users and the hydrology of the basin, a simple floodplain routine was introduced that works in essentially the same way as the existing SWAT wetland routine. However, instead of receiving water from a fraction of the subbasin like a SWAT "wetland", the "floodplain" receives water when water in the main reach of the subbasin spills over the banks.
- Since some model input data with a high sensitivity (rainfall, temperature, point source discharges and granted diversion amounts) for Pangani Basin are of low reliability, correction factors for these inputs were introduced. These correction factors could then be varied during the calibration and uncertainty assessment with SUFI-2 (see Tab. 1 and text below) like other model parameters, and their uncertainty could be included in the prediction uncertainty.
- The order of removal of water for irrigation and consumptive use was changed. In SWAT2005, water for irrigation is removed first. For the ecosystem services assessment, consumptive (domestic) use gets higher priority and was therefore set to be calculated first.

Further minor modifications included the printing of additional output variables (e.g., actually removing water amounts for consumptive use) and the reading in of .wus inputs at higher precision. The modified model version was called SWAT-P.

3.4 Model configuration

The model application in the current study posed challenges related to subbasin delineation that could not be handled with existing GIS interfaces. On one hand, since SWAT does not allow climatic differentiation within subbasins, very small subbasins would have to be created due to steep ecological gradients – consequently, the model would become very slow to run. On the other hand, the necessary inclusion of stakeholder data requires model outputs to be spatially compatible with available stakeholder data (usually linked to the geometry of administrative units). To automate subbasin delineation taking into account these factors and at the same time minimizing the number of subbasins created, a script in AML (Arc Modelling Language, © ESRI Inc.) was created with the following features:

- Flow accumulation can be weighted in order to form smaller subbasins in some areas than in others. In the current study, the weights were based on slope and mean annual rainfall. This resulted in smaller subbasins in humid and mountainous regions than in dry and flat regions of the basin;
- Any type of land units can be input so subbasin outlets are created at the intersection of their borders with streams. For the current application, Ward areas (lowest-level administrative unit) were used, so subbasin outlets were formed at each intersection of a stream with a Ward boundary.

- Any type of land units can be input so that their borders form additional subbasin boundaries (not necessarily following topographic divides). This is useful for instances in which the user needs to subdivide a subbasin that covers a large altitude range into elevation bands with different climatic conditions, instead of averaging climatic conditions over the entire altitude range. Such additional conceptual subbasins within a physical subbasin are linked through zero-length "pseudo-streams" in order to ensure correct water routing. When using this option, it should be noted that after running the model, reach outputs should only be used from the outlets of physical subbasins. When setting up the model, model parameters for surface runoff and erosion (longest tributary channel length, slope length, etc.) should be determined based on physical subbasins, and their distributed values for the additional subdivisions should be assigned the same way that SWAT internally assigns these parameter values to HRUs based on model subbasin inputs. In the current study, 400 m elevation bands were used for this option.

In order to create the input files required by SWAT, the outputs of the tool were processed together with the mentioned spatial and time-series input data using the ArcSWAT interface (Winchell et al., 2007).

3.5 Calibration, validation, and uncertainty assessment

Model calibration, validation, and uncertainty assessment were carried out using the SUFI-2 Algorithm (Abbaspour et al., 2007). SUFI-2 aggregates uncertainties in model concept, inputs and parameters and aims to obtain the smallest possible uncertainty (range) in predictions (Schuol et al., 2008). Starting with large, physically meaningful parameter ranges, SUFI-2 decreases these ranges iteratively; the aim is to bracket as much of the measured data as possible within 95% prediction uncertainty while narrowing this range as much as possible. The "p-factor" describes the percentage of data bracketed by 95% prediction uncertainty, and the "r-factor" describes the width of the 95% uncertainty interval in standard deviations of measured data.

In addition to the conventional SWAT parameters, the correction factors introduced with SWAT-P for precipitation, temperature, point source discharge and maximum diversion amounts were included in the uncertainty analysis.

Measured monthly discharge data from 16 stations in the basin, mostly from the period 1980-2005, were used. Measured data used to calibrate other model output variables were not available in time-series form. Due to numerous gaps in the measured series, a criterion was formulated that 3 years of data had to be available for both calibration and validation. At four stations, the available data series were enough for calibration only. At three further stations, the data series stopped around the beginning of the 1980's; therefore, earlier data (from 1960 onward) were used for calibration and validation at these locations.

An initial sensitivity analysis identified 16 parameters sensitive to discharge (Tab. 1). These parameters were varied using a regional approach. They differentiated by 11 parameter zones defined on the basis of climate, topography and geology (Fig. 1). For groundwater parameters, the zones in mountainous areas were internally further differentiated into a higher and a lower zone. Discharge from Nyumba ya Mungu Reservoir is determined by the daily decisions of the power plant operator. As this reservoir is located in the middle of the basin, the basin was divided into three parts for calibration and validation, the Kikuletwa and the Ruvu sub-catchments upstream of Nyumba ya Mungu and the lower basin downstream. Measured daily release rates were used as inputs from the Nyumba ya Mungu Reservoir into the lower basin. Consequently, the parameters for the sub-catchment between the Kikuletwa and Ruvu outlet gauges and the Nyumba ya Mungu outlet could not be directly calibrated. This was also the case for the lowermost portion of the basin between the gauge at Hale and the Indian Ocean (Fig. 1). For these areas, calibrated parameter ranges from parts of the respective parameter zone that lay within the gauged catchments were used.

Table 1. *Parameters sensitive to discharge calibrated using SUFI-2 (prefix v__ indicates that the parameter value is replaced by a given value; prefix r__ indicates the parameter value is multiplied by (1 + a given value) (Abbaspour et al., 2007)*

Parameter name	Description
v__PCOR.sub	Correction factor for precipitation (introduced in SWAT-P)
v__TCOR.sub	Correction factor for temperature (introduced in SWAT-P)
v__ALPHA_BF.gw	Base flow alpha factor [days]
v__GW_DELAY.gw	Groundwater delay time [days]
v__GWQMN.gw	Threshold depth of water in the shallow aquifer for return flow to occur [mm]
v__CH_K2.rte	Effective hydraulic conductivity in the main channel [mm/h]
v__RCHRG_DP.gw	Deep aquifer percolation fraction
v__PSCOR.sub	Correction factor for point source inflow (introduced in SWAT-P)
v__DIVCOR.hru	Correction factor for maximum diversion for irrigation (introduced in SWAT-P)
r__CH_N2.rte	Manning's n value for main channel
r__CN2.hru	SCD runoff curve number for moisture condition II
r__SOL_K.sol	Soil conductivity [mm/h]
r__SOL_AWC.sol	Soil available water storage capacity [mm H_2O / mm soil]
r__SOL_BD.sol	Soil bulk density [g/cm^3]
r__ESCO.hru	Soil evaporation compensation factor
r__EPCO.hru	Plant evaporation compensation factor

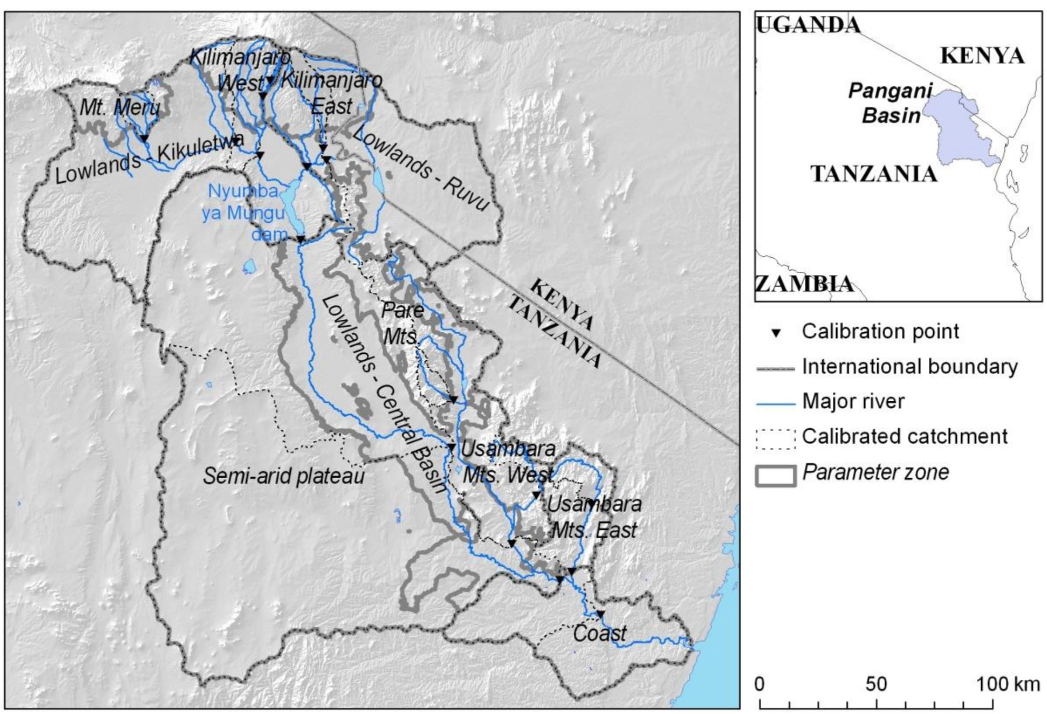

Figure 1. *Overview of Pangani Basin with calibration points and parameter zones*

4. Results and discussion

4.1 Pre-processing of climate input data

Considering the 24 nearest neighboring stations, IDW (with a power of 1) emerged as the overall best-performing technique for both rainfall and temperature among the univariate interpolation techniques. However, the best parameter settings for kriging performed almost as well and even outperformed IDW in the more data-scarce decade of the 1990's. Including elevation as a secondary variable by using a relative lapse rate of 3.6% per 100 elevation meters for rainfall and an absolute rate of -0.6°C per 100 m for temperature improved interpolation performance with a reduction of the RMSE by about 10% for rainfall and 45% for temperature. Therefore, rainfall and temperature inputs for SWAT were pre-processed (interpolation to model subbasin areas) using this method.

By identifying the most appropriate interpolation technique and including secondary high-resolution information on elevation, a more realistic spatial representation of climatic variables and a reduction of input uncertainty can be achieved. However, interpolation errors continue to be a significant source of uncertainty in modeling that need to be addressed in calibration and uncertainty assessment with SUFI-2 (see below).

4.2 Model configuration

The model setup that used the aforementioned inputs resulted in 1,853 physical (topographical) subbasins, 3,820 modeled subbasins due to elevation band subdivisions and 21,052 HRUs in the entire Pangani Basin. This configuration allows for maximum spatial detail and provides flexibility in using available inputs and producing the required outputs while keeping model complexity and computational demand as low as possible. Experiments showed that by using conventional subbasin delineation tools, tens of thousands of subbasins throughout the entire basin would have had to be created in order to reach a similar degree of detail in the critical areas. The creation of separate stream reaches per Ward allow water demand to be input at the scale at which it is available, producing differentiated outputs for any administrative unit or combination of such units as required.

Furthermore, the following points regarding model configuration can be noted:

- Large springs with known constant discharge in the footzones of Kilimanjaro and Mt. Meru were modeled as point sources. Water feeding these springs was conceptualized as leaving the modeled watershed on the upper mountain slopes as deep aquifer recharge (determined by the parameter RCHRG_DP) then entering the system again as point source inputs. The SWAT-P point source correction factor PSCOR was used to account for the uncertainty in these inputs during calibration with SUFI-2.
- Irrigated agriculture was modeled using auto-irrigation. Irrigation amounts were limited using the variable DIVMAX, based on the Pangani Basin Water Office water rights database. To account for uncertainty due to the incomplete database and lacking enforcement of abstraction limitations, the variable DIVCOR, also introduced with SWAT-P, was included in calibration with SUFI-2.

4.3 Calibration and validation results

So far, calibration and validation of monthly discharge have been completed in the upper basin (Ruvu and Kikuletwa sub-catchments, upstream of the Nyumba ya Mungu Reservoir). The preliminary results are satisfactory given the scarcity and quality of available data. Nash-Sutcliffe Efficiency (NSE) scores of ≥0.5 were achieved at 7 out of 8 gauges in the calibration period and at 4 out of 6 gauges in the validation period. On average, in the calibration period, the P-factor at all stations was 70%, and the R-factor was 0.61. In the validation period, the average P-factor was 66%, and the average R-factor was 0.78.

Comparison with previous studies shows that the estimation of non-calibrated water balance elements are consistent with their results: average deep aquifer recharge is estimated at a similar rate (i.e., Ndomba et al., 2008) in the Kikuletwa sub-catchment, and modeled actual evapotranspiration values for elevation bands on Kilimanjaro are very close to the assessment results using the CRAE approach by Rohr (2003).

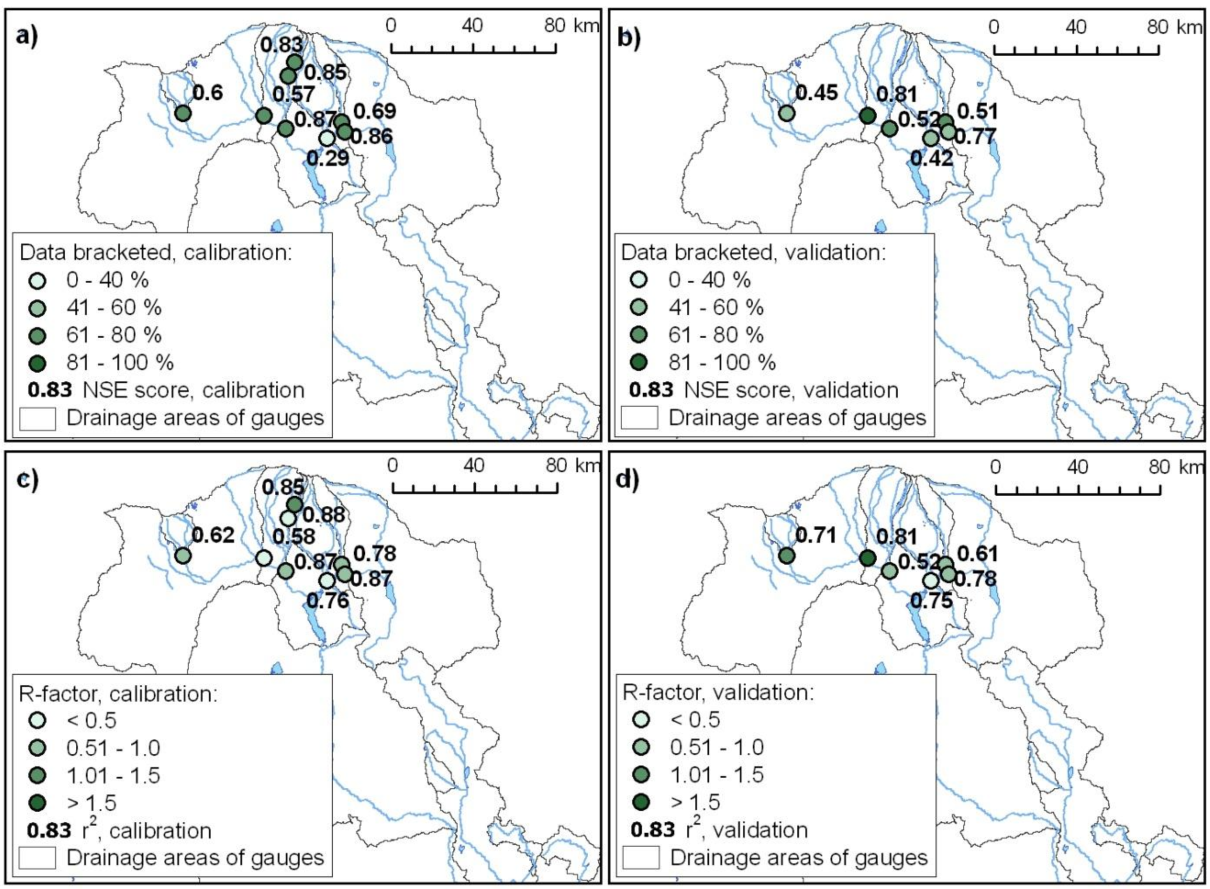

Figure 2. *SWAT calibration and validation results for the Upper Pangani Basin*

5. Conclusions and outlook

This study has demonstrated how SWAT can be set up in a large, data-scarce watershed in order to quantify water-related ecosystem services on the basis of the assumption that such services are realized if resource availability matches stakeholder demand. This in turn requires high spatial resolution and compatibility of outputs with the spatial geometry of socio-economic information. How proxies for ecosystem services can be derived from SWAT model outputs is discussed in Notter et al. [submitted]. The implementation of this step for the Pangani Basin is still in progress.

In particular, the study has shown that:

- Efforts to improve input data such as pre-processing of climatic inputs based on secondary information or combining different types of spatial information reduce input uncertainty and add spatial detail. However, the negative NSE scores at two gauges show that geo-information techniques can make up for a lack of measured information only to a limited extent.
- Minor modifications of the model code were necessary for the application in the study context. A major unresolved drawback of the program is the fact that separate input files are required for each subbasin and HRU, leading to tens of thousands of files at a spatial detail of those in the present study. Solving this problem would require a concerted effort of the SWAT user community due to the numerous other programs built around the model (like the GIS interfaces and the SUFI-2 software).
- More flexibility in the automation of the subbasin delineation process can lead to increased spatial detail while minimizing model complexity and to better compatibility of model outputs with other types of data like socio-economic information.
- The SUFI-2 procedure, in combination with the correction factors introduced in SWAT-P, allows for assessment of uncertainty in inputs that are very relevant but at the same time available in low quality in Pangani Basin, which could very well be the case in other tropical watersheds as well. The newest version of the SUFI-2 software (SWAT-CUP 2.1.4) allows uncertainty in precipitation inputs to be included in the SWAT2005 version by varying the inputs directly through the interface without the correction factor available only in SWAT-P.

In the coming months, proxies will be quantified for water-related ecosystem services for the current situation in the Pangani Basin as well as for possible future scenarios. A workshop at the Pangani Basin Water Office to discuss the preliminary results with authorities and concerned stakeholder representatives is planned for October 2009.

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Application of SWAT model to small agricultural catchment in Poland

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Abstract

Poland is obliged to implement the Water Framework Directive—WFD (2000/60/WE)—by the end of 2015 like other EU countries. The main objective of the WFD is to provide normative quality of all water resources. To reach this goal, a reduction in emissions from water polluters is required. Our project focuses on pollution from agricultural sources, whose share in global pollution is high and still growing. The small agricultural Zglowiaczka catchment was chosen as a pilot area where the WFD will be implemented.

State monitoring of surface water quality for the catchment is conducted at three points along the Zglowiaczka River. Periodically, at each of these three points, nitrate concentration significantly exceeds the allowable value of 50 mg $NO^{-3} \cdot dm^{-3}$. The highest average monthly nitrate concentration throughout years 1990–2007 occurs in February, March and April, which indicates that agriculture is a source of pollution. The Zgłowiączka catchment is an area where reduction of nitrogen runoff from agricultural lands is especially needed. The main goal of the Polish-Norwegian project is to propose different ways of reducing the migration of nitrate to surface water using a modeling approach. The paper presents the modeling of buffer zones with SWAT. We considered fitting the buffer zone width, depending on the flow rate of water travelling from fields to the stream.

Using the SWAT model interface, a map of potential flow was generated under intensive precipitation conditions. Next, the GRASS program was used to distribute the flow over the whole Zglowiaczka catchment, places with a high density of the temporal stream network. The map of stream "density" was created by assigning raster numbers. A raster number is the sum of raster in the neighborhood (the radius of a neighborhood being ≤ 25 raster). The most endangered subbasins were chosen based on visual evaluation of the surface flow density map.

The results show that filter strips on endangered areas are far more effective and therefore more appropriate. If the width of the vegetated buffer strip is not sufficient, it will not attain the desired effectiveness. Conversely, if the width is too great, it will result in agricultural land waste, deterring farmers' from cooperating with environmental preservation efforts. For the above reasons, it is important to set a reasonable width range. According to the results, we suggest wider buffer zones in endangered subbasins and narrower ones in other subbasins.

Keywords: SWAT, nitrates, buffer zones, agriculture, pollution

1. Introduction

The European Union Water Framework Directive (WFD) is one of the most significant legislative instruments dealing with water resources in recent years (Dworak et al., 2005). The main objective of the WFD is to achieve good Community water quality by 2015. To reach this goal, a reduction in water polluter emissions from both point and nonpoint sources is necessary. The control of nonpoint sources is much more complex than point sources in that nonpoint sources involve the complex transport and transformation of pollutants through different media (Drolc et al., 2008).

In many regions, intensive agriculture is a major source of diffuse pollution to both surface and groundwater (Kyllmar et al., 2005). Compared to point sources, in which treatment is the most effective pollution reduction method, abatement of diffuse pollution focuses on a set of different actions such as: land use, good agricultural practices and surface water management. For this reason, the implementation of WFD goals regarding intensive agriculture will be a very complex and long-lasting process that should involve all stakeholders including responsible administration as well as farmers and scientists.

Our project is focused on supporting the administration and self-governance of effective strategies in catchment management. Our approach for improving surface water quality is based on modeling. The strength of using models in scenario analyses is their capability to formalize complex decision making by quantifying the consequences of a large number of policy options in a consistent manner (Wolf et al., 2005). The modeling approach is helpful in the actual water quality assessment and enables early warning against an excessive pollution load. We chose the SWAT model, which was developed to predict the impact of land management practices on water, sediment and agricultural chemical yields at the watershed scale with varying soils, land use and management conditions over long periods of time (Neitsh et al., 2002).

The aim of this paper is to describe the progress and assess the effectiveness of applying the SWAT model as a tool for catchment management in a pilot catchment with intensive agriculture.

2. Materials and methods

2.1 Study area

The Zglowiaczka River is a left tributary of Vistula River. The investigations were carried out on the Upper Zglowiaczka River, above the Gluszynskie Lake. The Upper Zglowiaczka River catchment (124.3 km^2) is situated in central Poland. The catchment area has a very poor hydrographic network, which is formed only by open ditches and a subsurface drainage system. The subsurface drainage system covers about 75% of the whole catchment area. Drainage systems accelerate the circulation of water and nutrients in the catchment.

The catchment is highly arable. The dominant soil types are mainly of high agricultural quality—Phaeozems and Luvisols developed from sandy loams and loams underlain by loams with low permeability. In this area, agriculture is the dominant land use (90 %), grasslands occur only in small local land depressions and the river valley (3.9%). The landscape of the catchment is flat and typical of intensive agriculture: poor, open and without any midfield trees and forest complexes. There are no buffer zones along the river; fields adjoin directly to the river bed and ditches.

The yearly sum of precipitation in the catchment region is the lowest in Poland. The average yearly sum of precipitation is 500 mm (600 mm for Poland), about 300 mm of which occurs during the vegetation period. The water balance of field crops in an average year is negative. Potential evapotranspiration in the Zglowiaczka catchment is 650 mm per year and between 450 – 500 mm in the vegetation period (Zlonkiewicz et al., 2007). The water deficit for arable crops is a main factor limiting agricultural production and efficiency of fertilizer use. The excess precipitation (as related to potential evapotranspiration) occurs during winter time. The subsurface drainage system combined with the open ditches protects soils against waterlogging.

In the catchment area, water needs and water balance data for the main crops are known. However, there is lack of water balance analyses at the catchment scale that take into consideration spatial crop structure and fertilization levels, which change depending on economic conditions.

In 2004, nearly the entire catchment was designated as a Nitrate Vulnerable Zone (NVZ) according to the Nitrate Directive of European Union (91/676/EEC). The NVZs in the European Union Member States were designated on the basis of state monitoring results indicating surface water impairment due to nitrate pollution from agriculture. In the Zglowiaczka catchment, state monitoring is conducted at three points along the river. Surface water samples have been taken since 1990 at the point above Gluszynskie Lake. Monitoring has been conducted since 2000 at the two other points. Periodically, nitrate concentration significantly exceeds allowable levels of 50 mg $NO_3 \cdot dm^{-3}$ (Fig. 1).

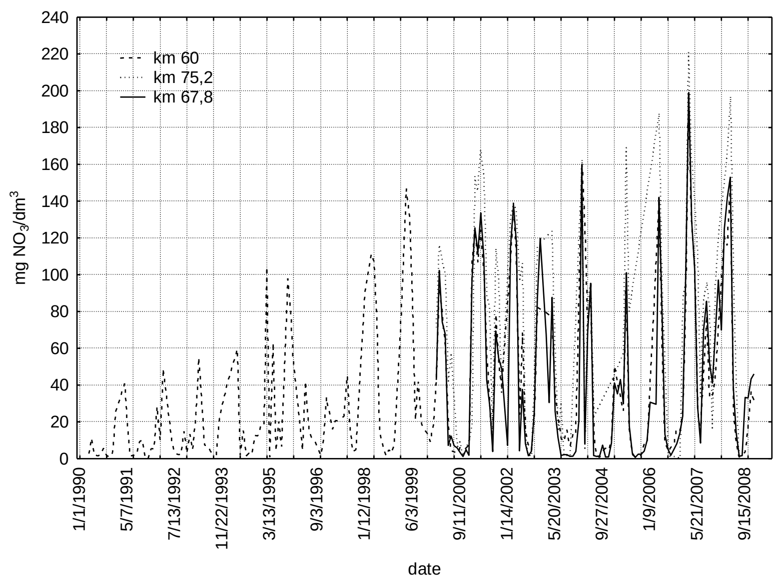

Figure 1. *Nitrate concentration in the Upper Zglowiaczka River in years 1990-2008 (according to Voivodship Monitoring System).*

The nitrate nitrogen load ($kg \cdot ha^{-1}$) from the catchment was calculated using equation 1:

$$L = \sum_{t=1}^{t=T} (\overline{Q_t} \cdot C_t^{\,I}) \quad (1)$$

Where:

L – $N\text{-}NO_3^-$ load outflowing from the catchment in a given time period T, (e.g., 365 days),

C_t^l – average $N\text{-}NO_3^-$ concentration value (for days between two subsequent analyses, the value was determined using linear interpolation),

$\overline{Q_t}$ – average daily outflow,

t – subsequence days.

The nitrate nitrogen load was calculated for the year 2007 due to the lack of outflow data for other years. In contrast to periodic high nitrate concentrations, the yearly $N\text{-}NO_3^-$ load amounts to only 20 $kg \cdot ha^{-1}$. As explained by the low outflow coefficient, which amounted to 0.14 in 2007.

2.2 Model description

The Soil and Water Assessment Tool (SWAT) model is a continuation of 30 years of nonpoint source modeling (Neitsh et al., 2002). It is a physically based, time continuous simulation model that operates on a daily time step at the catchment scale. It is designed to evaluate the impacts of management practices on water quality and sediment production in large watersheds with varying of soils and land use over long periods of time. The watershed is divided into a number of subbasins, where the HRU (Hydrological Response Units), the smallest unit of discretization, is the result of the overlay of the same soil type, land use and slope.

Modeling processes, such as soil water content, surface runoff, nutrient cycling, crop growth and management practices, are simulated for each HRU then aggregated for the subbasin by weighted average (Grizzetti et al., 2003). SWAT simulates the complete nitrogen and phosphorus cycles, taking into account nutrient mineralization, decomposition and immobilization. For nutrient inputs, SWAT takes into account natural sources and anthropogenic contribution, including both fertilizer applications (nonpoint sources) and wastewater from treatment plants (point sources).

SWAT is widely used throughout the world for modeling of diffuse nutrient emissions and water quality in rural areas (Sheperd et al., 1999; Conan et al., 2003; Bouraoui et al., 2005; Feng et al., 2008) SWAT is also a helpful tool for the evaluation of management actions to be implemented by the WFD among EU countries (Bärlund et al., 2007). Our project's aim was to create (using SWAT) a tool for catchment management to support the administration in implementing the WFD in Poland.

2.3 Input data

SWAT is a hydrological model that requires a great deal of data related to topography (Digital Elevation Model), soil type, land use and meteorological conditions. The problem lies in both the availability and resolution of these data in Poland, especially for small catchments.

For the project purpose, we created a database with all data required for SWAT. This allowed us to collect diffuse environmental data about the study area.

The digital elevation model was obtained from SRTM mission (radar satellite imagery) with 90 m resolution. In this specific area of the Zglowiaczka catchment, the pixel size was not enough for SWAT to recognize the stream network, so the map was supported by an additional stream network vector layer generated from a topographic map.

We encountered two problems with soil type—old soil data and an incompatibility between polish soil classifications and US ones. Therefore, basic pedological field investigations and soil sample analyses were done to complete the SWAT soil database.

Detailed information about crops planted in the research area is not available. It is possible to get this information at the community level through surveys made by local administration, but only about selected farms. Therefore, we assumed that select farms represent the entire area well enough. According to survey information, the main crops in the research area are: winter wheat (~ 37%) and spring barley, canola, corn, sugar beet and vegetables (mainly onion)—all about 12% of the area. The range of arable land was determined by satellite imagery from Landsat. The spatial resolution of 30 m allows the model to distinguish between settlements, forests and agricultural land. The next step was to divide arable land into polygons representing different crops so that the area of the polygons is similar to the data from the local administration. This too was made on the basis of the Landsat image. A three band composition (two infrared bands and one red) was used for this purpose (Miatkowski et al., 2006). The image is from the beginning of vegetation season (early May), so only parts of the fields are covered with vegetation. We assumed that fields with vegetation are winter wheat and canola fields. Others are without vegetative cover during this part of the year. According to this information, pixels covered with vegetation were divided into two groups: winter-wheat and canola. Other pixels were divided into four groups: vegetables, spring barley, corn, and sugar beet. With this method, we avoided a totally random distribution of crops.

SWAT requires daily meteorological values, such as precipitation, max and min temperature, wind speed, relative humidity and solar radiation. These data were collected from automatic meteorological stations for eleven years (January 1997 – December 2007) by the Institute of Meteorology and Water Management (Division in Kraków). Precipitation, wind speed, temperature and relative humidity were gathered from one station, located in Koluda. Solar radiation data were collected from two other stations, Toruń and Koło, which are located close to the research area. The default weather generator was later replaced by a user generator with values calculated for Kołuda, which better represents the specific meteorological conditions of the research area.

3. Results

We loaded the collected input data into the model. The whole watershed was divided into 23 subbasins. First, we assumed the most simple HRU classification—dominant soil type, land use and slope, then completed some simulations. The problem of proper calibration is in the availability of specific data about flow and nitrate concentration. Only hourly measurements of water levels from January to December 2007 are available. With those values and some manual flow measurements, a discharge curve was constructed. The daily discharge values calculated on the basis of the discharge curve were loaded to SWAT–CUP (Calibration and Uncertainty Programs) and compared with the simulation discharge from SWAT. The NS coefficient for the uncalibrated flow model was between -0.44 and -0.62 depending on the management scenarios. Also, a manual comparison of the general parameters was done. The accuracy of the model was tested based on general water balance parameters and yields. The values and their annual changes came out as expected. Manual approaches are still frequently used for calibration, although they are tedious, time consuming and require experienced personnel (Muleta et al., 2005). The potential evapotranspiration (calculated using Penman-Monteith method) and soil moisture was measured similarly. To collect data for precise calibration and validation of the model, investigative catchment monitoring is being organized that considers hydrology and surface water chemistry. The preliminary monitoring results and those of SWAT simulations indicate that nitrate leaches mainly from the catchment through subsurface drainage.

Although the SWAT model is still in calibration phase, we did some simple analyses of nutrient reduction management options. Buffer zones were one option analysed. Appropriate streamside vegetation and land cultivation restrictions will control nonpoint source pollution, enhance water resource utilization and aid conservation (C. Y. Lin et al., 2002).

Parts of the model interface for data preparation were used to determine surface outflow in high risk areas and prepare visualizations for educational purposes pertaining to the use of buffer zones as a way to reduce nutrient loads leaching to surface waters**.** Using the GRASS program, the next step was to distribute places with a high density of temporal stream networks over the entire Zglowiaczka catchment. The vector lines of temporal streams were changed on raster format with resolution of 30 m. The map of stream "density" was done by assigning raster numbers, which are the sum of raster in the neighborhood (the radius of a neighborhood being ≤ 25 raster). Then sub-catchments with the highest density of potential surface flow were picked up (created by SWAT model). The most endangered sub-catchments were chosen based on a visual evaluation of the surface flow density map.

The use of SWAT in the preliminary analysis of filter strip effectiveness shows that buffer zones on endangered areas are highly effective in the protection of surface water quality against nitrate outflow. If the width of the vegetated buffer strips is not sufficient, it will not attain the desired effectiveness. Conversely, if the width is too great, it will cause agricultural land waste, deterring farmers' interest in cooperating with environmental preservation efforts. For the above reasons, it is important to set a reasonable width range (Lin et al., 2004). According to the results, we suggest wider buffer zones in endangered subbasins and narrow ones in other subbasins (Fig. 2).

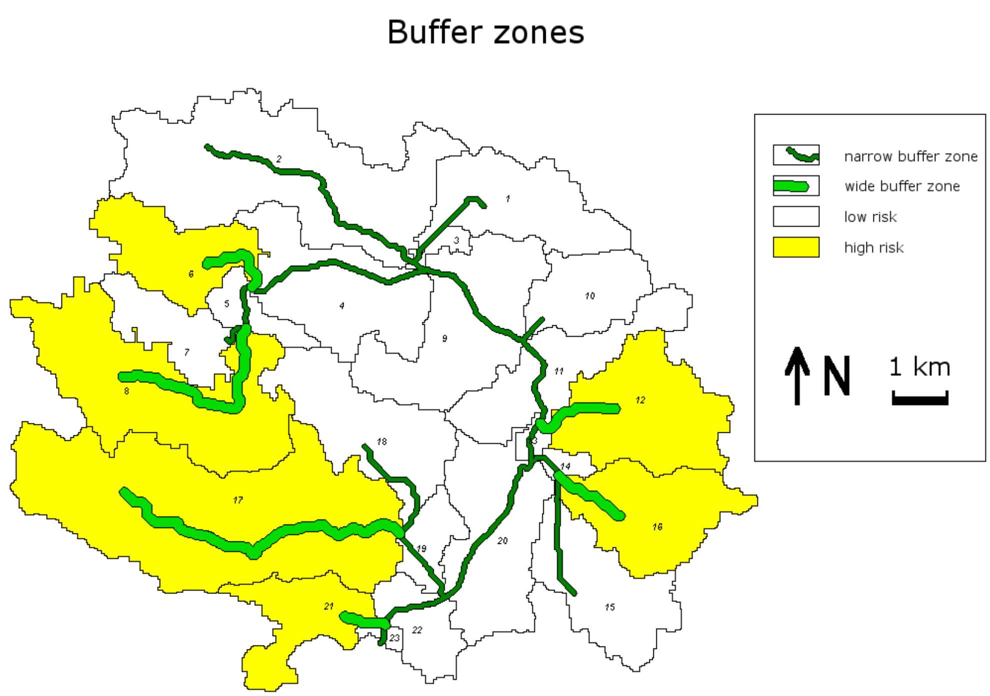

Figure 2. *Suggested buffer zones along the river and ditches in Zglowiaczka catchment*

4. Conclusions

1. The Water Framework Directive is one of the most difficult EU charges to fulfill. The project focuses on the creation of a tool that can aid local administration in the implementation of effective management strategies using a modeling approach. As it is shown above, the SWAT model can be a very helpful tool for implementation of the WFD, even without precise calibration and validation.
2. After verification, the calibrated and validated model is a useful tool for examining economic and climatic changes. It gives the user the opportunity to test some climate change scenarios and different management strategies to find the most effective and profitable solutions for the protection of surface water quality.
3. In the framework of this project, we organized hydrological and chemical monitoring. Data from these investigations will be used for more precise calibration and validation of the model.
4. Despite the fact that the most of catchment area is flat, there is a local risk of nitrate surface outflow. Correctly designed buffer zones can significantly decrease the risk of nitrate outflow from the catchment area to surface waters. The idea of creating buffer zones using SWAT can also be used in other catchments in Poland.

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How To: Understanding SWAT Model Uncertainty Relative to Measured Results

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Abstract

Watershed models contribute to most policy-making decisions of watershed management, and the demand for an accurate account of complete model uncertainty is rising. Generalized likelihood uncertainty estimation (GLUE) is a widely used method for quantifying uncertainty in hydrological models because of its ease of use and versatility in adaptation. In this paper, we examine the assumptions of GLUE and how they can be used to gain an understanding of the different parts of model uncertainty using the hydrologic model SWAT. Although GLUE, like other uncertainty methods, makes no attempt to account for the inherent uncertainty in model structures, structural uncertainty is addressed by evaluating GLUE uncertainty bounds for predictive capacity and the uncertainty range required to achieve this predictive capacity. It has been shown that, while parameter uncertainty is overestimated using both formal (Bayesian) and informal likelihoods, formal likelihoods have the ability to reduce these overestimations with increased information and provide a more accurate understanding of the structural uncertainty inherent in SWAT.

Keywords: Uncertainty, GLUE, SWAT, Bayes Theorem

1. Introduction

With the increased use of complex hydrologic models in policy-making, including uncertainty analysis in any hydrologic study is becoming increasingly necessary. However, there is much disagreement in the scientific community over how to quantify this uncertainty. GLUE (Beven and Binely, 1992) is an uncertainty estimation method that uses the response surface of different parameter sets to place limits on uncertainty. Instead of looking for a 'best fit' parameter set, GLUE acknowledges that a wide range of parameter combinations could result in acceptable model outputs and uses a likelihood function to distinguish and rank the 'probability' of each of these scenarios. Likelihood functions are assessed by comparing the model output from each complete parameter set to the observed data, implicitly considering parameter covariance. Likelihoods in GLUE do not necessarily correspond to statistically accurate probabilities because the only requirements described in Beven and Binely (1992) are that the likelihood value must increase with increasing probability of occurrence and must sum to one. Because of this, GLUE uncertainties are subject to debate due to the statistical accuracy of the method’s transformation of goodness-of-fit measures into a probability distribution and its ability to quantify uncertainty outside of parameter uncertainty. When informal likelihood functions like the Nash-Sutcliffe efficiency and inverse variance are used in GLUE, posterior probability distributions are too large and thus overpredict the uncertainty (Mantovan and Todini, 2006). Stediger et al. (2008) says that this overprediction is the reason for making a distinction between 'behavioral' (plausible) and 'non-behavioral' (implausible) parameter sets when using GLUE. When using a likelihood function that is statistically consistent with Bayes theorem, implausible parameter sets are implicitly disregarded.

Because GLUE uses responses from the most likely parameter sets, uncertainty from the model structure is not included in the resulting uncertainty bounds. To examine the structural uncertainty in the model, we used field data from two study watersheds: WE38 (7.3 km2) and its nested sub-watershed FD36 (39.5 ha). They are experimental sub-watersheds of the Mahantango Creek Watershed located about 80 km northeast of Harrisburg, PA. Mahantango Creek flows into the Susquehanna River and ultimately the Chesapeake Bay. With two simple metrics, we compared field data from these watersheds to the uncertainty bounds created by GLUE in order to indirectly measure the structural uncertainty of SWAT. By reducing overestimation as much as possible in the parameter uncertainty estimation, the accuracy and precision of the parameter uncertainty bounds can be used to separate structural uncertainty from the total estimated uncertainty. If natural variation in rainfall, streamflow and other measurements is included in the measured data, structural uncertainty in SWAT is the percentage of points not within the uncertainty bounds, and overestimation of other types of uncertainty can be evaluated by comparing the “precision” of different likelihood functions.

2. Methods

A meaningful value of total uncertainty in a hydrologic model must include all sources of model uncertainty: natural uncertainty, parameter uncertainty and model structure uncertainty. To examine the rainfall/runoff aspect of the SWAT model, we had to consider the natural variability in observed rainfall and streamflow readings. According to Harmel et al. (2007), under average sampling conditions, streamflow data can be estimated to have up to 20% uncertainty. This uncertainty in streamflow data coupled with a 20% uncertainty in rainfall data was used to calculate variable uncertainty in Montanari (2005). Thus, in this study, random, non-correlated sampling errors in directly measured input and output variables were simulated by 'corrupting' the observed precipitation and streamflow datasets. Each data point was multiplied by a random factor ranging from 0.8 to 1.2. This uncertainty was quantified by the coefficient of determination between the 'corrupted' and original datasets.

Parameter uncertainty comes from an incomplete knowledge of the parameter values in a given watershed. There are at least twenty parameters in SWAT that can be adjusted to provide a better model fit. Some, like parameters related to the curve number or lag time in the watershed, have a physical basis but are difficult, if not impossible, to measure directly. Even directly measurable physical parameters are subject to uncertainty because of inexact measuring methods or spatial and temporal variability. Due to the uncertainty surrounding parameters in any kind of environmental model, a range of values must be sampled to ensure the entire parameter space is considered. Monte Carlo sampling is a widely used method for this task.

Using the concept of equifinality (Beven and Binely, 1992), our lack of direct knowledge about the parameters led to a large number of parameter combinations that could possibly describe the model behavior. Equifinality caused the parameter sets to be treated as if there was no 'correct' parameter set, with each parameter set having a certain probability of reproducing observed data. Outputs from each of these parameter sets then needed to be compared to an observed dataset. Model outputs, created using 'corrupted' rainfall data, were compared to 'corrupted' streamflow data to include the uncertainties from input and output variables in our complete uncertainty analysis (Montanari, 2005). Parameter sets were assigned a likelihood based on their goodness-of-fit using either a formal, probabilistic method (Stedinger et al., 2008) or an informal likelihood measure (Beven and Binely, 1992).

In this study, we used the Nash-Sutcliffe efficiency coefficient as an example of a widely used informal likelihood function (Equation 1), where O is the observed data point, M is the modeled data point and A is the mean observed data point. If informal likelihood measures are used, parameter sets have to be judged to be either 'behavioral' or 'non-behavioral' based on a goodness-of-fit measure, with non-behavioral sets subsequently rejected as incorrect and assigned a probability of zero. For this study, we rejected parameter sets with a Nash-Sutcliffe efficiency rating of less than zero as 'non-behavioral'. The likelihoods of all behavioral sets were then set so that they summed to one, creating a pseudo-probability distribution. Uncertainty bounds were created for the entire time series by ordering the model outputs for each day from highest to lowest then weighting the parameter sets by their likelihoods and selecting the middle 95% of the cumulative distribution function.

We used Bayes Theorem under the assumptions of uniform prior parameter distribution and random, uncorrelated errors as our formal likelihood measure (Stedinger et al., 2008). Application of this theorem is shown below in Equation 2, where L is the likelihood, n is the number of points in the dataset, O is the observed data point, M is the modeled data point and MLE is the model data point corresponding to the parameter set with the lowest sum of squared error value. Stedinger et al. (2008) argue that if a correct Bayesian statistical procedure is used, no distinction needs to be made between 'behavioral' and 'non-behavioral' sets. Thus, uncertainty bounds were created in the same fashion as with equation 1, except no parameter sets were disregarded as non-behavioral.

$$R^2 = 1 - \frac{\sum (O-M)^2}{\sum (O-A)^2}$$ Eqn 1

$$L = e^{\left(\frac{(-n)*\left(\sum (O-M)^2\right)}{2*\sum (O-MLE)^2}\right)}$$ Eqn 2

There are benefits and drawbacks to choosing either a formalized statistical method or an 'informal likelihood measure' to designate parameter set likelihoods. Informal methods are easy to implement over a wide range of initial parameter distributions, but they require an arbitrary 'cutoff' point between behavioral and non-behavioral parameter sets and don't reflect a statistically accurate Bayesian probability in their likelihood values (Stediger et al., 2008). Formal methods require simplified assumptions about parameter distributions and model errors to create workable likelihood functions. In this study, we examined both informal and formal likelihood measures with respect to total uncertainty.

The formal and informal likelihoods were created by calibrating each to the observed data in two different ways. In the first method, we calculated the likelihood of each parameter set using the entire dataset. In the second method, we created two different likelihood values for each parameter set, one calculated with respect to days with low streamflows and the other calculated during days of high flow. Uncertainty bounds for low-flow days were calculated with low-flow likelihood values. Similarly, the bounds during high-flow days of were calculated with the high-flow likelihood values. Low-flow was taken to be 0.025 m^3/s for the smaller watershed, FD36, and 0.1 m^3/s for WE38.

Model structure uncertainty is the most difficult aspect of uncertainty to quantify, especially because we were working with only one model, in this case SWAT. Model structure uncertainty is the uncertainty rising from the fact that no matter how complex a model, it can never accurately portray the actual physical complexities of the natural system. To address this, uncertainty bounds created by the uncertainty analysis can be tested for their accuracy and precision in capturing the fluctuations of observed data (Faramarzi et al., 2008) through two metrics. The first, 'N,' measures uncertainty accuracy (the percentage of observed points contained within the uncertainty bounds). In a perfect model with a perfect description of the parameter prior probabilities, the 95% confidence intervals should contain 95% of the observed points. The second metric, 'P,' measures precision of the uncertainty bounds by comparing the average width of uncertainty bands against the standard deviation of observed output data. To avoid 'over-calibration', parameter set likelihoods are established using the first three of four years of observed data, while the 'N' and 'P' values are calculated using the fourth year of data.

3. Results

Input and output uncertainties were accounted for by 'corrupting' rainfall and streamflow datasets to simulate random, non-correlated errors. The r-squared value of the corrupted versus original data was 0.99 for rainfall and 0.98 for streamflow. These values are higher than those normally reported in studies of the literature and in practical applications (Montanari, 2005), which suggests that improvements in estimating natural uncertainty may be necessary.

'N' and 'P' values were calculated for the four likelihood measures in each watershed (Table 1). 'N' values represent accuracy, and values approaching one represent the uncertainty bounds accurately containing 100% of the observed data. 'P' values represent precision of the uncertainty bounds. A 'P' value of one represents uncertainty bounds spanning an average of one standard deviation of the observed data, with lower numbers representing more precise bounds.

Table 1. *Informal (Equation 1) and formal (Equation 2) likelihood measures and two objectives (all days or low- versus high-flow) for a small (FD36) and large watershed*

	FD36		WE38	
Likelihood Type	N - value	P - value	N - value	P - value
Formal, single objective	0.61	0.57	0.52	0.43
Informal, single objective	0.75	0.69	0.59	0.56
Formal, double objective	0.27	0.48	0.38	0.35
Informal, double objective	0.77	0.76	0.60	0.59

These numbers (and their corresponding uncertainty bounds) do not reflect actual complete model uncertainty because they do not include uncertainty arising from the model structure, but structural uncertainty can be observed 'by omission'. That is, the bounds created by using 95% confidence intervals of the posterior probability distribution should contain 95% of the model output if all uncertainty has been included. 'N' values less than 0.95 represent structural uncertainty in the model. Year 4 of the measured streamflow time series is shown along with the corresponding uncertainty bounds from the SWAT output in Figures 1 and 2.

When choosing both the formal and informal likelihood functions, assumptions made lead to overestimation of the parameter uncertainty. Because they are not representative of statistically accurate probabilities, informal likelihood functions tend to overpredict uncertainty more than formal methods, as evidenced by flatter parameter posterior probability functions (Mantovan and Todini, 2006; Stediger et al., 2008). Figure 3 illustrates this for one parameter. The formal likelihood function also overestimates parameter uncertainty due to the presence of correlated errors and the initial use of a uniform parameter distribution. Because of this, the combined uncertainty of the parameters, input variables and output variables does not technically account for the entire predictive fraction implied by the 'N' value, and the model structure uncertainty is therefore larger than it appears here.

In this study, likelihood functions were assessed both over the entire dataset (Figure 4) and over a separation of low and peak flows (Figure 5). This was done as an attempt to reduce overestimation in parameter uncertainty based on the assumption that some parameter sets would describe peak flows better than low flows while others would describe low flows better. When this distinction was introduced, the formalized likelihood functions narrowed the average width of the uncertainty bounds and reduced the fraction of points contained by the bounds. By formalizing the likelihood function and splitting parameter calibration into different hydrologic regimes (to remove some sources of correlated error), overestimation of parameter uncertainty was reduced and a more accurate description of SWAT structural uncertainty was created. However, this distinction had no impact on informal likelihood measures. The 'flattened' posterior parameter distribution obtained when using informal likelihood measures leads to the inability of the function to reduce uncertainty when presented with 'new information'.

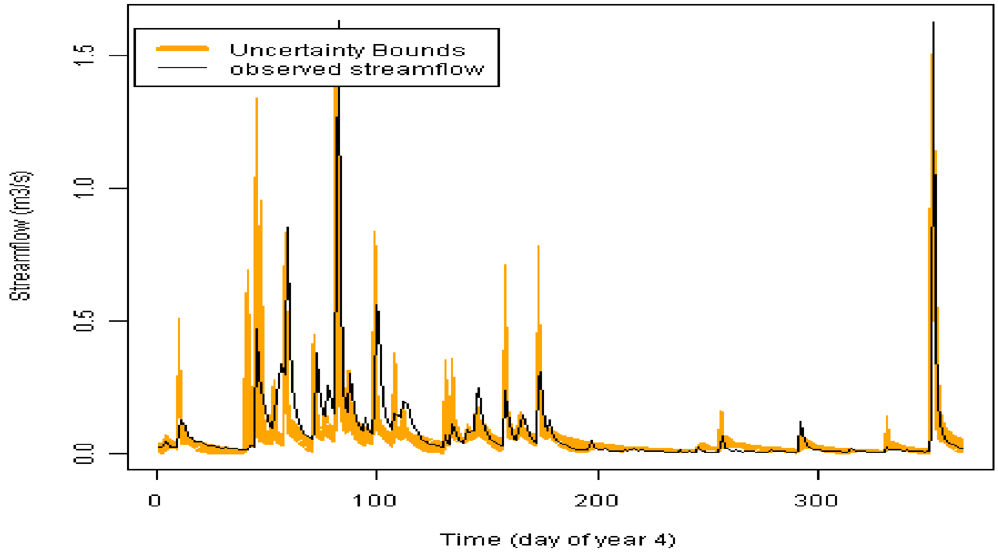

Figure 1. *Uncertainty bounds through the recorded time series in the WE38 watershed using formal likelihood and calibrating modeled data to the entire dataset*

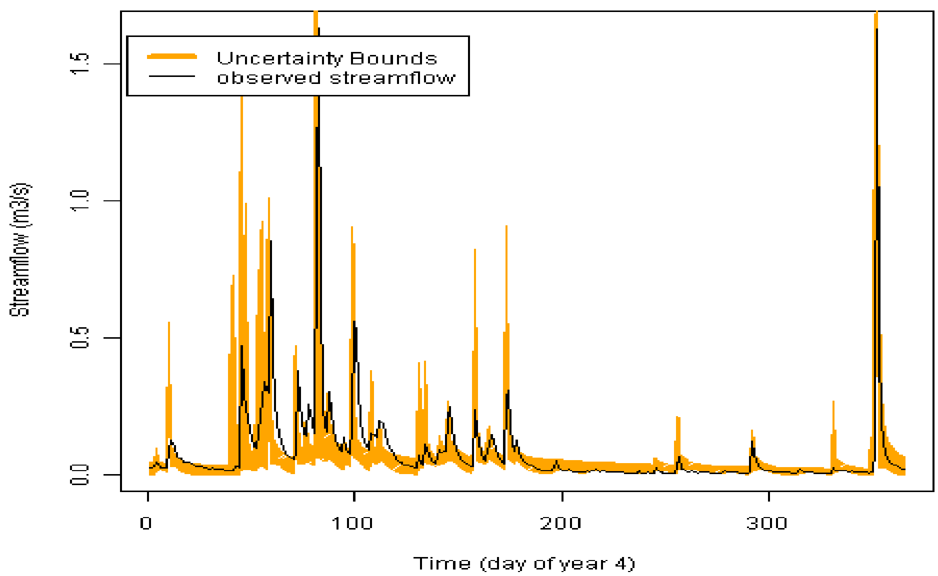

Figure 2. *Uncertainty bounds through the recorded time series in the WE38 watershed using informal likelihood and calibrating modeled data to the entire dataset*

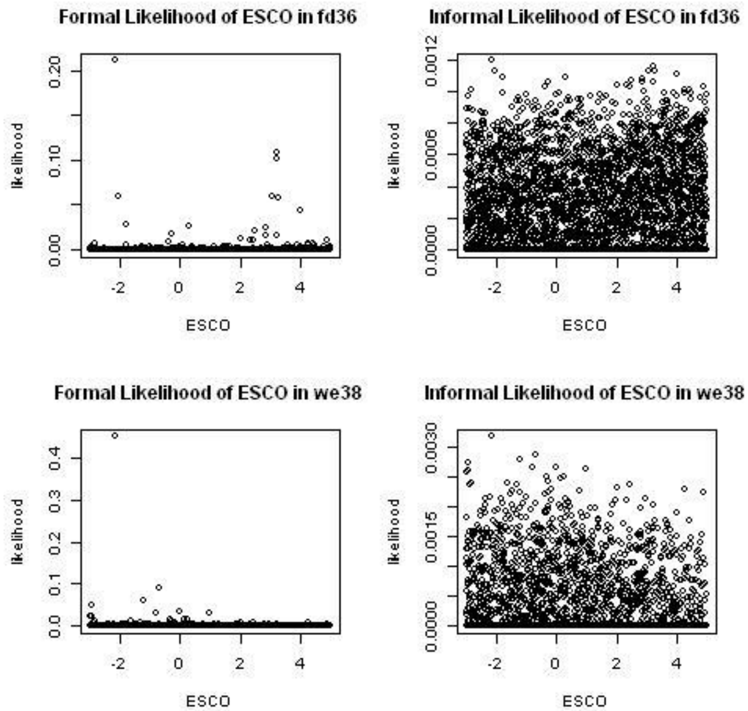

Figure 3. *Posterior parameter distributions for the SWAT parameter ESCO using formal and informal likelihood measures in the small (FD36) and large (WE38) watersheds*

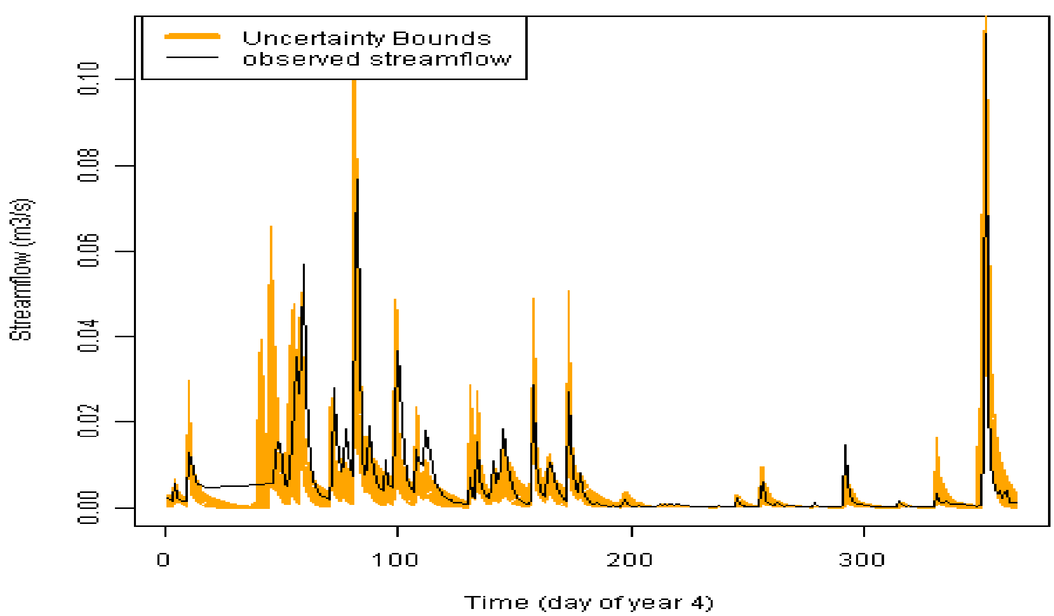

Figure 4. *Uncertainty bounds through the recorded time series in the FD36 watershed using formal likelihood and calibrating modeled data to the entire dataset*

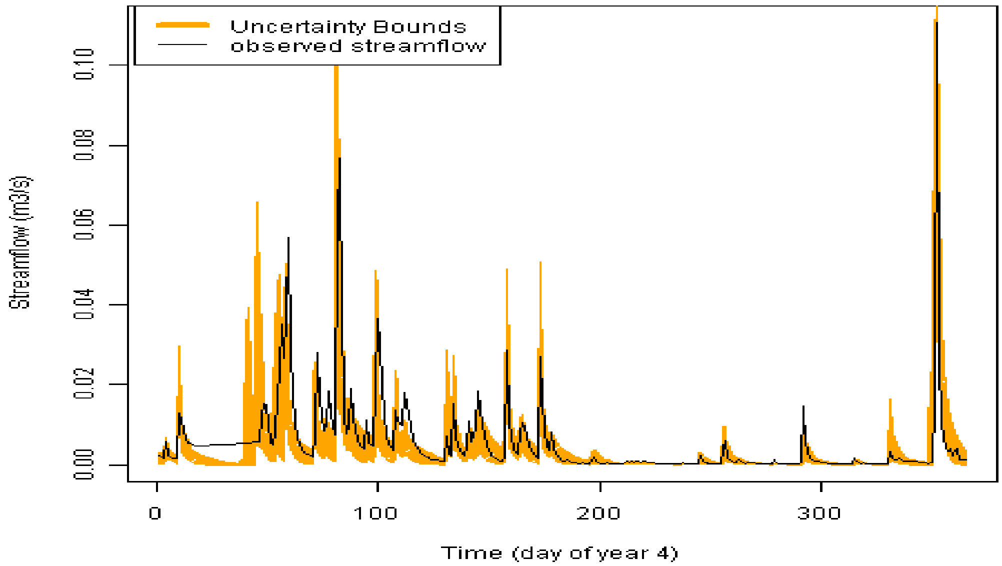

Figure 5. *Uncertainty bounds through the recorded time series in the FD36 watershed using formal likelihood and calibrating modeled data individually to low and high flows*

4. Conclusion

GLUE is a user friendly, highly malleable method for quantifying uncertainty. GLUE was applied using an informal likelihood measure to quantify SWAT model uncertainty in a watershed and a nested sub-watershed. GLUE was also applied using a formal likelihood measure to provide a more accurate statistical context for decreasing estimations of parameter uncertainty calculated using the informal measure. When measured and modeled uncertainty bounds overlapped, the formal likelihood technique estimated less parameter uncertainty than did the informal technique. Calibrating the parameter sets to different parts of the hydrological time series further decreased the uncertainty bounds created by the formal likelihood measures by removing one source of correlated errors. Distinctions beyond low- and high-flow may further decrease uncertainty. Cross-model comparisons would help determine structural uncertainties of multiple hydrological models and refine estimation techniques.

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Bacteria modeling with SWAT for assessment and remediation studies: a review

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Abstract

A module to simulate bacteria fate and transport in watersheds was first tested in SWAT2000 and fully integrated into the SWAT2005 code. Since then, few investigators have utilized SWAT to model the fate and transport of bacteria or pathogens in spite of bacterial impairment being a major concern in United States' streams and rivers. In this paper, bacteria modeling applications from Missouri, Kansas and Georgia (USA) and from Brittany (France) were reviewed, highlighting the modeling successes and challenges. These applications include watersheds that range from 16 km^2 (Georgia) to 3,870 km^2 (Missouri). In all cases, land use included agricultural (cropland and pastures) and forested land with a mixture of point and nonpoint pollution sources. Nonpoint sources included indirect (manure deposited on land) and direct contributions from cattle or wildlife to the streams. In some cases, urban and residential contributions were also taken into account. Strategies representing the different sources were determined and compared. Changes to the model's code necessary for handling contributions from urban areas were reviewed. Calibration methods, parameter sensitivity and goodness-of-fit were compared. Research needs in the following areas should be addressed: data collection to characterize runoff event bacteria concentrations and understanding of the runoff extraction and transport of bacteria. Equations that represent these processes and parameterization of these equations need to be addressed.

Keywords: bacteria modeling, fecal coliform, E. coli, bacteria fate and transport, watershed

1. Introduction

The SWAT2000 model was the first version of this particular model in which bacteria fate and transport were simulated. The equations developed by Sadeghi and Arnold (2002) were based on previous modeling work and field studies conducted in Virginia. Although few modifications have been introduced since then, additional improvements are still expected for further fine-tuning of bacteria fate and transport processes. The model is based on a two-population assumption, a mix of persistent and less persistent pathogen strains that reflect the two-stage kinetic decay observed in field studies. Considering this assumption, bacteria fate and movement is simulated by deposition of manure from grazing animals or fertilizer applications, adsorption to soil, decay, infiltration, incorporation through tillage and runoff. These equations were first successfully tested at the watershed level in the Shoal Creek watershed (Baffaut, 2003).

Since then, the model has been applied in other watersheds and by different modelers for various sources of contamination. The goal of this review is to learn from past model applications and experiences to understand the research and model development needs that will hopefully lead to better representation of bacteria sources and simulation of their fate and movement in the environment. Our objectives are to:

- Present and synthesize a set of SWAT applications for bacteria fate and transport,
- Highlight strategies to represent and quantify bacterial loadings on the landscape,
- Present changes to the model if any were made,
- Identify changes that needed to be made,
- Highlight calibration methods, parameter sensitivity, and goodness-of-fit, and
- Identify future research needs.

2. Description of SWAT bacteria applications

2.1 Missouri studies

Several studies were conducted in southwest Missouri, USA where poultry and cattle operations are important economic activities. These operations, along with urban centers, residential housing and tourism, contribute to elevated surface loadings in the landscape and direct discharges into streams. The high rock content of the soils and the karst features of the region impede the filtering and self-treatment capacity of these soils, leading to high bacteria counts in streams and lakes. Two watersheds were studied: the Little Sac watershed (Baffaut, 2006) and the James River Basin (Baffaut and Benson, 2009). Nonpoint sources included grazing cattle, failing septic tanks, poultry litter applications and wildlife. Point sources included bacteria contained in discharges from wastewater treatment plants and in spring flow. In the Little Sac, 30 years of continuous flow were available at one station and one year of weekly (March-October) or monthly (November-February) E. coli concentrations were available at 2 stations. In addition, bacterial source tracking was performed to quantify the contributions of each bacteria source. In the James River Basin, more than 30 years of continuous flow were available at five stations in the watershed. Monthly E. coli concentrations were measured for 7 years at 4 stations.

2.2 Kansas studies

Three watersheds in the Upper Wakarusa watershed in northeast Kansas, USA were studied for bacteria transport: Rock Creek watershed, Auburn watershed and Deer Creek watershed. Sources included livestock (cattle), humans (failing septic tanks) and wildlife. About 10% of the source discharges were considered to be direct (load directly deposited in the stream without prior surface transport with runoff) and 90% were deposited on land. Monitoring data included two years of weekly (April-September) or monthly (October-March) fecal coliform concentrations at the outlet of each watershed. Flow at the time of sampling was estimated using the Manning's equation. Bacterial source tracking using antibiotic resistance was performed in the three watersheds. Information about this work was obtained from Parajuli et al. (2006; 2009).

2.3 Brittany study

The study concerns a small coastal watershed in Brittany, France that was heavily impacted by runoff from dairy operations and point discharges from urban centers. Sources included the application of dairy manure on crop fields and point discharges from wastewater treatment plants. The stream discharged into an estuary used for shellfish harvest. Monitoring data included one year of weekly flow and E. coli concentrations at four points in the watersheds, with additional E. coli concentration values available at one of the stations. Continuous flow data were available at one of the four points. Additionally, shellfish E. coli concentration data collected from 1991 to 2007 were available and used as a surrogate for E. coli concentrations in the waters of the estuary. Information about this work was obtained from M. Bougeard (scientist with Idhesa, Plouzané, France, personal email communications, May through June 2009).

2.4 Georgia study

The study concerns a 16.7 km^2 sub-catchment of Little River watershed in south central Georgia, United States. The soils there are sandy and underlain by limestone at a depth of 2 meters. The land use within the watershed is characterized by row crop agriculture (45% of watershed) and forested areas (55% of watershed) used for recreational hunting. Wildlife is the primary source of bacteria loadings both directly and indirectly. However, no attempt was made to identify and quantify the source of the stream bacteria loadings. Direct inputs from bacteria into the streams and application rates on the landscape were considered calibration parameters for the model. Continuous flow data were available for seven years during which 53 instantaneous samples were collected at the outlet of the watershed and analyzed for fecal coliform. Results and information about this study were obtained from Chin et al. (2009).

3. Strategies to represent and quantify bacteria loadings on the landscape

In Missouri, Kansas and Brittany, bacteria loadings were estimated based on land uses within the watershed as well as agricultural statistics. Agricultural activities were inventoried from local knowledge and quantified from county based agricultural statistics or surveys. In Missouri and Kansas, the National Agricultural Survey Statistics were used as a way to estimate mean cattle and poultry numbers, poultry litter application rates, grazed areas and grazing densities. Final loadings were estimated from the number of animals and published manure bacteria content. Permitted facilities were defined by either the permitted flow or, when available, actual averaged or measured daily flow discharge obtained from the facilities or the state information database. In Brittany, bacteria loadings were estimated from livestock numbers (cattle, hogs and poultry), which were estimated from farm surveys and aerial photos, watershed population and published manure bacteria content. Data were available to quantify the discharges from wastewater treatment plants and their bacteria concentration.

On the other hand, in the Georgia study, bacteria surface loadings and instream inputs were considered unknown parameters of the model and adjusted during the calibration phase. There was no attempt to quantify these loadings by other means. This methodology was likely justified because the main source of bacteria in that watershed came from wildlife, which is not well quantified anywhere.

4. Changes to the code

All of these studies were performed with SWAT2005. Some additional changes were incorporated to the model to accommodate urban areas and karst features in the Little Sac and James River Basin studies in Missouri.

The model was modified to account for the high bacteria concentrations of urban surface runoff. Set concentrations for urban surface runoff were defined as follows: 549 colonies/100 mL for the Little Sac study (the average value measured in this region) and 5000 colonies/100 mL for the James River study, assumed to better represent runoff from impervious areas.

Karst hydrology was an important factor in these two studies as well. The problem was handled in two different ways. In the Little Sac study, high infiltration rates were specified for the stream channels classified as losing streams. In addition, springs were defined as point sources. Since these springs were sometimes contaminated with bacteria, an average concentration was derived from available measurements and specified in the point source definition. In the James River study, losing streams were defined in the same way. For sinkholes and springs, a modification of the code was introduced to allow rapid vertical infiltration of water through sinkholes to the shallow aquifer. Return flow was then calculated by the model as a function of water depth in the shallow aquifer. No springs were defined, but increased return flow resulted from the additional rapid infiltration. These changes resulted in a modified partition of surface and groundwater flow and improved simulation results during droughts (Baffaut and Benson, 2009). Bacteria fate and movement equations were not modified.

To our knowledge, the SWAT code was not modified for the Kansas, Georgia and Brittany studies.

5. Calibration methods, parameter sensitivity and goodness-of-fit

5.1 Flow calibration

In Missouri, flow calibration was achieved manually using the r^2 and Nash-Sutcliffe efficiencies for daily flow values. One gauge was available on the Little Sac River, and five gauges were available for the James River Basin. The length of the flow records available for calibration and validation was 30 years in both cases.

In Kansas, flow was manually calibrated at the outlet of only the Rock Creek watershed. Since only 3 years of data were available, the model was verified using data from the two other watersheds instead of validating over a different time period.

In Brittany, flow auto-calibration based on the Shuffled Complex Evolution algorithm was performed at one gauge using 4 years of daily data. Three years of daily flow data were available for the validation of the model. In addition, simulated flow values at the outlet of two other subbasins were compared to weekly measurements made over 6 months.

In Georgia, flow auto-calibration was based on a maximum likelihood method (Chin, 2009) for 3 years of data. The model was not validated in the bacteria study. However, other studies for which a SWAT model has been calibrated and validated for sub-catchment K suggest that the authors had a good understanding of the model behavior in that watershed (Feyereisen et al., 2007; Van Liew et al., 2007).

5.2 Bacteria calibration based on concentration frequency curves

Frequency curves using fecal coliform concentrations were the basis of calibration in the Missouri and Brittany studies. Concentration frequency curves of measured and simulated values were developed for each sampling point using all the data available during the calibration period. The prediction efficiency (PE) (i.e., the coefficient of determination, r^2) served as a goodness-of-fit indicator, calculated by comparing measured and simulated values. True r^2 and Nash-Sutcliffe efficiencies (NSE) were also calculated. The following parameters were adjusted to obtain the highest prediction efficiencies: bacteria soil partitioning coefficient (BACTKDQ)—also called the bacteria runoff extraction coefficient, the bacteria adsorption factor (BACTKDDB), the fraction of manure containing active colony forming units (BACT_SWF), spring bacteria concentrations, bacteria stream decay rates (WDPRCH and WDLPRCH) and bacteria decay rates in soil solution and adsorbed to soil particles (WDPQ, WDLPQ, WDPS, and WDLPS).

This methodology demonstrates that the correct ranges and frequencies of concentration values are consistently reproduced. However, the method has limitations in that it does not guarantee the models are correctly simulating bacteria fate and movement. Interestingly, for land managers, it ensures that the model can be utilized to compare the impact of different land management scenarios on the fecal coliform concentration's frequency of occurrence. Note that the best use of SWAT bacteria is for "comparative analyses" assessment.

5.3 Calibration based on Nash-Sutcliffe efficiencies and r^2 of concentrations

In the Kansas study, the Nash-Sutcliffe efficiency and r^2 were directly used to manually adjust two parameters of the model during bacteria calibration: BACTKDQ and the temperature adjustment factor for bacteria die-off (TBACT). Final values were equal to initial default values (i.e., the default values were those producing the best results).

In the Georgia study, landscape and stream inputs were also adjusted during calibration. In total, six bacteria parameters were identified as sensitive and selected for calibration: BACTKDQ, the bacteria percolation coefficient (BACTMIX), the concentration of direct instream inputs assuming a flow of 0.01 m^3 d^{-1} (BCNST), the bacteria application rate on agricultural and forest land (CFRT_KG), WDPRCH, and WDPQ.

6. Results

Tables 1 and 2 compare goodness-of-fit criteria between the different applications for fecal coliform or E. coli concentrations and parameter values. The Little Sac watershed was not included in

Table 1 because the goodness-of-fit between the concentration frequency curves was assessed only visually. In Table 2, surface loadings and stream inputs for the Missouri and Kansas studies were not homogeneous throughout the watershed, so an average value was calculated.

In all watersheds, flow information was available on a continuous basis and aggregated on a daily basis for comparison with SWAT output. On the other hand, all bacteria datasets consisted of grab samples collected at best on a weekly basis. No watershed had access to a refrigerated auto-sampler or to a sample collection protocol that would have allowed the systematic collection and analysis of storm water samples. Analysis of the Little Sac sets showed that 24% of the samples were collected during storm flow conditions, or 9 samples out of 38. Thus, it is expected that base-flow conditions were over-represented relative to storm events in all datasets, and none of the watersheds had sufficient bacteria data to adequately calibrate the model over the full range of flow conditions. The authors are not aware of any watershed-scale application in which the protocol was designed to systematically and accurately sample storm flow events and analyze them for fecal coliform or E. coli. The limit of four to six hours between collection time and analysis is a challenge that is difficult and expensive to address.

Table 1. *Comparison of calibration and validation goodness-of-fit criteria for four groups of studies in the U.S. and France*

Study	Missouri		Kansas			Georgia	Brittany, France	
Watershed	James River	James River	Rock Creek	Deer Creek	Auburn	Little River Sub-catch. K	Point 1	Points 2, 3 and 4
Run type	CAL*	VAL*	CAL	VER*	VER	CAL	CAL	VER
Sample size	30 - 43	18-33	60	60	60	53	49	36-39
NSE	-6.0 - .11	0.0 - .21	.20	.31	-2.2	.73	-1.0	N/A
R^2	0.0 - .24	0.0 - .26	.42	.41	.36	N/A	0.0	N/A
PE	.65 - .88	.33 - .99				N/A	.99	.96 - .99

* CAL: calibration, VAL: validation, VER: verification

In all watersheds, direct stream inputs of bacteria were specified. In Missouri, they were estimated from monitoring of WWTPs and springs, amounting to 15% and about 100% of the pasture deposits in the James River Basin and in the Little Sac watershed, respectively. In Kansas, direct stream inputs were assumed to be 10% of the watershed surface loadings. In Georgia, stream inputs were calibrated and amounted to 27% of the overall watershed surface deposits. In Brittany, data were also available to estimate the inputs from WWTPs. All investigators pointed to the importance and the sensitivity of these direct stream inputs. The sensitivity of the model to direct stream inputs could be a direct consequence of the overrepresentation of base-flow conditions compared to storm flow conditions in some datasets.

The stream decay rate of fecal coliform bacteria was different in all cases but reflected the climatic conditions in each area. In the cooler spring-fed waters of Little Sac and the James River, the decay rate was lower (1.05 d^{-1}). The Kansas value corresponds to a faster decay rate seen in warmer, non spring-fed waters (2.01 d^{-1}). In the Little River of Georgia, warmer temperatures could again explain the higher stream decay rate (2.33 d^{-1}). In Brittany, the cooler temperatures and higher cloud cover explain the lower decay rate (0.35 d^{-1}).

Table 2. *Comparison of input parameter values for five studies in the U.S. and France, values in italics indicate that no information about these parameters was found and default values were assumed.*

Study	Unit	Little Sac, MO	James River, MO	Rock Creek, KS	Little River, GA	Mignonne River, Brittany, France
BACTKDQ	$m^3\ Mg^{-1}$	75	90	175	0.53	90
BACTKDDB	--	0.9	0.9	0.9	0.9	0.9
THBACT	--	1.07	1.07	1.07	1.07	1.07
BACTMIX	$10\ m^3\ Mg^{-1}$	10.	10.	10.	5.6	10.
SWF	--	0.55	1.0	0.15	0.15	1.0
WDPRCH	d^{-1}	1.05	1.05	2.01	2.33	0.35
WDPQ	d^{-1}	0.32	0.11	0.40	0.0	2.01
WDPS	d^{-1}	0.032	0.01	0.04	N/A	0.023
Direct stream input	x 10^6 cfu d^{-1}	1.5 10^4	1.3 10^4	2.2 10^4	0.03 10^4	6.0 – 29 10^4
deposit_forest	x 10^6 cfu $ha^{-1}d^{-1}$	1.1 $10^{4\,*}$	6.3 $10^{4\,*}$	N/A	2.2 10^3	N/A
deposit_ag land	x 10^6 cfu $ha^{-1}d^{-1}$	1.6 10^4	8 10^4	2.25 10^5	2.0 10^2	0.56 10^4

N/A: value not available

* averaged over all wooded areas.

The calibrated surface loadings and stream inputs in the Georgia study were consistent with what one would expect from wildlife contributions. Final bacteria loadings from wildlife on agricultural land in Georgia were two to three orders of magnitude smaller than in the Missouri and Kansas studies where loadings were due to cattle grazing and poultry litter applications. Wildlife loadings on wooded areas in Georgia were one order of magnitude smaller than what was estimated from winter grazing in wooded areas in Missouri. Similarly, direct stream inputs for Georgia were two orders of magnitude smaller than those estimated in the Missouri and Kansas studies.

On the other hand, the automatic calibration algorithm utilized in the Georgia study led to a much higher Nash-Sutcliffe efficiency but very different values for the bacteria extraction coefficient (BACTKDQ) and decay rate of bacteria in soil solution (WDPQ). The BACTKDQ of the Georgia study was very low compared to those used in Missouri, Kansas and Brittany. This parameter is defined as the ratio of bacteria concentration in the surface soil layer to that in surface runoff. It affects how much bacteria will move with runoff given the runoff depth and how many bacteria are present in the soil solution. A value of 0.56 implies that for all but the smallest events, all of the bacteria in soil solution will be transported. A value of 175 implies that only the largest events will carry away all of the bacteria, and smaller events would transport only part of what is available. In addition, WDPQ in the Georgia study was zero, indicating no decay of bacteria in the soil solution. These large differences in input parameters indicate a need for better determination by field experimentation.

7. Conclusion

The five studies presented in this paper all pointed to the importance of direct stream inputs. However, the sensitivity of the model goodness-of-fit to this type of input could be an artifact of the datasets used in these studies. Weekly or monthly sampling emphasizes base-flow conditions for which direct stream inputs (i.e., discharges from wastewater treatment plants, cattle and wildlife direct deposits, and spring contributions) are the only source of bacteria. Bacteria runoff is not well represented in these datasets. To further test the model at the watershed scale, sampling protocols need to be designed to characterize bacteria concentrations during storm events. This presents some challenge because samples must be analyzed within 4 to 6 hours of collection.

The automatic calibration of the bacteria parameters led to significantly different values in the runoff extraction coefficient and the decay rate of bacteria in soil solution, indicating a need for additional field research to improve our knowledge of the transport and decay processes and to determine the parameterization of the equations that represent them.

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Including Sediment-Associated Bacteria Resuspension and Settling in SWAT Predictions of Microbial Water Quality

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Abstract

Streambed sediments have been shown to serve as environmental reservoirs for bacteria, including pathogenic strains. The Soil and Water Assessment Tool (SWAT) has been augmented with a bacteria subroutine in the 2005 version. Bacteria die-off is the only instream process considered in the current SWAT model. The purpose of our work was to evaluate the potential significance of bacteria resuspension and settling for SWAT microbial water quality simulations. In the newly developed submodule, bacteria were partitioned into free-floating and sediment-associated bacteria. Only sediment-associated bacteria were allowed to settle with depositing sediment while both bacteria were involved in sediment resuspension. SWAT with the bacteria resuspension-settling submodule was applied to the Little Cove Creek watershed, Pennsylvania. Land uses included forestry, dairy pastureland and field crop. Streamflow, *E. coli* in both the water and streambed, and weather have been monitored for two years. The model input— streambed *E. coli*—was approximated with a log-scale sine curve function using monitored data. Observed streambed *E. coli* peaked in summer to values of $2 \cdot 10^5$ CFU/g and decreased in winter to $2 \cdot 10^2$ CFU/g. Hydrologic parameters were calibrated with the monitored streamflow, and model performance was evaluated with monitored instream *E. coli* data. The sediment-associated bacteria resuspension explained the *E. coli* persistence in stream water while surface runoff was an important reason for the peak *E. coli* concentrations in stream water. Results indicated that improvements in sediment-associated bacteria transport components in SWAT could strengthen SWAT capability to predict bacteria fate and transport in streams.

Keywords: Soil and Water Assessment Tool (SWAT), *E. coli*, sediment, resuspension, and deposition

1. Introduction

Improved characterization of bacteria sources and bacteria fate and transport processes is needed to advance related modeling efforts at the watershed scale (Benham et al., 2006). Runoff from fields, pastures, etc. and inputs from wildlife are often mentioned as the nonpoint sources of bacteria in rural watersheds. Recently, streambed sediment has been increasingly attracting attention as a reservoir of bacteria. Sediment microorganisms can be released to water in substantial amounts when sediments resuspend (Muirhead et al., 2004). Streambed sediment provides a favorable chemical and biological environment for bacteria (Gannon et al., 1983) and can protect bacteria from protozoan predators (Davies et al., 1995).

Soil and Water Assessment Tool (SWAT), a watershed-scale, physically based, continuous-time model, has been developed to simulate fate and transport of pollutants from nonpoint sources and has been augmented with the bacteria transport subroutine by Sadeghi and Arnold (2002). The main sources of bacteria in SWAT are grazing operations and manure application to cropland. Bacteria can be partitioned into the foliage and the soil solution, and their die-off is controlled by temperature. Bacteria on the foliage can be washed off by rainfall. These bacteria, along with bacteria from the soil solution, can reach streams in surface runoff as free-floating and/or sediment-associated organisms. Sediment transport in surface runoff is computed using the Modified Universal Soil Loss Equation (MUSLE). After bacteria reach the stream, the temperature-dependent bacteria die-off is the only fate and transport component included in the current SWAT2005 version (Neitsch et al., 2005).

Most modeling of bacteria fate and transport in streams and lakes has been done for *Escherichia coli* (*E. coli*). This organism has been used in recent environmental research and regulations as a common indicator of fecal contamination and microbial water quality. The purpose of this study was to evaluate the potential significance of sediment bacteria release and bacteria deposition for SWAT simulations of *E. coli* concentrations. Flow and *E. coli* monitoring data from Little Cove Creek, Pennsylvania, were used in the modeling.

2. Materials and Methods

2.1 Study area and data acquisition

The study area, Little Cove Creek watershed, is located in Franklin County, southern Pennsylvania, within the Chesapeake Bay watershed in Appalachia. Little Cove Creek, after merging with Licking Creek, enters the Potomac River near Hancock, Maryland. The headwater of Little Cove Creek is located in a forested area. The creek flows through forested land for approximately 2.5 km before entering a campground area and subsequently an agricultural area with both crops and grazing (cattle and horses). The watershed area is 68 km^2, the total length and average slope of the main second order stream (Little Cove Creek) are 17.7 km and 0.014 m/m, respectively, and the average tributary slope in Little Cove Creek is 0.035 m/m. The predominant soil texture within the watershed is silt loam (93%), and the major land uses are pasture (25%) and forest (72%).

Three stream monitoring sites, CM2, CM3 and CM7, have been established within the watershed at distances of 7.2 km, 12.1 km and 17.7 km from the stream source, respectively.

Precipitation and streamflow data were collected for two years, and bacteria concentrations in water and sediment were measured weekly for 14 months.

2.2 Instream sediment and bacteria modules in SWAT

The instream sediment transport model in SWAT includes sediment resuspension and deposition as a function of the peak stream velocity, which is the stream velocity (v_{ch}, m/s) multiplied by the peak rate adjustment factor (*prf*). The maximum concentration of sediment ($conc_{sed,\max}$, ton/m^3) that can be transported from a stream segment to the next downstream segment is computed by an empirical function, the simplified Bagnold's stream power equation (Neitsch et al., 2005):

$$conc_{sed,\max} = c_{sp} \cdot (prf \cdot v_{ch})^{spexp} \quad [1]$$

where c_{sp} and *spexp* are user-defined linear and exponent parameters, respectively. If the initial concentration of sediment for a time step ($conc_{sed,i}$) is smaller than $conc_{sed,\max}$, streambed sediments will be resuspended, and the amount of resuspended sediments ($M_{S,res}$) will be a function of the channel erodibility factor (K_{ch}) and the channel cover factor (C_{ch}):

$$M_{S,res} = (conc_{sed,\max} - conc_{sed,i}) \cdot Q \cdot K_{ch} \cdot C_{ch} \quad [2]$$

where Q is the volume of water in the stream segment (m^3). Otherwise, suspended sediments will be deposited in the streambed, and the amount of deposited sediments ($M_{S,dep}$) will be a function of streamflow:

$$M_{S,dep} = (conc_{sed,i} - conc_{sed,\max}) \cdot Q \quad [3]$$

Streambed *E. coli* release and deposition modules included in SWAT use the model's sediment resuspension and deposition modules. When streambed sediments were resuspended, the amount of *E. coli* released ($M_{B,res}$, CFU) was determined as:

$$M_{B,res} = M_{S,res} \cdot C_{B,B} \quad [4]$$

where $M_{S,res}$ is the mass of resuspended sediments (ton) computed by Eq. [2], and $C_{B,B}$ is the *E. coli* concentration in streambed sediments (CFU/g sediment). When suspended sediments in stream water were deposited, the *E. coli* in stream water were partitioned into free-floating and sediment-associated *E. coli* based on Bai and Lung's (2005) assumption about the linear relationship between them. Then, only sediment-associated *E. coli* was deposited with the settling sediments:

$$M_{B,dep} = M_{B,W} \cdot \frac{K_p \cdot M_{S,dep}}{Q + K_p \cdot M_{S,W}} \quad [5]$$

where $M_{B,dep}$ is the number of *E. coli* deposited (CFU), $M_{B,W}$ is the number of *E. coli* in the water (CFU), K_p is the partitioning coefficient of *E. coli* (m^3/ton or mL/g), $M_{S,dep}$ is the mass of deposited sediments computed by Eq. [3] (ton) and $M_{S,W}$ is the mass of sediments in the water (ton).

2.3 Sensitivity analysis and calibration

Sensitivity analysis was performed with the LH-OAT method (van Griensven et al., 2006), which combines the Latin Hypercube (LH) sampling and One-factor-At-a-Time (OAT) design. Latin Hypercube sampling is based on random sampling methods, such as Monte Carlo sampling, but uses a stratified sampling approach to avoid significant computational costs due to a large number of input parameters. One-factor-At-a-Time design, which modifies only one input parameter between two successive runs of the model, is an example of integration between a local and global sensitivity method. In LH-OAT sampling, *N* ranges of each parameter are uniformly distributed by LH sampling, and then, random parameter values are generated within each range. Each of the *N* random combinations of parameters becomes the initial point for an OAT design. A partial effect, $S_{i,j}$ (%), for each parameter (e_i) around each LH point *j* is defined by:

$$S_{i,j} = \left| \frac{100 \cdot \left(\frac{M(e_1,\cdots,e_i\cdot(1+f),\cdots,e_P) - M(e_1,\cdots,e_i,\cdots,e_P)}{[M(e_1,\cdots,e_i\cdot(1+f),\cdots,e_P) + M(e_1,\cdots,e_i,\cdots,e_P)]/2} \right)}{f} \right| \quad [6]$$

where $M(\cdot)$ refers to the model functions, *f* is the fraction by which the parameter e_i is changed (a predefined constant) and *P* is the number of input parameters. Therefore, the LH-OAT method requires a total of $N \cdot (P+1)$ runs for a robust and efficient analysis. Finally, global sensitivity measures (*S*) for each parameter are calculated by averaging these partial effects ($S_{i,j}$) in each *N* random combination.

For calibration, SWAT employs the Shuffled Complex Evolution method developed at the University of Arizona (SCE-UA), which is known as a global calibration method and an efficient technique for calibrating watershed models. Details about the method are well described by Duan et al. (1994). The calibration criterion is the Nash-Sutcliffe efficiency (*NSE*):

$$NSE = 1 - \frac{\sum (O_i - P_i)^2}{\sum (O_i - \overline{O})^2} \quad [7]$$

where O_i and P_i are daily observed and predicted data, respectively, and $\overline{O}$ is the average of O_i.

3. Results and Discussion

3.1 Sensitivity analysis and calibration of hydrologic parameters

The runoff curve number (CN2) was the most sensitive parameter (*S* = 1.97) followed by a group of nine parameters with much smaller sensitivity (*S* = from 0.1 to 0.4). This group included snowmelt related parameters (SMFMX, TIMP and SMTMP), base/lateral flow parameters (SOL_K, ALPHA_BF and SOL_AWC), watershed morphology parameters (SLOPE and SOL_Z) and an evapotranspiration parameter (ESCO). The parameter sensitivity ranking was in agreement with rankings obtained in other SWAT sensitivity studies. The curve number (CN2) was usually ranked first or second, and ESCO and SOL_AWC were usually ranked within the five most sensitive parameters (e.g., van Griensven et al., 2006). The snowmelt parameters were highly sensitive due to the relative importance of lateral flow and snowmelt in the Little Cove Creek watershed.

The highly ranked (*S* > 0.1) hydrologic parameters, except watershed morphology parameters (SLOPE and SOL_Z), were calibrated using daily streamflows at all three monitoring sites. The median CN2 value across the watershed was 34 with a maximum of 38 and a minimum of 24. Pasture CN2 values were 34, indicating that more than 75% of pastures are not heavily grazed, and soil above a depth of 100 cm is highly permeable (Neitsch et al., 2005). Forest CN2 values varied from 26 to 36, indicating that forest litters and brushes almost adequately cover the highly permeable soil (Neitsch et al., 2005). The calibrated soil hydraulic conductivity in forests (median SOL_K = 67 mm/hr) was greater than that of pastures (median SOL_K = 22 mm/hr). High ALPHA_BF (= 1) values indicated that the base or groundwater flow rapidly responded to changes in recharge (Neitsch et al., 2005). Due to the rapid response of baseflow, sharp increases and decreases in predicted streamflow were expected. The calibrated available water capacity of soil (SOL_AWC) was relatively higher than the default soil texture value. The high SOL_AWC values imply substantial potential precipitation retention in soil, corresponding with decreases in recharge and lateral flow.

3.2 Performance of modified bacteria module in SWAT

Sensitivity analysis of bacterial parameters was conducted for two versions of the SWAT bacteria module. When only surface runoff was considered as the *E. coli* source (original SWAT version), parameters related to the grazing operation (BIO_MIN and PHU_PLT) and to available *E. coli* fractions in manure (BACT_SWF and BACTKDDB) were most sensitive. When sediment-associated *E. coli* concentration was considered, the most sensitive parameters were those related to instream sediment routing (SPEXP, PRF, and SPCON) and streambed sediment erosion (CH_COV and CH_EROD). Interestingly, the percentage of clay in sediments (CLAY), a determinant parameter of *E. coli* partitioning and deposition, was ranked low (rank 21).

Spatial and temporal variations in streamflow, surface runoff, sediment resuspension and deposition, and *E. coli* concentration for the calibrated model results are shown in Figure 1. Streamflow during the winter and spring was high, whereas summer and fall were relatively dry. Although surface runoff in the wet season was relatively higher than in the dry season, the overall streamflow contribution of surface runoff was not large due to the high permeability and storage capacity of soils across Little Cove Creek watershed as estimated during the calibration of hydrologic parameters. Sediment resuspension dominated throughout the watershed, even though the annual amount of resuspended sediments was competitively less than deposited ones. Sediment deposition mainly occurred in the dry season due to low streamflow. *E. coli* concentration was generally affected by a combination of streamflow and surface runoff.

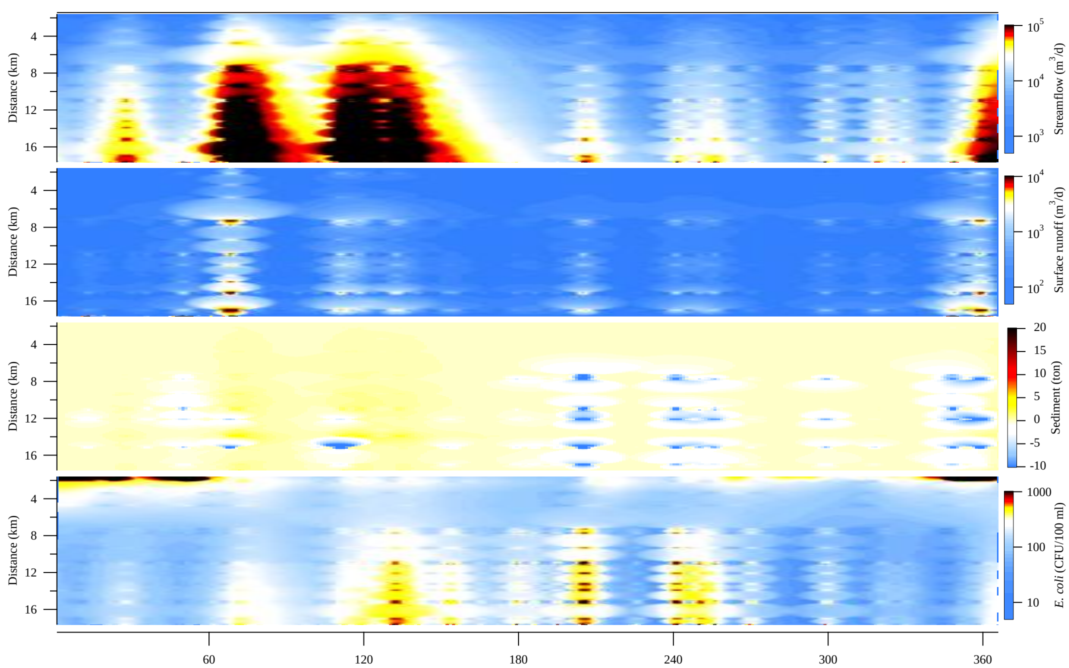

Figure 1. *Spatial and temporal variations of streamflow, surface runoff, sediment resuspension/deposition and E. coli concentration for the calibrated model results*

Observed and predicted temporal *E. coli* concentrations, with and without streambed *E. coli* release, at each stream monitoring site are plotted in Figure 2. When streambed *E. coli* release was not considered, the predicted *E. coli* concentration had scattered spikes during the grazing season (from April to October). This could be explained by the rare but substantial surface runoff events (Fig. 1). Outside the grazing season (from November to March), no *E. coli* influx to the stream was predicted, although more surface runoff was predicted (Fig. 1). However, when the streambed *E. coli* release was considered in the modified SWAT model, the predicted presence of *E. coli* in stream water became persistent, and the *E. coli* coming from surface runoff resulted in the *E. coli* peaks.

NSE values at CM2, CM3 and CM7 were -0.2, -0.7 and 0.2, respectively. The calibration performance measures of the modified SWAT model were relatively low, although they were substantially improved compared with the original model that did not account for the streambed *E. coli* release (Fig. 2). Even when the streambed *E. coli* release was accounted for, *E. coli* concentration in the dry season was mostly underestimated at each monitoring site (Fig. 2). The relatively low accuracy of the model can be partly attributed to the uncertainty of *E. coli* concentrations in streambed sediment and to possible inputs from wildlife. *E. coli* input from wildlife was not considered in this study. It can be divided into indirect (via surface runoff) and direct (deposition in streams) inputs (Benham et al., 2006). If the indirect input from wildlife is considered, the runoff-related peaks of *E. coli* in Fig. 2 may be higher, or parameters related to surface runoff and grazing operations may be changed. However, die-off during long periods without runoff will still result in stream concentrations that are negligible compared with observed values. Furthermore, smaller CN2 values and higher hydraulic conductivity in forest soil will reduce the effects of indirect deposits from wildlife on runoff water quality. However, if persistent direct deposits from wildlife are considered, *E. coli* concentrations might become higher, and thus, the gap between observed *E. coli* and predicted *E. coli* in dry season is expected to improve model performance.

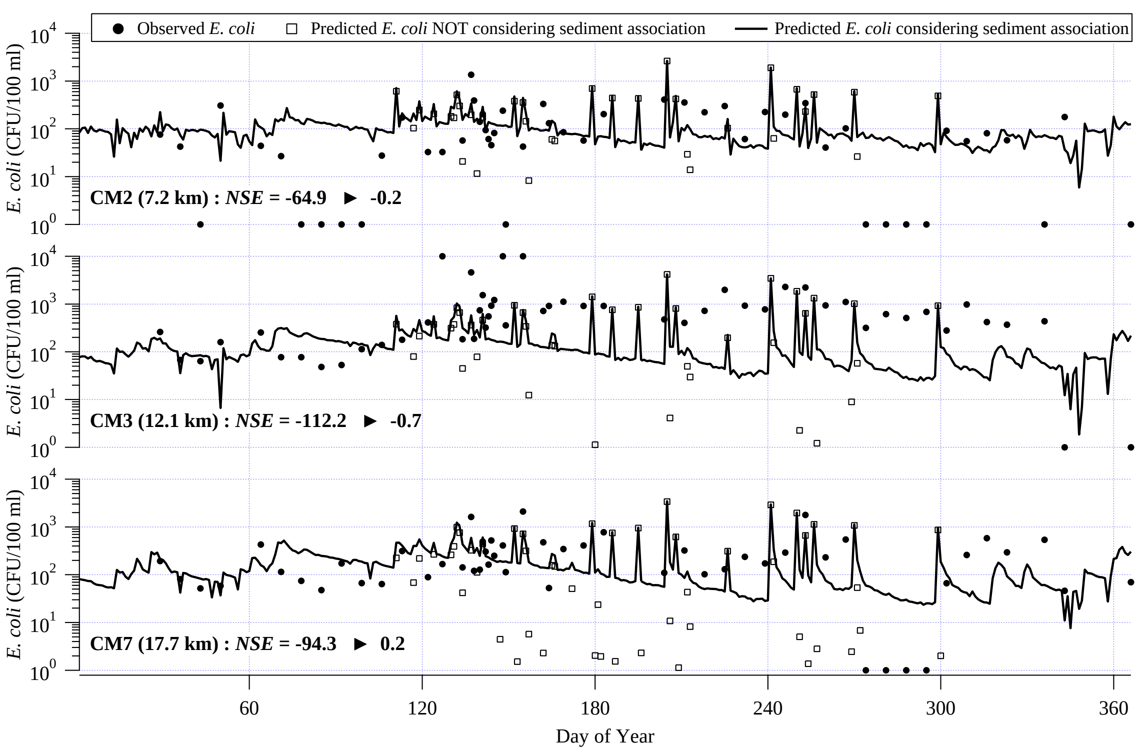

Figure 2. *Temporal variations of observed and predicted E. coli concentrations and calibration performances (NSE) at each stream monitoring site from the calibration results*

4. Conclusion

In this study, SWAT was modified by including streambed *E. coli* release with sediment resuspension and deposition. The SWAT model with the streambed *E. coli* release and deposition module showed better performance in predicting *E. coli* concentration in stream water when compared to the original SWAT model. Although the uncertainty surrounding *E. coli* in streambed sediments and wildlife contributions probably hampered the performance of the modified SWAT model, this study qualitatively confirmed the significance of streambed *E. coli* release and deposition for SWAT microbial water quality simulations.

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Integration of tropical and subtropical wetlands in regional catchment modeling

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Abstract

Hydrological processes in tropical and subtropical wetlands often differ substantially from those in temperate zones where wetlands are subject to management and regulation and the natural plant cover has been altered to facilitate agricultural production.

A key pattern in most tropical and subtropical river basins is the strong seasonality of the flow regime, especially in areas that have a monsoon climate. Large areas are inundated during the rainy season, changing the entire runoff pattern and increasing evapotranspiration and groundwater recharge due to additional water surfaces. However, these wetlands are temporal, and the conditions completely change during the drought season.

The aim of this study is to conceptually understand the role of wetlands under such conditions and to find a methodology to integrate tropical and subtropical wetlands in regional hydrological modeling.

Key words: Hydrological modeling, wetland, inundation, water resources, tropical river basins

1. Introduction

Wetland areas are of paramount importance to both hydrological processes and ecology within a river basin as well as food production and human development. Fertile wetlands formed the economic basis for the development of the very first civilizations (Junk, 2002). Many wetlands in Europe, Africa, Asia and America were utilized for extensive agricultural and fishery purposes, thereby ensuring the human survival and forming the basis for subsequent development (Tockner and Stanford, 2002).

Wetlands provide a number of important ecosystem services, such as nutrient retention, groundwater recharge, flood mitigation, water quality maintenance and improvement, habitat functions, etc. Riverine flood plains cover an area greater than 2×10^6 km^2 worldwide (Tockner and Stanford, 2002).

Modeling studies can help us understand the impact of riparian zones and wetlands on overall water and nutrient balances in river basins (Hattermann et al., 2006). While simple methods, like regression models, export-coefficient approaches and GIS-based mass balances, can roughly estimate the relative significance of different processes and sources (Behrendt, 2000), more sophisticated, dynamic, process-based approaches are needed to analyze the role of wetland processes in catchments. In such models, the interrelation of groundwater dynamics, soil moisture, nutrient leaching and retention, plant growth and plant water, and nutrient uptake should be considered (Bogena et al., 2003). However, the process-based modeling of wetland processes in catchments, especially in large-scale river basins, is still a challenge. Integration of riparian zones in catchment modeling is even more challenging because of the complex interactions and feedbacks between hydrology, vegetation and soils in wetlands (Hattermann et al., 2008). In tropical and subtropical catchments, these processes can be caused by the monsoon climate and the much higher evapotranspiration rate, which significantly vary from those in temperate climates.

Usually, the changing conditions of these processes are not sufficiently integrated in large and medium scale hydrologic modeling approaches. But due to the enormous impact that temporarily inundated areas have on the water balance and flow regime, it is absolutely essential to better account for these processes.

This paper describes a conceptual approach to incorporate these processes into the semi-distributed, ecohydrological model SWIM (Soil and Water Integrated Model, see Krysanova et al., 1998; 2000). Spatial distribution is realized by the concept of Hydrologic Response Units (HRUs) as explained in Krysanova (2000), Neitsch et al. (2004) and Flügel (1995). Subjects of this article are a) the delineation of temporarily inundated areas, b) the definition of inundation zones according to the level of inundation, c) flood modeling and water release processes, and d) the transformation of Hydrologic Response Units (HRUs) from the land phase to the water (lake) phase, forming a basis that accounts for the consequences for hydrological and ecological functions. However, processes related to ecological functions are not discussed in this article.

2. Model description (SWIM)

The SWIM model is a continuous-time, spatially semi-distributed ecohydrological model. It was developed from SWAT version '93 (Soil and Water Assessment Tool, see Arnold et al., 1993) and

MATSALU models (Krysanova et al., 1989) for climate and land use change impact assessments. SWIM simulates hydrological processes, vegetation growth, erosion and nutrient dynamics at the river-basin scale.

3. Methods

3.1 Delineation of temporarily inundated areas

A first approach to delineate potentially flooded areas can be realized by using GIS functions, such as the GRASS GIS module *r.lake* or the *lake* module in SAGA GIS. This module simulates the filling of a lake from a seed (reference point) at a given level using a digital elevation model. The reference point should be located at the wetland's outlet, and its altitude must be known. By defining a target water level, the module fills the area that is (1) below this level, (2) is connected to the reference point or grid cell and (3) is not a no data value.

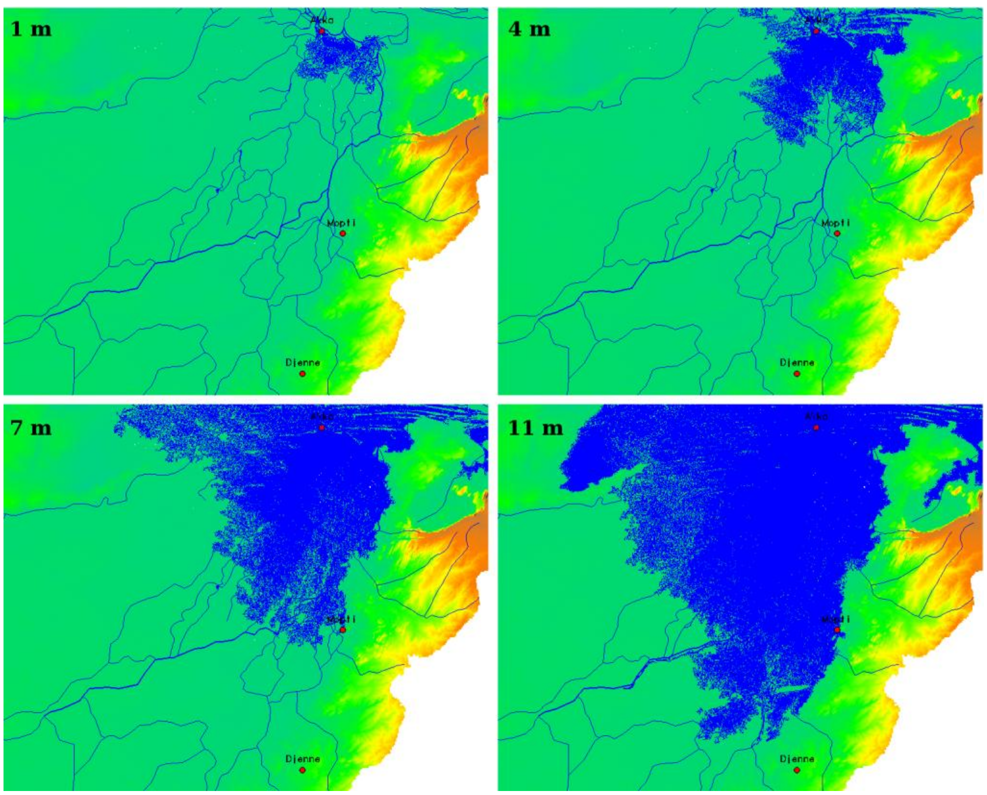

***Figure 1**. Flooding of the Inner Niger Delta using GRASS GIS module r.lake*

Figure 1 shows an inundation time series from the Inner Niger Delta in Mali (Africa). These maps were created on the basis of SRTM data (Jarvis et al., 2008) with a horizontal resolution of 90 meters and a vertical resolution of 1 meter. The reference point was set to a location in the Niger River, close to the city of Akka at an altitude of 161 meters above sea level. The figure shows the extent of the inundated areas when the water level at the reference point reaches the value indicated in the corresponding map (1 to 11m). Please note that the resolution of SRTM data might not be sufficient for small wetlands. However, in the case of the Inner Niger Delta, with an area of approximately 80,000 km^2 (Zwarts et al., 2005), the resolution is adequate.

If data regarding the maximum extent of flooded areas are available, it could be used as a mask. For instance, this information could be estimated from satellite images.

The GRASS GIS module *r.lake* automatically calculates the inundated area and the volume of water for each inundation level. These values are used to define corresponding thresholds in the next steps, the definition of inundation zones and the simulation of flooding processes.

3.2 Definition of inundation zones

The number of inundation zones is not fixed but can be determined by the user. In the simple version, the definition of the number of inundation zones basically depends on the vertical resolution of the DEM, the maximum inundation depth and the level of complexity the user wants to implement. If the maximum inundation depth is 2 meters and the vertical resolution of the DEM is 1 meter, it would be reasonable to assign no more than two classes, or inundation zones, respectively.

In an advanced version of inundation zone delineation, one could further take the flow distance and the surface roughness into account. However, the approach described in this article is only based on inundation extents estimated by the *r.lake* module.

In the example above, the maximum water level at the reference point is 11 meters, as shown in Figure 1. Hence, we distinguished 11 inundation zones. For each zone, the area and the water volume required for total inundation were calculated using GIS functionalities.

3.3 Wetland HRUs

Hydrologic response units (HRUs) are portions of a subbasin that posses unique land use and soil properties (Neitsch et al., 2004). Such a map is produced by overlaying the land use, subbasins and soil map. Units with similar land use and soil properties can be scattered throughout a subbasin. Although the geographic location of these units is known, HRUs can be considered the total area of these units lumped together. Against this background, information about the geographic location of HRUs gets lost.

To implement the wetland module in the SWIM model, it is necessary to identify unique units that are located inside a certain inundation zone. Therefore, a new model parameter at the HRU level is required (*ind_zone_nbr* = number of the inundation zone in which the unit is located). This parameter is assigned to the units, units outside the inundation zones are 0 and all other units receive a corresponding inundation zone number. Thus, only unique units with similar inundation zone numbers are lumped together to form one HRU. HRUs that are located inside one inundation zone will hereafter be called "Wetland HRUs".

3.4 Flooding and release processes

What follows in this section is a description of the parameters and processes associated with inundation zone flooding simulations.

The general conceptual approach is: if simulated discharge exceeds the maximum water volume that can pass through the channel, it is assumed that the fraction of water volume greater than the maximum possible volume contributes to the flooding of adjacent areas (starting with inundation zone 1). If inundation zone *n* is totally flooded and simulated discharge still exceeds the maximum possible water volume, inundation zone *n+1* will be flooded and so on. Figure 2 illustrates the conceptual approach of the flooding process. The release of water from the inundation zones starts if simulated discharge is below the maximum possible water volume in the channel.

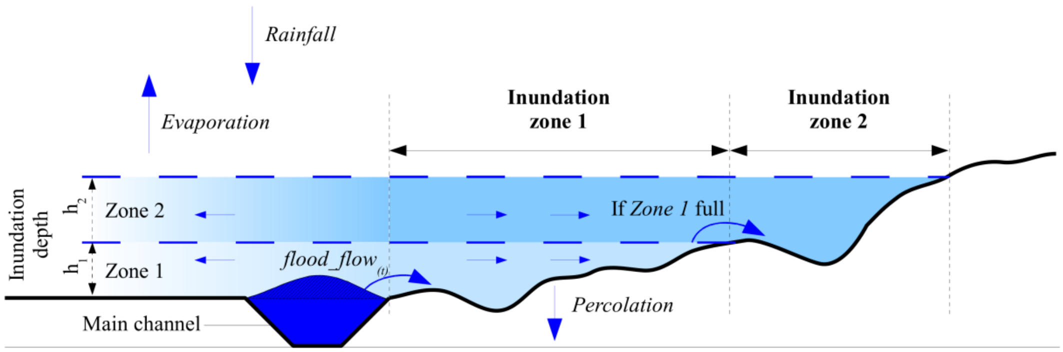

***Figure 2**. Conceptual scheme of the flooding process*

3.4.1 Flooding

The parameters cross section area (*cs_area* [m^2]) and average flow velocity (*flow_vel* [$m*s^{-1}$]) determine the maximum possible water volume in the channel. If this value is exceeded by simulated discharge (Q_{sim} [m^3*s^{-1}]), the flooding process of adjacent areas (inundation zones) beings. The water volume that contributes per unit time to flooding (*flood_flow* [m^3*s^{-1}]) is estimated on a daily time step (*t*) using the following equation:

$$flood\_flow_{(t)} = Q_{sim(t)} - cs\_area * flow\_vel_{(t)} \quad (1)$$

consequently $Q_{sim(t)}$ must be updated:

If $flood\_flow_{(t)} > 0$, then $Q_{sim(t)} = Q_{sim(t)} - flood\_flow_{(t)}$ (2)

The parameter *cs_area* can be derived from observations, the literature or be calculated based on assumptions made about stream geometric dimensions. In addition, *cs_area* can also be calculated using cross sections from the GRASS module *r.stream.att* (Srinivasan and Arnold, 1994), where the width and depth of the stream are exponential functions of drainage area (Rosenthal et al., 1995). The flow velocity is the average channel velocity estimated by applying Manning's equation and assuming a trapezoidal channel with 2:1 side slopes and a 10:1 bottom width to depth ratio (Krysanova et al., 2000).

Each inundation zone is parameterized by its area (*ind_area* [m^2]) and its maximum storage volume (*ind_vol_mx* [m^3]). Both parameters are calculated with the GRASS module *r.lake*. The actual storage volume of an inundation zone (*ind_vol_act* [m^3]) is calculated on a daily time step:

$$ind\_vol\_act_{(t)} = ind\_vol\_act_{(t-1)} + flood\_flow_{(t)} - ET_{(t)} - PERC_{(t)} + PCP_{(t)} \quad (3)$$

If $ind\_vol\_act_{(t)} < 0$, then $ind\_vol\_act_{(t)} = 0$.

If $ind\_vol\_act_{(t)} > ind\_vol\_mx$, then see equation 4.

The flooding process continues as long as *flood_flow* > 0. If *flood_flow* < 0, then the water storage of the upper inundation zone starts to decrease by flowing back to the channel (release process). Percolation (*PERC* [mm]) and evapotranspiration (*ET* [mm]) reduce the actual inundation storage whereas rainfall (*PCP* [mm]) contributes to it. Percolation through the soil layers is only allowed if the respective lower soil layer is not saturated.

If a lower inundation zone is flooded and $flood\_flow_{(t)}$ is greater 0, the next higher inundation zone will be flooded.

$$ind\_vol\_act_{[n+1](t)} = ind\_vol\_act_{[n+1](t-1)} + ind\_vol\_act_{[n](t)} - ind\_vol\_mx_{[n]} \quad (4)$$

Due to natural heterogeneity of the land surface, the actual inundation depth (*ind_depth_act* [m]) cannot be calculated by simply dividing volume by area. Instead, a normalizing factor (*FAC)* is used here.

$$ind\_depth\_act_{(t)} = FAC \frac{ind\_vol\_act_{(t)}}{ind\_area} \quad (5)$$

With $FAC = ind\_area \dfrac{h_{[n]}}{ind\_vol\_mx_{[n]}}$ (6)

where h[n] is the maximum inundation depth of zone *n*, as illustrated in Figure 2.

The method used to estimate evaporation depends on the actual inundation depth. As long as the actual inundation depth is below a user-defined threshold (*ind_et* [mm]), the predefined evapotranspiration method is used. If the actual inundation depth exceeds this threshold, evaporation will be calculated as following, assuming evaporation from a water surface:

If $ind\_depth\_act_{(t)} > ind\_et$,

$$ET_{(t)} = \eta * ET_{pot(t)} * ind\_area \quad (7)$$

where η is an evaporation coefficient (0.6) and ET_{pot} is potential evapotranspiration (Neitsch et al., 2004).

3.4.2 Release process

The release process is the reverse function of the flooding process. A fraction of the inundation storage water volume is allowed to contribute to discharge in the main channel at each time step. The process starts with the inundation zone with highest elevation.

In this conceptual approach, we assume that the inundation storages have linear storage properties in which the outflow is directly proportional to the storage volume. The recession constant α determines the volume that will be released per time step.

$$Q_{storage(t)} = \alpha \frac{ind\_vol\_act_{[n](t)}}{86400} \quad (8)$$

where $Q_{storage(t)}$ is the volume of water contributing to simulated discharge $Q_{sim(t)}$, *n* is the number of the inundation storage and α is a value between 0 and 1.

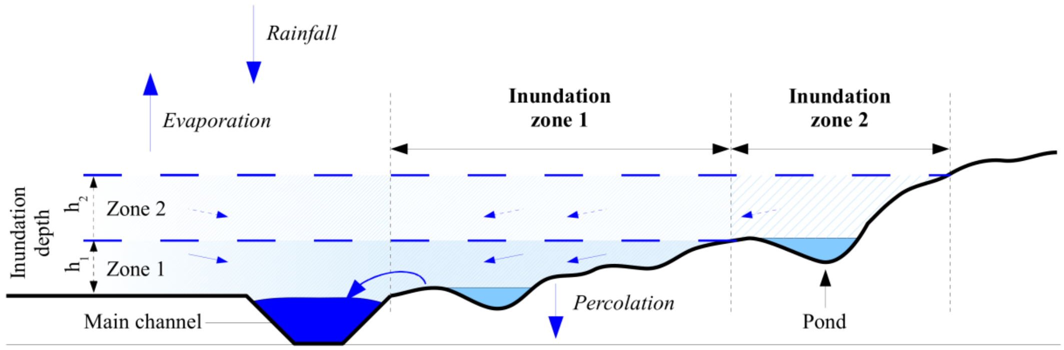

***Figure 3**. Conceptual scheme of the release process*

Figure 3 shows the conceptual approach of the release process. The blue arrows indicate the main direction of water flows. As illustrated in Figure 3, the entire inundation storage volume will not contribute to streamflow, depending on the heterogeneity of the wetland's topography. Rather, a fraction of it will remain in lakes and ponds from which it will evaporate or percolate into the shallow aquifer. In order to account for the volume of water stored in such ponds, the volume of the total area that lies below the inundation level inside an inundation zone will be calculated by using GIS and the digital elevation model.

3.5 Wetland HRU switching

Since inundation storage is driven by discharge, rainfall, evaporation and percolation, the status of inundation zones can switch from "flooded" to "not flooded" and vice versa. According to the inundation depth (see equation 5), the status of affected Wetland HRUs can switch between the land and the water phase. In equation 7, a user-defined threshold (*ind_et)* was introduced. This threshold can be considered as a switching controller. We assume a threshold value of 100 mm would result in switching of HRUs from land to water phase if the average water depth of an inundation zone is greater than 100 mm. If the average inundation depth is below 100 mm, the Wetland HRUs switch back to the land phase.

In SWIM, a Wetland HRU in the land phase acts like a "normal" HRU. If a Wetland HRU turns to the water (lake) phase, the conditions for several processes (hydrologic and ecologic) change considerably. By switching to the water phase, it is possible to change the functions used to simulate these processes. Changing the evapotranspiration method (e.g., switching from Penman-Monteith or Turc-Ivanov) to a method that estimates evaporation of a water surface as shown in equation 7 is expected to result in significant changes. Rainfall in the water phase would not contribute to surface runoff. Instead, it would increase the volume of the upper inundation storage.

Processes related to ecological functions, such as biomass production or how certain vegetation types deal with being temporarily inundated etc., are further challenges in this context. However, these issues will not be addressed in this article.

4. Conclusions

The aim of this article was to introduce a simple conceptual approach that accounts for wetland processes in river basin modeling rather than the presentation of modeling results. The focus was on the implementation of a wetland module in the ecohydrological model SWIM. This wetland module simulates the dynamic flooding and release processes of wetland areas.

An important objective was to develop a simple method that keeps the complexity and data requirements as low as possible. The basic data requirements of the wetland module are a digital elevation model of adequate resolution, which mainly depends on the wetland area size, and two calibration parameters (the inundation threshold controlling HRU-switching (*ind_et*) and the inundation storage recession constant (α)). All other parameters can be derived from the DEM or are already model parameters. Potentially, the parameters determining the cross-section geometry could be considered calibration parameters because they are a source of large uncertainty when derived from a DEM.

Whether this simple approach is applicable in real tropical and subtropical catchments, like the Inner Niger Delta, or needs to be improved by more sophisticated methods will be investigated within the EU project WETwin (http://www.wetwin.net/).

In addition to the integration and improvement of hydrological processes related to the flooding and release of wetland areas, it will be rather challenging to adequately account for ecological functions. Ecological functions in this context are processes such as plant growth, biomass production, vegetation die-off as a result of flooding, nutrient sedimentation and erosion, etc.

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Evaluating the Effectiveness of Unconfined Livestock BMPs using SWAT

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Abstract

Innovative market-based approaches for environmental management, such as Best Management Practice (BMP) auctions, have recently gained more attention due to their cost-effectiveness and practical success in dealing with specific pollution problems. In a BMP auction, agricultural or livestock producers submit their own BMP proposals that are ranked based upon the quantity of pollutant reduction per dollar. Winning bids are awarded accordingly to achieve the greatest environmental impact for the lowest cost. This study presents a field-scale modeling approach to assess the effectiveness of livestock BMP proposals using SWAT. A pasture field, used to represent an actual bid, was divided into floodplain, riparian buffer and multiple grazing land areas, having unique land characteristics similar to SWAT Hydrologic Response Units (HRUs). Multiple sets of grazing operation scenarios with a range of applied stocking rates within each pasture area were simulated by running the SWAT model in the Lower Marais des Cygnes watershed, located at the Kansas and Missouri border. The annual average nutrient loads for each watershed HRU were collected and statistically analyzed, and the least-square error trends were determined. Given the unique pasture features in each submitted bid, including pasture geometry, land characteristics and management operation schedule, the BMP effectiveness index was calculated based on the pollutant load values interpolated from trend charts and an expert-formed ranking table. A stand-alone, user-friendly interface was developed to help the bid evaluation expert team pre- and post-process individual BMP proposals.

Keywords: SWAT, livestock, BMP, auction

1. Introduction

Grazing management on livestock pasture significantly affects runoff of sediment and nutrient loads into streams (Haan et al., 2006). To minimize the loads, many incentive programs have been established to motivate producers to adopt pollution prevention BMPs. Among other programs, there has been an increased interest in market-based approaches, such as BMP auctions. To date, three BMP auctions have taken place in Kansas and four more are scheduled. For example, a committed $70,000 will be awarded to producers through an auction in the Lower Marais des Cygnes watershed (410,700 ha), located at the Kansas and Missouri border.

In a BMP auction, the producers submit bids to an agency investing in BMPs. An expert team is formed to assess the BMP proposals and rank their water-quality impacts based upon nutrient and sediment load reduction. The most cost-effective and environmentally efficient proposals are awarded. To quantify the environmental impact, the expert team requires a hydrologic modeling tool that provides rapid assessment of the livestock BMP proposals. While there are many models available for evaluation of agricultural BMPs, the number of models for livestock/pasture assessment is limited (White et al., 2009). The unique pasture features, including pasture geometry, land characteristics and management operation schedules, must be accounted for in determining BMP effectiveness.

The objective of this study is to develop a framework that utilizes unique pasture features to determine average annual pollutant loads and to calculate a BMP effectiveness index that helps an expert bid evaluation team rank BMP proposals. Application of this framework to the Lower Marais des Cygnes watershed and computed results will also be discussed.

2. Methodology

In this study, we used the following pasture layout. The pasture was split into the following four subareas as shown in Figure 1: a floodplain (area 1), riparian buffer (area 2) and two grazing lands (areas 3 and 4). The floodplain represented a flat area along both sides of the stream. If grazing occurred in the floodplain, it was assumed that the majority of manure deposition was introduced directly into the stream. Area 2 was a riparian buffer that separated grazing land from the stream and served as a runoff buffer. Most of the time, the buffer is a part of the floodplain, but in this setup, we assumed it to be an independent area. Areas 3 and 4 were both grazing lands where livestock spent most of their day. Splitting the grazing areas into two subareas helped to manage spatial distribution of the cattle. All pasture areas may have had different soil types, average slopes and land cover conditions.

The main water sources for livestock were watering sites located in areas 2, 3 and 4 and a stream within Area 1. Watering sites can be represented by a trough, a pond or any other watering facility. Pastures with access to the stream are known to produce higher sediment loading due to cattle eroding the stream bank and greater water quality concerns from direct deposition of manure into the stream. Locations where cattle frequently rest in the shade, such as the buffer zone, can also decrease the quality of land cover, increasing nutrient loads and causing significant environmental impacts. To prevent such conditions and block access to the streams, recommended BMPs include fencing the stream or buffer accompanied by altering grazing management practices. One such method is to attract livestock to areas farther away from the stream by creating alternative watering sites (Ohlenbusch and Harner, 2003).

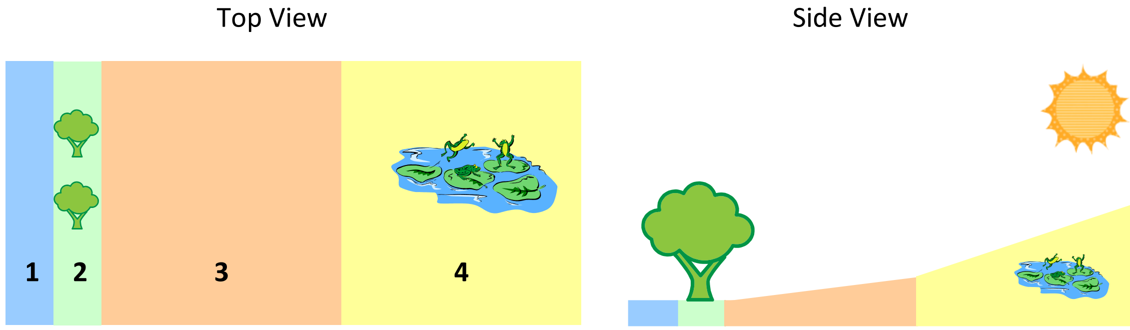

Figure 1. *Schematic of the pasture split into four subareas, Area 1 is a floodplain with a stream, Area 2 is a riparian buffer that separates grazing land from the stream, and Areas 3 and 4 represent the grazing land with unique soil and slope characteristics.*

Spatial and temporal distribution of cattle within the pasture was difficult to model due to limited knowledge of what affects grazing patterns. Factors may include (Ohlenbusch and Harner, 2003):

- Location of preferred watering site,
- Location of preferred shade,
- Prevailing wind direction,
- Quality of available forage in grazing areas,
- Topography.

One simple way to account for different distributions within the pasture is to assume a uniform spatial distribution within individual pasture areas. The stocking rate within each subarea can be used as the distribution input parameter, which is defined as the number of animal units (1 AU = 1,000 lbs) allocated to a given land area per day (Ohlenbusch and Watson, 1994). Knowing the total number of animal units grazing in the pasture gives an average pasture stocking rate (Sr_{AVE}) that is related to subarea (i) stocking rates (Sr_i) and areas (A_i) by the following formula:

$$Sr_{AVE} = \sum_{i=1}^{4} \left(Sr_i A_i \right) \Big/ \sum_{i=1}^{4} A_i$$

For individual pasture scenarios, the stocking rates were specified for each area during the grazing season.

The Soil and Water Assessment Tool (SWAT) model (Arnold et al., 1998) was used to simulate livestock grazing in the pasture and make quantitative predictions about average annual sediment loss and nutrient loadings at the pasture and basin scales. SWAT is a complex, continuous, basin-scale model that incorporates a set of both physically and empirically-based equations to calculate a large variety of hydrologic parameters. SWAT uses Hydrologic Response Units (HRUs) as the main footprints for hydrologic simulations. Each HRU represents spatially aggregated parts of the watershed that share unique combinations of soil type, land cover and average slope. In applying the SWAT approach, we represented subareas within the pasture by their corresponding HRUs. More specifically, the riparian buffer was represented by the HRU formed with deciduous forest (classified as FRSD) and pastureland (classified as HAY) referred to the grazing areas. SWAT results were not applied to the floodplain as its loadings were calculated directly based on the amount of manure applications.

***Table 1**. SWAT Input Parameters for Grazing Management Operation*

Description	**Parameter**	**Units**
Grass type	CROP	—
Daily manure	MANURE_KG	kg/ha
Start of grazing	YEAR,MONTH,DAY	—
Number of grazing days	GRZ_DAYS	—
Type and amount of fertilizer	FRT_ID, FRT_KG	—, kg
Biomass consumed and trampled daily	BIO_EAT, BIO_TRMP	kg/ha
Initial pasture and buffer conditions	CN2	—

SWAT requires a large number of input parameters. Default values for many parameters can be found in the SWAT database. Some parameters represent user inputs, and their values are based on the literature or local knowledge. Parameters related to grazing management (operation OPNUM=9) within the pasture are listed in Table 1. These parameter values were modified to accommodate grazing in FRSD and HAY HRUs. The specified minimum amount of dry forage at which grazing is permitted and the initial condition of the riparian buffer were defined by the curve number value (CN2) for corresponding HRUs. Amount of biomass consumed and trampled daily as well as fertilizer application date, type and amount were also entered into the project input database based on the grazing operation.

Daily precipitation and temperature data were collected from the National Climatic Data Center while other daily weather information was generated by the weather prediction model embedded in SWAT. For each HRU, SWAT calculated average loadings per hectare of an HRU land ω_i. Total loadings for each output variable, W, for the entire pasture were calculated as a sum of the loadings for each subarea in the pasture:

$$W_{past} = \chi M \, Sr_1 A_1 + \omega_2 A_2 + \omega_3 A_3 + \omega_4 A_4$$

Floodplain loadings, the first term in the formula, were estimated based on nitrogen and phosphorous amounts in directly applied manure, where $M = 8.5$ kg is the amount of solid manure produced by 1000 kg of live animal mass and χ is the percent of the selected constituent or SWAT variable in solid manure. If the floodplain and buffer were fenced, then we assumed corresponding areas did not contribute to total pasture loadings due to grazing.

The set of nine BMP scenarios assessed in this study was comprised of different combinations of stream and buffer fencing options as well as the relocation of watering sites (see Table 2). Pasture subarea soil and topography significantly affected BMP efficiency. Stocking rates within each area determined how much manure was applied to the land daily. High stocking rates and lack of available forage decreased pasture quality through production of higher nutrient loads, higher curve number values and increased soil erodibility.

***Table 2**. Grazing management scenarios and associated stocking rates for four subareas in pasture (F refers to floodplain, B to buffer, and G1 and G2 to the two grazing subareas), the average stocking rate is equal to 1 AU/acre.*

			Stocking Rates			
	Fence	**Watering Site**	**F**	**B**	**G1**	**G2**
1	-	F	2.00	2.00	0.96	0.96
2	-	B	1.50	2.00	0.97	0.97
3	-	G1	0.93	2.00	1.50	0.00
4	-	G2	0.26	0.50	0.80	1.45
5	F	B	0.00	1.40	1.40	0.28
6	F	G1	0.00	1.50	1.50	0.09
7	F	G2	0.00	0.51	0.51	2.00
8	B	G1	0.00	0.00	1.60	0.00
9	B	G2	0.00	0.00	0.53	2.00

To assess water quality efficiency for the BMP proposal during the bid evaluation process, the following approach was developed. First, the expert team specified a realistic range of stocking rates for each subarea in the pasture and identified grazing management practices for the entire range of stocking rates that were converted to SWAT inputs for HAY and FRSD HRUs. Secondly, the stocking rate ranges were divided into 20 equal intervals, and previously defined inputs were applied to the SWAT model. Finally, the SWAT model was run consecutively 21 times with inputs changed according to the assigned stocking rate. For each run, the outputs for all HAY and FRSD HRUs were collected and stored in a separate database. Once all runs were completed, each output variable from HRUs with similar characteristics throughout the various sub-watersheds was plotted on one chart, and the least-square error polynomial trend was determined. Pollutant load values (W_i) were interpolated from each pasture subarea trend according to subarea stocking rate.

In Scenario 1, no fencing was used, and the stream served as a primary watering site. In determining the BMP effectiveness index, Scenario 1 was considered a baseline. The BMP effectiveness index (I_{EFF}) was calculated relative to the baseline scenario output values by the following formula:

$$I_{EFF} = \frac{1}{N}\sum_{j=1}^{N}\phi_j\left(1-\frac{W_j}{W_j^{base}}\right)$$

with superscript base defining the baseline and N representing a total number of output SWAT variables. Based on the main environmental goal of the livestock BMP auction process, various weights (ϕ_j) in the formula above can be assigned to SWAT variables. Table 3 presents a list of SWAT output variables and an example of the weighting factors skewed toward the importance of phosphorous reduction in BMP implementation.

The BMP effectiveness index was calculated for each BMP proposal then all proposals were ranked from most to least water-quality efficient. The proposals exhibiting higher effectiveness have a higher probability of being awarded. We note that the technical expert team must consider other aspects, such as cost-effectiveness of BMP investments and TMDL priorities in that area, before making a final decision on which proposal to award.

Table 3. *Weighting factors (ϕ_j) for SWAT variables in ranking index calculations (SWAT variable abbreviations shown in the lower row)*

Sediment	Organic Nitrogen	Organic Pho	Mineral Pho	Nitrates in Surface Runoff	Nitrates in Lateral Flow	Nitrates with Ground water	Soluble Pho	Total
SYLD	**ORGN**	**ORGP**	**SEDP**	**NSURQ**	**NLATQ**	**NO3GW**	**SOLP**	
0.05	0.10	0.20	0.20	0.10	0.05	0.05	0.25	1.00

A spreadsheet tool was developed to assist the expert team with the bid evaluation process. The SWAT model executable file was called many times from this spreadsheet tool to conduct multiple model runs and collect the output data. Each individual BMP proposal was entered into the spreadsheet and the BMP effectiveness index was evaluated.

3. Application and Results

The approach presented in the previous section was applied to the Lower Marais des Cygnes watershed, which was selected by the Kansas Department of Health and Environment for conducting a livestock BMP auction in 2009. Lower Marais des Cygnes watershed is a part of the Marais des Cygnes river basin and is located south of the Kansas City metropolitan area with 60% of its land in Kansas and 40% in Missouri. Three counties (Miami and Linn Counties in Kansas and Bates County in Missouri) cover 90% of the entire watershed. Total drainage area of the watershed is 410,700 ha with almost 50% (49.81% = 204,582 ha) used for rangeland and pastures.

After researching the watershed land use maps and communicating with extension specialists in that area, 16.2 hectares (40 acres) was chosen as the total area representative of pasture with a floodplain 300 meters long and 10 meters wide (area of 0.3 ha) and a riparian buffer of 12 meters wide (area of 0.36 ha). The grazing lands were split into 10 ha for Area 3 and the remaining 5.54 ha for Area 4. The floodplain length was determined based on average stream length per total pasture area within the entire watershed.

The watershed was delineated into 45 sub-watersheds with total of 2833 HRUs. The STATSGO soil database identified 13 soils predominantly of C and D hydrologic soil type, and the watershed was divided into areas with either greater or less than 3 percent slope. The same weather data was applied to all sub-watersheds belonging in each of the three counties that allowed three independent subsets of output data. Within each subset, outputs from all similar HRUs were collected for FRSD and HAY land uses.

The stocking rates of 9 different BMP scenarios for all pasture subareas are presented in Table 2, assuming $Sr_{AVE} = 1$ as a reference value. For the studied watershed, the average stocking rate is equal to 0.5, thus all stocking rates in Table 2 must be scaled down by half. Based on management practices in that watershed, the grazing season starts in mid-April and ends at the beginning of December. Pasture has perennial grasses like brome or tall fescue growing in it, which are fertilized in mid-February with 50 lbs of nitrogen fertilizer applied to each acre of land. The amount of forage consumed by 1 AU is 14 lbs dry matter per day with 7 lbs dry matter wasted or trampled per day.

The SWAT model was run for 17 years from 1992 to 2008 with the first 5 years used as a warm-up period. After the SWAT simulations with stocking rates ranging from 0 to 4 AU/acre were completed, the average annual values for phosphorous constituents (listed in Table 3) were collected for each of the three subsets of output data, and polynomial trends and coefficient of determination (R^2) were calculated. The results for the grazing land (a) and the buffer subarea (b) are shown in Figure 2. For both land uses, the output values increase as stocking rate grows.

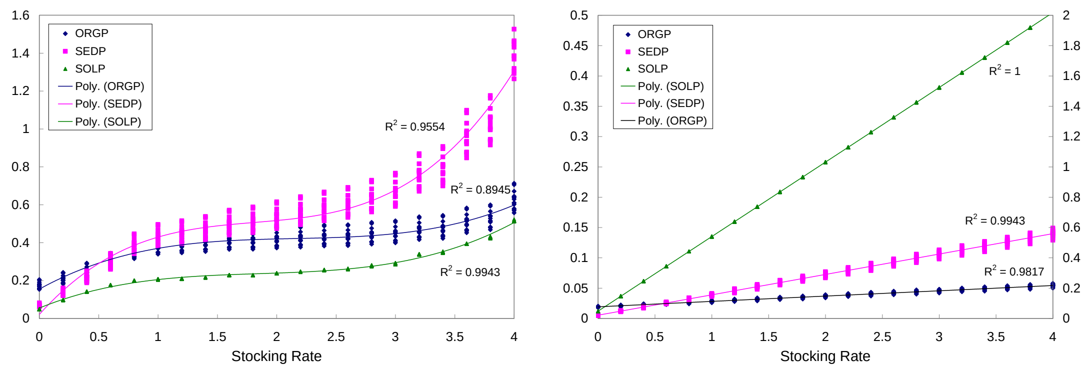

Figure 2. *Phosphorous loads in kg/ha for grazing land (a) and buffer (b), HRUs with "Summit" soil (hydrologic group D) and slope more (a) and less (b) than 3%*

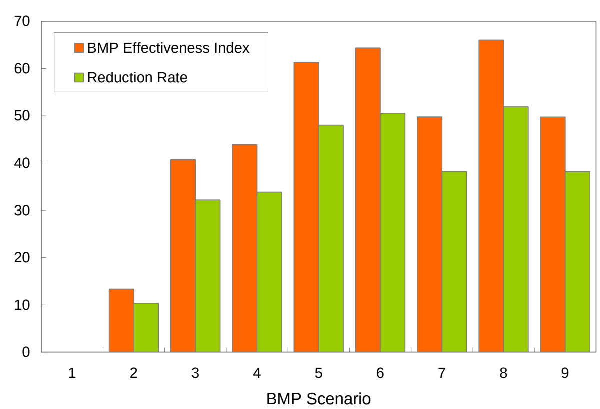

Figure 3. *BMP effectiveness index and cumulative pollutant reduction rates for various scenarios*

Constructing a pasture of D group soil and flat subareas 1, 2, and 3 as well as high slope subarea 4 as an example of an actual BMP bid proposal, we calculated the BMP effectiveness index and pollution reduction rates for all 9 scenarios shown in Figure 3 with stocking rates presented in Table 2. BMP effectiveness reached its highest value in Scenarios 6 and 7, where the stream is fenced and the watering site is located in flat subarea 3. Fencing the stream appears to be the most effective conservation practice for small livestock operations.

4. Conclusions

A modeling framework to support livestock BMP auctions was developed and applied to Lower Marais des Cygnes watershed in the U.S. Midwest. The framework involved running the SWAT model with input pasture data provided by the expert team, processing the SWAT output data and determining the least-square error trends for each of the output variables, and then interpolating the trend charts to fit the pasture design in the submitted BMP proposal. An expert-formed ranking table was established and used to calculate the BMP effectiveness index that is utilized by the expert team to rank bids on environmental and water-quality effectiveness. A stand-alone, user-friendly spreadsheet tool was also developed to help the bid evaluation expert team pre- and post-process individual BMP proposals.

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Use of the SWAT model to evaluate the sustainability of switchgrass production at a national scale

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Abstract

As the US begins to integrate biomass crops and residues into its mix of energy feedstocks, tools are needed to measure the long-term sustainability of these feedstocks. Two aspects of sustainability are long-term potential for profitably producing energy and protection of ecosystems influenced by energy-related activities. The Soil and Water Assessment Tool (SWAT) is an important model used in our efforts to quantify both aspects. To quantify potential feedstock production, we used SWAT to estimate switchgrass yields at a national scale. The results from this analysis produced a map of the potential switchgrass yield along its natural eastern range. To quantify ecological protection, we are using the SWAT model to forecast changes in water quality and fish richness as a result of landscape alterations due to incorporating bioenergy crops. We have implemented the SWAT model in the Arkansas-Red-White region, which drains into the Mississippi River, and we present our methods here. We identified two sub-watersheds for sensitivity analysis and calibration of the water quality results, and then, explored ways to apply the calibration results to the whole region and validate the model setup. We also present an overview of our research in which results from the calibrated regional SWAT model were used to analyze potential changes in fish biodiversity. Only by evaluating the energy and environmental implications of landscape changes can we make informed decisions about bioenergy at the national scale, and the SWAT model will enable us to reach that goal.

Keywords: sustainability, bioenergy, biodiversity, water quality, switchgrass

1. Introduction

Projecting how changes in the agricultural landscape influence water quality is a complex issue that requires an appropriate modeling tool capable of representing important aspects of the system. Our research is focused on quantifying the changes in water quality associated with introducing dedicated energy crops to some parts of the current landscape and harvesting residues of other crops. Our choice of a watershed model was dependent on two factors: 1) its ability to predict both the yields of bioenergy crops and crop residues, and 2) its ability to represent watershed influences on water quality at regional-to-national spatial scales.

Working at regional-to-national scales placed a number of constraints on our choices. First, although bioenergy land covers are the focus of our research, we must include other land covers because they also influence water quality. Therefore, we require a model that can address the influence of natural, agricultural and bioenergy vegetation as well as urban and other non-vegetated land covers on the watershed. Second, the model must be capable of using spatially explicit input data that are generally available throughout the conterminous US. Third, the model must be capable of representing watershed influences on water quality adequately at relatively coarse spatial scales consistent with the resolution of national GIS input datasets. The size of sub-watersheds used in modeling is limited by the ability to process high-resolution digital elevation maps and the inherent resolution of satellite-derived spatial data. We identified the Soil and Water Assessment Tool (SWAT) as an appropriate candidate for our efforts to quantify bioenergy crop yields and water quality effects at regional-to-national scales. Another advantage of the SWAT model is its large user community, which has led to testing in a wide variety of settings (Gassman et al., 2007).

Applications of SWAT to large, regional river basins are much less common (e.g., Arnold et al., 2000, Upper Mississippi River basin) than those for smaller spatial areas (e.g., Vache et al., 2002; Nelson et al., 2006, 45 subbasins spanning 119,400 ha). A number of applications have examined the relationship between sensitivity of SWAT predictions and scale. Scale is likely to have little influence on biomass yield predictions. However, water quality and nitrate, in particular, can be better predicted (up to a point) with higher resolution data (Jha et al., 2004; Chaubey et al., 2005).

In this paper, we present three sections that provide an overview of three studies at regional and larger scales. First, we present the results of a study to estimate Alamo switchgrass yields within its natural range in the eastern US using SWAT. Second, we present calibration results from a companion study to predict water quality from current Midwest landscapes. Finally, we present an overview of our research to predict how bioenergy landscapes will alter fish biodiversity. Only by evaluating energy and environmental implications of landscape changes can we make informed decisions. Therefore, we are looking to the SWAT model as a tool that will enable us to reach that goal at a national scale. We also discuss challenges of working at this scale, including difficulties involved in model validation and scaling-up calibration results.

2. Background

2.1 Estimation of Bioenergy Feedstock

Biomass productivity is an important aspect to address when considering the large-scale sustainability of a bioenergy future (Hall, 1997). Unfortunately, there are a limited number of sites where dedicated energy crops have been planted and production potential measured. Better estimates of dedicated energy crop productivity are essential to providing more accurate spatial estimates of resource potential. The purpose of this analysis was to estimate switchgrass yield for major hydrologic regions of the United States using SWAT. We focused our analysis on the natural eastern range of switchgrass (Parrish and Fike, 2005), so the SWAT model was run by each 2-digit hydrologic region spanning this range. Parameters for the lowland variety of Alamo switchgrass were used for the model runs.

2.2 Modeling water quality

Modeling water quality at a regional scale involves a number of steps that consider the scale of the problem for large spatial extents. Some of the issues to consider include data availability, scaling of results and computing capabilities. We assembled data from different sources and modeled water quality for the Arkansas-White-Red River (AWR) basin. We then performed sensitivity analysis and streamflow calibration at two subbasins and afterward scaled up these results to the whole region.

2.3 Modeling aquatic biodiversity

With the nation's increasing interest in the production of switchgrass as a bioenergy crop, it is important to understand and evaluate the potential effects of switchgrass production on water quality and stream aquatic biota. We used SWAT to link land-use changes brought about by biomass production with changes in aquatic habitat for fish. We are developing empirical models for fish richness at the regional scale based on a number of predictors, including SWAT-predicted nutrient concentrations and flows.

3. Methods and Results

3.1 Estimation of Bioenergy Feedstock

As the first step, subbasins were delineated for each region of interest using a 1-km resolution digital elevation model (DEM) based on Shuttle Radar Topography Mission - SRTM data (Farr et al., 2007). We superimposed the network of larger, main-stem streams onto the DEM. The main-stem streams were identified from the National Hydrologic Dataset (NHDPlus) (NHDPlus 2009) as reaches with a "thinnercod" value of 1. The average delineated subbasin size was set to 500,000 hectares (or 100,000 hectares in cases where a drainage area of 500,000 was too large to capture all the area within a region).

SWAT predictions of switchgrass yield were made for each hydrological response unit (HRU) within each subbasin. An HRU is a unique combination of land cover, soil and slope class. For the purpose of obtaining regional estimates of switchgrass yield, we created two land cover classes within each subregion by reclassifying all land cover classes other than water to Alamo switchgrass in the 30-m resolution 2001 National Land Cover Dataset (Homer et al., 2004). The reclassified land cover had two classes — switchgrass and water. Soil characteristics were defined by the STATSGO dataset (Soil Survey Staff, 1994). We defined three slope classes, slopes of 0 to1%, 1 to 5% and greater than 5%, based on the 1-km resolution SRTM data. All HRUs created using the aforementioned land cover, soil and slope data were used in the SWAT runs.

The SWAT default parameters for Alamo switchgrass were used except as noted below. The defaults are nearly all derived from Kiniry et al. (2005). Because switchgrass is a perennial grass, switchgrass was already planted and had an initial leaf area index of 0.5 and biomass of 500 kg/ha when we initialized simulations. Each year, we assumed that switchgrass required 1,100 physiological heat units to reach maturity. This estimate is at the low end of the reported range (Kiniry et al., 2005). To allow for crop drying, we delayed harvesting until reaching the 120% of heat units required to reach maturity and assumed that 80% of the above-ground biomass was harvested each year.

Starting from 1985, SWAT was run for 21 years with simulated climate (using the SWAT weather generator). We treated the first two years of the model run as spin-up years and excluded them from our reported time-averaged switchgrass yield predictions. To produce spatially-explicit predictions, we averaged predicted switchgrass yields for the remaining 19 years (Figure 1). Consequently, our yield predictions should be treated as those of mature stands of switchgrass.

SWAT-projected switchgrass yields varied from zero in the northern latitudes to over 16 Mg/ha in southern Illinois, Arkansas, western Kentucky and Tennessee (Figure 1). In addition to the latitudinal gradient, predicted yields increased while moving east from very low values west of the 100th parallel (Figure 1). Predictions across the southern extremes of the eastern US were typically between 6 and 12 Mg/ha (Figure 1). The low values at higher latitudes reflect the fact that the parameters used are for a lowland ecotype. Future efforts will examine yields for the upland ecotype, which is grown successfully at higher latitudes as well.

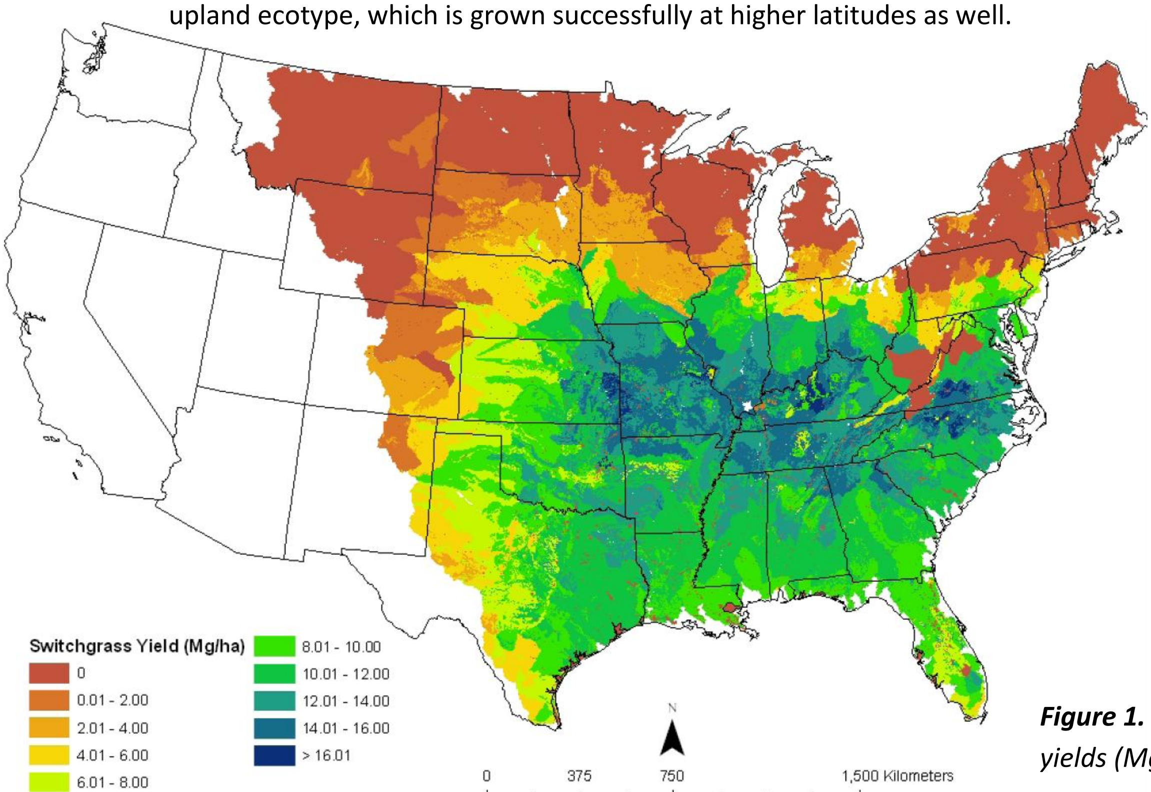

Figure 1. *Average Alamo switchgrass yields (Mg/ha) projected by SWAT*

3.2 Modeling water quality

To quantify water quality and biodiversity implications of biofuel production at the regional scale, we used USGS-defined, 8-digit hydrologic units (HUC) obtained from NHDPlus as subbasins instead of SWAT-delineated subbasins. Because SWAT requires one major stream reach per subbasin, we used the following procedure to derive main reaches from NHDPlus data. Within each subbasin, we identified the collection of reaches sharing the largest stream order. To identify the main channel, we selected the reach with the smallest value of "levelpathi" as the one farthest downstream (levelpathi is a code assigned to all channels from the stream's mouth to the stream's headwater and can be defined as a unique identifier for the mouth of a stream network). The final set of reaches was merged to produce a GIS layer with one stream feature per subbasin.

HRUs within each subbasin were defined as unique combinations of dominant soil type, land cover and slope as described earlier with a few modifications. We used the 2008 Crop Data Layer (CDL-08) to define land cover, substituting 2001 NLCD for one state (NM) lacking CDL-08 data. We assigned CDL land cover categories to SWAT land cover categories with the help of expert advice (personal communication with Anthony Turhollow). Each unique STATSGO map unit and land cover category that comprised more than 10% of a subbasin was used to define HRUs.

We reclassified a 30-m digital elevation model (DEM) of the AWR basin to 56 m and used it as the elevation input. This reduced resolution was necessary due to the large size of the study area and limitations on processing a 30-m DEM. We were able to process the AWR basin using the 56-m DEM, which also matched the resolution of the CDL land cover data. Using the 56-m DEM, we categorized slope into three categories, <2%, 2-5% and >5%, and we required all categories to be included in the definition of HRUs regardless of area.

We simulated tile drainage because it is common in the AWR basin and because simulating tile drainage has been shown to improve flow predictions (Green et al., 2006). We assumed that tile drainage was present in cropland areas with poorly drained soils with less than 2% slope. We assumed a tile depth of 1.1 m and a 36 h drain time.

We used climate data from DAYMET (Thornton et al., 1997) estimated for the center of each subbasin over the period 1980 to 2003. Daily climate input variables we included were total precipitation (mm), minimum and maximum temperatures (°C) and solar radiation (MJ/m2/day). Wind speed, relative humidity and potential evaporation were simulated by SWAT.

We performed a sensitivity analysis to identify parameters with the largest influence on streamflow (van Griensven et al., 2006). The analysis was conducted for each of two subbasins — one heavily forested and the other with grassland, shrubland and agricultural land (referred to as "agricultural") (Figure 2). Monthly flows were most sensitive to the baseflow alpha factor (Alpha_Bf) in the forested subbasin and to the curve number (CN2) in the grassland-agriculture subbasin. In both subbasins, the parameter ranked second was soil evaporation compensation factor (Esco in Table 1). The results of the sensitivity analysis helped to identify a subset of parameters that could be used to calibrate the model effectively.

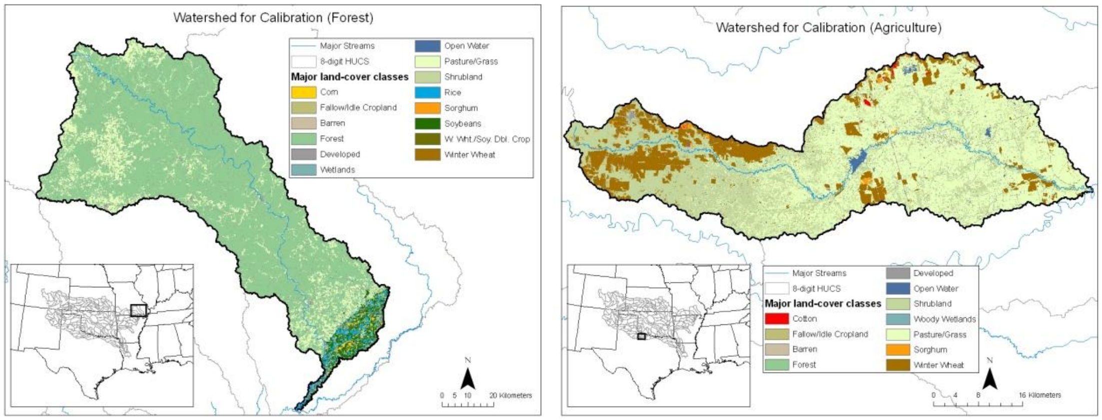

Figure 2. *Land cover in two subbasins used to calibrate parameters against monthly flow data*

We calibrated monthly flows against monthly streamflow records from USGS gauging stations near the outlets of the two subbasins of interest. We selected parameters that had the most influence on streamflow and entered them into the auto-calibration routine. SWAT-predicted monthly flows were automatically calibrated against monthly flows between 1985 and 1996. The quality of calibration results is typically measured using the Nash-Sutcliffe efficiency (NSE), which ranges from zero to one. Values greater than 0.75 are considered very good, and those above 0.65 are considered good (Moriasi et al., 2007). The NSE for the calibrated forested subbasin was 0.74, and the NSE for the calibrated agricultural basin was 0.78. For each subbasin with its individually calibrated parameters, we validated SWAT-predicted monthly streamflow using data from 1997-2003. The validation data NSE for the forested subbasin was 0.75, and 0.65 for the agricultural basin.

We compared parameter changes suggested by the calibration runs for the two basins (Table 1). To apply the calibration results for the whole region, we selected parameters from the two calibrated subbasins with similar final calibrated values. The parameters selected were baseflow alpha factor, maximum canopy storage, channel effective hydraulic conductivity, soil evaporation compensation factor and surface runoff lag time (Table 1). Of these parameters, the 'best' values from the forested and agricultural subbasins were selected and averaged. The average parameter values were then applied over the whole region. For other parameters, such as the curve number, calibrated results were different in the two subbasins. There was a need to reduce the curve number for the agricultural basin and increase it in the forested basin. Consequently, we retained default values for these parameters in the regional run.

Table 1. *Results from sensitivity analysis and auto-calibration of streamflow parameters for the forested and agricultural subbasins (* - parameters chosen for calibration across the whole region; ** - Parameter variation methods: 1 – replacement of initial parameter by value, 2 – adding value to initial parameter and 3 – multiplying initial parameter by value (in %)).*

Parameter code	Parameter description	Sensitivity analysis ranking		Parameter variation method**	Parameter changes for		
		Forested basin	Agricultural basin		Agricultural basin	Forested basin	Average
Alpha_Bf*	Baseflow alpha factor (days)	1	4	1	0.06	0.06	0.06
Blai	Maximum potential leaf area index	6	8	1	1.00	1.00	
Canmx*	Maximum canopy storage (mm)	4	10	1	0.14	0.00	0.07
Ch_K2*	Channel effective hydraulic conductivity (mm/hr)	7	7	1	6.86	8.06	7.46
Cn2	Initial SCS CN II value	8	1	3	-0.34	4.73	
Epco	Plant uptake compensation factor		11	1	0.44	NA	
Gw_Delay	Groundwater delay (days)	12		2	NA	9.84	
Esco*	Soil evaporation compensation factor	2	2	1	0.80	0.01	0.41
Gwqmn	Threshold water depth in the shallow aquifer for flow (mm)	5	9	2	503.76	-868.14	
Revapmn	Threshold water depth in the shallow aquifer for "revap"(mm)	3	12	2	-95.58	99.81	
Sol_Awc	Available water capacity (mm H2O/mm soil)	11	3	3	2.03	-21.03	
Sol_Z	Soil depth (mm)	10	6	3	-3.18	24.95	
Surlag*	Surface runoff lag time (days)	9	5	1	1.79	1.00	1.40

The performance of the five-parameter calibrated run in the forested basin provided good results with an NSE of 0.63. The performance of the five-parameter calibrated run on the agricultural basin was fair with an NSE of 0.45.

The five parameters selected in the calibration were applied over the whole study region, and the model was run from 1980 to 2003. The results from the first two years (1980 and 1981) were skipped in the output. This model setup needed to be validated with data that spanned the whole study region. For this purpose, we obtained streamflow data for each subbasin from NHDPlus data. These streamflow estimates were originally calculated by the unit runoff method in NHDPlus and represent mean annual flow in cubic feet per second (cfs) estimated at the bottom of a flowline (NHDPlus, 2009). The NHDPlus streamflow values were converted to units of cubic meters per second (cms) and then subtracted from SWAT average daily streamflow predictions (in cms), averaged over the 22-year period to obtain the amount by which SWAT over or under predicts streamflow when compared with NHDPlus streamflow estimates.

The results indicate that SWAT overpredicts streamflow in the downstream basins along the eastern regions of the study area and under predicts streamflow in some of the upstream basins (Figure 3). These results suggest that flows predicted by SWAT are higher than expected based on watershed area (unit-runoff method) farther downstream and lower than expected based on watershed area upstream. These results are not surprising because the unit-runoff method does not account for variations in precipitation, and precipitation follows a strong east-west gradient (wetter in the east).

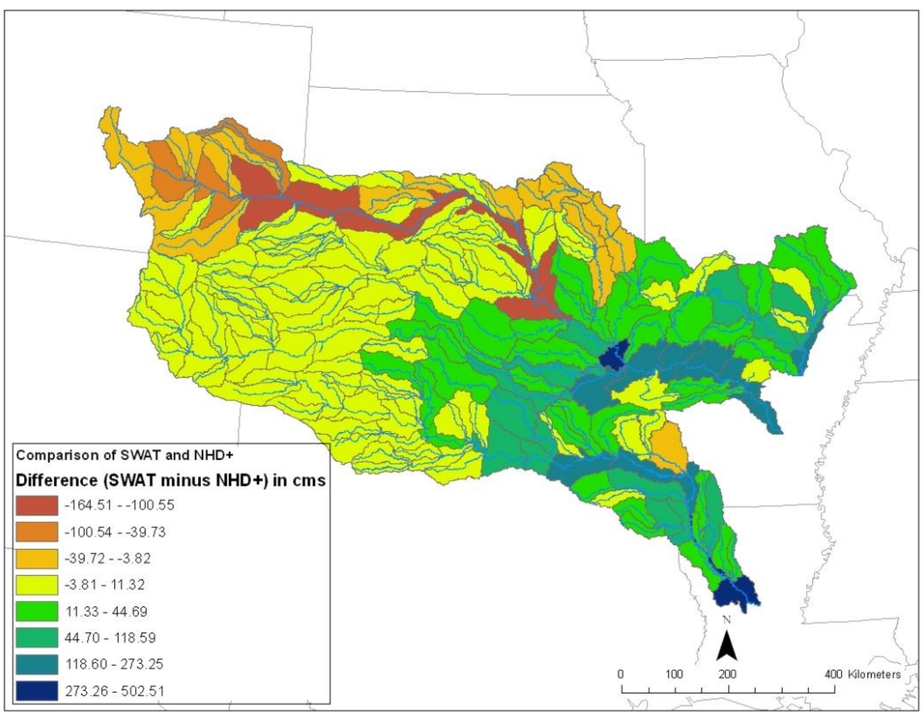

Figure 3. *Long-term flow comparison between SWAT and NHDPlus model predictions*

Our next step will be to evaluate changes in water quality using the validated model to compare current and future land use scenarios based on output from the Policy Analysis System (POLYSYS) (Ugarte and Ray 2000).

3.3 Aquatic biodiversity

We are developing empirical models for fish richness at the regional scale based on a number of predictors, including SWAT-predicted nutrient concentrations and flows. We used SWAT model output for stream discharge, nutrient concentration and sediment loadings to describe watershed water quality (8-digit USGS hydrologic units, HUC). We worked under the premise that streams and rivers with a high biodiversity of fish species need to be protected from declining water quality that can affect aquatic biota (Hails, 2008). Our hypothesis is that the cultivation of switchgrass on agricultural lands can reduce sediment and nutrient loadings to streams and hence improve future water quality and habitat for fish (Berkman and Rabeni 1987; Berka et al., 2001).

Our study focused on the Arkansas-White-Red River (AWR) basin. In building empirical models for biodiversity, we included several SWAT water quality and quantity outputs as predictors (average annual discharge and concentrations of nitrate, total phosphorus and sediment). These were averaged over a 22 year period. Additional predictor variables included mean annual precipitation, upstream drainage area, elevation at watershed outlets, percent land cover and the relative position of each HUC watershed along a downstream longitudinal gradient.

For watersheds in the AWR river basin, measures of streamflow and other predictors correlated with streamflow (e.g., % forest cover) had the largest influence on the species richness of native fish. Among headwater basins, watershed effects on biodiversity were dominated by the percent of forest, which was correlated with percent agriculture.

Our next step will be to predict aquatic species diversity in future agriculture land use scenarios. SWAT-derived water quality and discharge data will play a large role in our future efforts to model patterns in aquatic biodiversity.

4. Conclusion

The methods and results outlined here have shown how SWAT can be useful for exploring the productivity and environmental sustainability of switchgrass as a bioenergy crop at regional to larger scales. As our work with modeling switchgrass production and watershed modeling of bioenergy landscapes continues, we can improve our understanding of which areas provide the highest economic and environmental potential for biomass feedstock production. With the need for better understanding at a national scale, the approach we have outlined can be applied to other regions to produce guidance at this scale.

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Modeling Upland and Channel Sources of Sediment in the Le Sueur River Watershed, Minnesota

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Abstract

The Le Sueur River Watershed (LRW) drains 2,850 km² through the Minnesota River and generates 302,000 t/yr of sediment, which contributes to sedimentation and turbidity impairments in Lake Pepin and the Mississippi River. The LRW accounts for only about 7% of the area, but 53% of the Total Suspended Solids (TSS) leaving the Minnesota River Basin (Water Resources Center, 2008). Sediment sources in the LRW are spatially heterogeneous and include slumping river bluffs, ravines, stream banks and eroding upland agricultural lands. The objective of our research was to use the Soil and Water Assessment Tool (SWAT) to quantify the contribution of upland areas to sediment loads at various locations within the LRW. Predicted upland sediment loads were compared to measured stream sediment loads to indirectly estimate the sediment contributions from channel sources of sediment, including river bluffs, ravines and stream banks.

The SWAT model was calibrated and validated from 2000-2006 in the Beauford sub-watershed, where the landscape has no bluffs or ravines. The calibrated model was applied to the entire LRW in order to estimate sediment losses from upland regions of the watershed. We estimated channel source contribution by determining the difference between the sediment load at the outlet of the LRW and predicted contributions from upland sediment. SWAT model simulation results for 2006 showed that upland agricultural regions of Le Sueur River sub-watersheds contribute 14% of the total annual sediment yield. By inference, the remaining 86% of the sediment load arises from river bluffs, ravines and eroding stream banks.

Keywords: SWAT, calibration, validation, sediment yield, Total Suspended Solids (TSS), channel sources, Le Sueur River watershed.

1. Introduction

The Minnesota River Basin drains 4 million ha of productive agricultural land in Minnesota. The Minnesota River enters the Mississippi River in St. Paul, where discharge from the Minnesota River represents nearly half of the Mississippi River flow. The Minnesota River is impaired by sediment at several locations (MPCA, 2009). This sediment enters the Mississippi River and subsequently flows to Lake Pepin, which is also impaired by sediment. Roughly 85% of the sediment entering Lake Pepin comes from the Minnesota River Basin (Kelley and Nater, 2000). The Le Sueur River Watershed (LRW) accounts for about 7% of the area but 53% of the TSS leaving the Minnesota River Basin (Water Resources Center, 2008). The LRW transports over 200 mg/L of sediment to the Minnesota River, which is higher than all other major watersheds in the basin (Water Resources Center, 2002).

Because the LRW is impaired by sediment, a Total Maximum Daily Load is being established, and the sources of sediment are being evaluated. Three principal sources contribute sediment to the LRW, soil erosion of upland areas, head cut and knick point migration of ravines, stream bank erosion and river bluff slumping. The streams of the LRW flow through glacial till or lacustrine plains, cutting deep into the soils and working upstream into agricultural lands. This has resulted in the head cut and nick point migration that initiates the development of ravines and slumping of river bluffs. The Blue Earth River Watershed is adjacent to the LRW and has very similar geology, soils and landscapes. Sekely et al. (2002) showed that this watershed generates roughly 44% of its sediment load from slumping river bluffs. Based on this research, we hypothesize that sediment loads in the LRW are dominated by channel sources of sediment, including bluffs, eroding stream banks and ravines. As a corollary, we hypothesize that sediment contributions from upland agricultural regions will be much smaller than channel sources.

There are few studies that attempt to quantify the relative impacts of upland versus channel sources of sediment in agricultural watersheds (Evans et al., 2003). The objective of this study was to use the process-based distributed modeling approach of the Soil and Water Assessment Tool (SWAT) to quantify sediment loads from upland source areas at various locations within the LRW. By comparing these predicted upland sediment loads with measured stream sediment loads, we wish to estimate the relative proportions of upland versus channel sources of sediment in the LRW.

2. Methodology

2.1 The Study Area

The Le Sueur River Watershed (HUC 07020011) is one of twelve major watersheds in the Minnesota River Basin located in South Central Minnesota. It covers 2,850 square km, and agricultural land use accounts for 87% of the available acres. About 93% of the agricultural land is managed using a two-year corn-soybean rotation. The rest of the area is occupied by small grains, hay, grasslands, Conservation Reserve Program (CRP) land and residential land uses. Average annual precipitation in the LRW is 841 mm.

The LRW drainage network consists of the major tributaries of the Maple River, Big Cobb River and the Upper Le Sueur River (Fig. 1). Soils present are fine textured mollisols formed in glacial till or lacustrine sediments, which are very deep and poorly drained. Mollisols are tile drained for optimum crop production. The watershed consists of nearly level (82% of the area is in the 0-2% slope class), poorly drained soils and gently sloping (14% of the area is in the 2-6% slope class), well-drained loamy soils. Near the mouth of the Le Sueur River is a region where the river flows through deeply incised channels surrounded by high bluffs known to contribute a significant amount of sediment to the river.

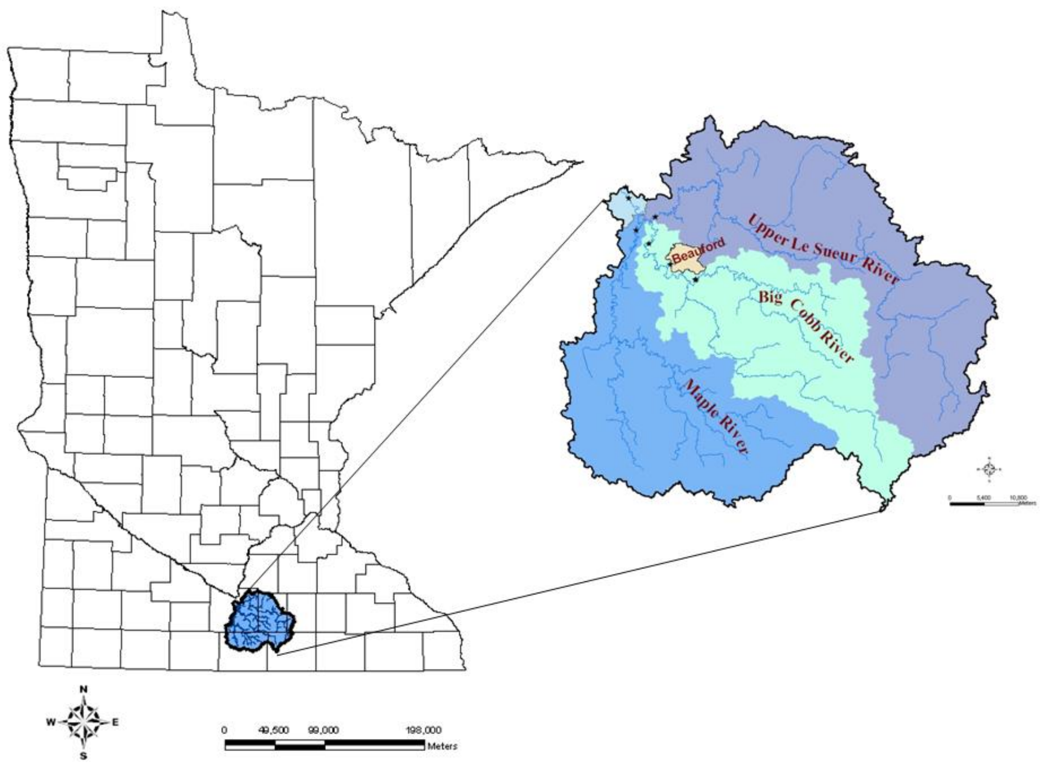


Figure 4. *Location Map of Le Sueur River Watershed*

2.2 Model Setup and Input Data Acquisition

The LRW was subdivided into a total of 84 sub-watersheds and 4818 Hydrologic Response Unit (HRUs) based on a USGS 30-m DEM and Minnesota Department of Natural Resources (DNR) watershed subdivisions.

The MN State Climatology Office provided weather data from 2000-2006 at nine different gauging stations. We used measurements of streamflow and water quality recorded in 2006 by the USGS, MN Metropolitan Council, MPCA, DNR and MDA for model simulation, calibration and validation. LOADEST (Runkel et al., 2004) was used along with measured streamflow and water quality data to estimate sediment loads. To build the model, we used detailed USDA NASS crop land data (CLD) for the year 2006, SSURGO soils data from the USDA NRCS and the stream network from the Minnesota River Basin Data Center (MRBDC). All necessary spatial datasets and database input files for the LRW SWAT model were organized following SWAT model guidelines (Neitsch et al., 2005).

2.3 Model Calibration and Validation

The model was calibrated for a selected normal year (2000) and validated over the years 2001-2006 in the Beauford sub-watershed where the landscape has no bluffs or ravines. Thus, the channel degradation coefficient was set to zero so that the model only simulates upland erosion and sediment yield processes. Finally, the model simulation efficiency was evaluated using the Nash–Sutcliffe coefficient of efficiency (NSE; Nash and Sutcliffe, 1970).

Calibration of the hydrology was accomplished first, followed by sediment calibration. We applied the calibrated model input parameters to the entire LRW in order to estimate sediment losses from agricultural upland regions. Predicted upland sediment loads were subtracted from the measured total sediment loads to indirectly estimate the sediment contributions from channel sources, including river bluffs, ravines and stream banks.

3. Results and Discussion

The overall SWAT model efficiency during calibration and validation of discharge in the Beauford sub-watershed was excellent (Figs. 2-3), with NSE values of 0.77 and 0.89, respectively. The model simulated baseflow hydrology very well. However, the model underestimated peak flows in the month of June (Fig. 2).

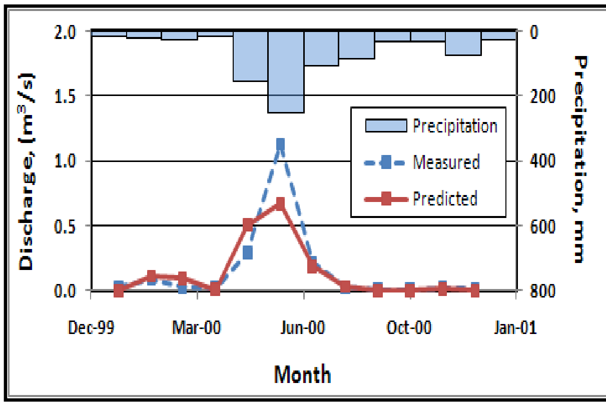


Figure 5. SWAT model calibration of flow in Beauford

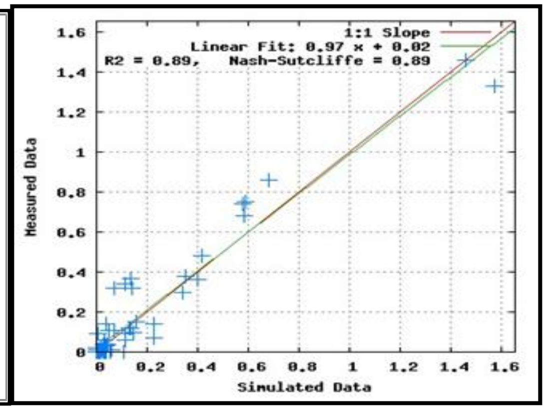


Figure 3. SWAT model validation of flow in Beauford

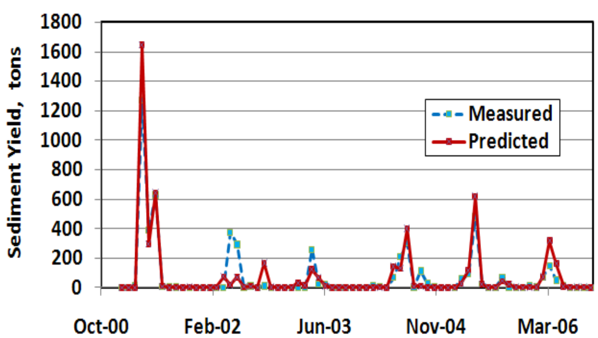


Figure 4. SWAT model validation of sediment in Beauford

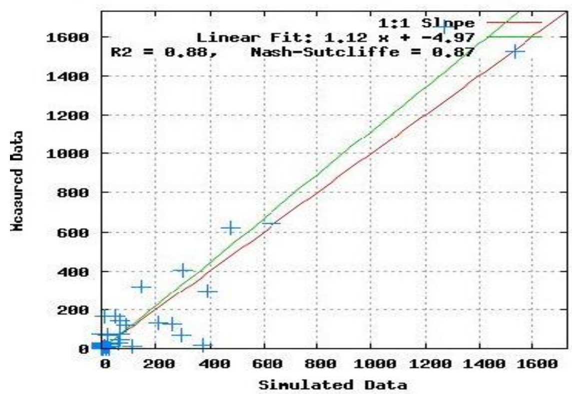
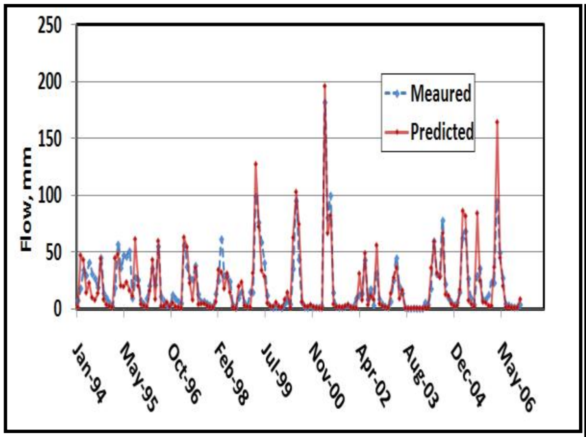


Figure 5. SWAT model validation of sediment in Beauford

The SWAT model validation of sediment yields was excellent (Figs. 4-5), with an NSE value of 0.76. Since the Beauford sub-watershed has no stream bluffs or ravines, most of the sediment arises from upland agricultural lands. The high NSE values for both flow and sediment in the Beauford sub-watershed indicate that the model was well parameterized, and the calibrated model parameters can satisfactorily be applied to the entire LRW watershed.

The calibrated SWAT model was applied to the entire LRW and three major tributaries of the LRW namely, the Big Cobb, Maple and Upper Le Sueur (Fig. 1). At the LRW scale, the calibrated SWAT model predicted discharge very accurately, with an NSE value of 0.73 (Fig. 6). The SWAT model predicted much smaller sediment loads at the mouth of the LRW than those given by measured water quality data (Fig. 7).

This is not surprising, since most of the sediment loads at the mouth of the LRW arise from channel rather than upland sources.



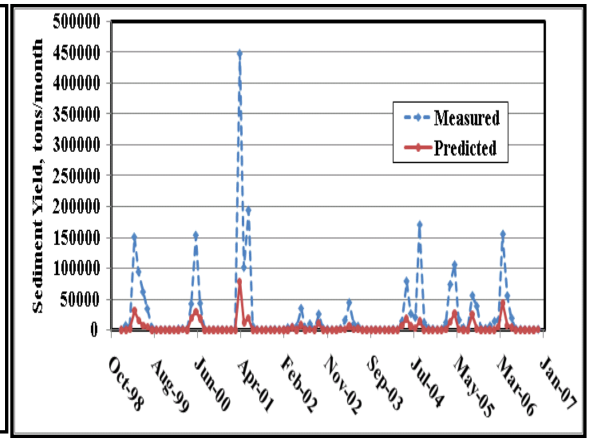


Figure 6. *SWAT model validation of LRW flow*

Figure 7. *SWAT Model Validation of LRW Sediment Yield*

The relative contributions of predicted upland and inferred channel sediment sources for each of the three major sub-watershed outlets and the LRW outlet for the 2006 growing season are shown in Table 1. During 2006, the measured sediment yield of the LRW was about 230,502 tons. The SWAT model predicted 32,893 tons at the LRW outlet, which means that the upland contribution to total sediment load was 14%. Based on HRU level sediment loss estimates for the entire LRW, only about 9% of the sediment loss at the HRU scale reaches the outlet of the LRW. By inference, most of the sediment (86%) was generated from channel sources, including river bluffs (Fig. 8), stream banks and ravines. About 93% of the sediment losses in the LRW occur during the growing season (April to September). At scales finer than the entire LRW, the SWAT model predicted that agricultural uplands in the Big Cobb, Maple and Upper Le Sueur sub-watersheds contributed 38%, 22% and 12%, respectively, of the sediment loads measured at their outlets during 2006. By inference, the Big Cobb, Maple and Upper Le Sueur sub-watersheds generate 62%, 78% and 88% of their sediment from channel sources, respectively. These differences in sediment loads can be explained in terms of differences in upland slope steepness class distributions and differences in the frequency of river bluffs and ravines.

Figure 8. *Steep river bluff along the Le Sueur River*

Table 1. *Predicted and measured sediment loads from the LRW and its major tributaries in the 2006 growing season*

Sub-watershed	Predicted Upland Sediment Load		Channel Erosion (estimated by difference)		Measured Total Sediment Load	Average Sediment Yield
	tons	%	tons	%	tons	tons/ha
Beauford	178	83	36	27	214	0.10
Big Cobb	8998	38	14785	62	23783	0.30
Maple	11047	22	39290	78	50337	0.57
Upper Le Sueur	20019	12	146462	88	166481	1.44
LRW	32893	14	197609	86	230502	0.81

4. Conclusions

This study uses the strength of the SWAT model, namely its ability to predict sediment losses from upland agricultural regions, to estimate the proportion of total measured sediment loads in the Le Sueur River watershed that arise from upland agricultural regions. The SWAT model was calibrated and validated in a small watershed (Beauford) that lacks significant channel sources of sediment and was found to be very accurate at predicting discharge and sediment loads. The calibrated and validated model was extrapolated to the entire LRW and its sub-watersheds and accurately predicted discharges at these larger scales. Predicted sediment loads were much smaller than measured sediment loads, indicating that upland sediment sources are only a small fraction of the total sediment losses at these large scales. Based on the SWAT model simulation results, about 14% of the LRW sediment arises from upland agricultural areas while 86% arises from river bluffs, ravines and eroding stream channels.

Acknowledgments

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Instream Water Quality Processes in SWAT with Different Routing Methods and Adapted Water Quality Modules for Daily or Sub-Daily Time Steps

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Abstract

The European Water Framework Directive's new approach to pollution problems from both point sources and diffuse sources is management at the river basin scale. An integration of catchment modeling and river water quality modeling can help modelers predict the efficiency of source driven measures. In this study, we used the Soil and Water Assessment Tool (SWAT) to integrate catchment modeling and river water quality modeling. The Grote Nete River Basin in Belgium has point source pollution problems originating from households, industries and wastewater treatment plants and from diffuse sources including rainfall, fertilizer application and pollution from soils.

We studied the effects of instream water quality processes in SWAT by running the model with and without instream water quality processes using two different routing methods: Muskingum and adapted Manning routing method (van Griensven et al., 2006). In these methods, water quality processes are calculated in the river reach. We originally tried the Variable Storage method, but it had problems during the entire simulation period. The Muskingum method gave us problems in modeling water quality processes when there was a decrease in flow and storage in the river. However, the adapted routing method based on the Manning equation, combined with a time-step based river water quality module, gives logical water quality results because there is always water stored in the reach in this method. SWAT lacks the processes to reduce PO_4; thus, only the PO_4 calibration was unsatisfactory.

Keywords: water quality processes, SWAT, routing methods

1. Introduction

The EU Water Framework Directive (WFD) has introduced a new approach to water resource protection, shifting from a focus on the control of point source pollution (emission-based regulations) to integrated pollution prevention at the river basin level by setting water quality objectives for receiving waters (imission-based regulations). This new policy requires integration between water quality issues related to both point and diffuse pollution sources at the river basin scale. In order to model the effectiveness of water resource protection measures, it is necessary to integrate catchment modeling (aimed at estimating the flow of water and pollutants released from a draining catchment into receiving waters) with modeling of water quality processes in receiving waters. Past and present efforts in wastewater treatment for industries and households have greatly reduced point source pollution. However, diffuse pollution sources, such as agriculture or groundwater recharge, are becoming a major concern and are often the main cause of nutrification and eutrophication of water bodies.

The Soil and Water Assessment Tool (SWAT) is a physically based, time-continuous model developed by the USDA Agricultural Research Service (ARS) for simulating the impact of land management activities on water, sediment, pesticides and nutrient yields in large, complex watersheds over long periods of time. SWAT is also an integrated model that is able to estimate the effects of diffuse pollution sources at the catchment level down to the water quality of a river. There are many studies applying SWAT to predict pollution loads from agriculture and groundwater recharge. Kang et al. (2005) applied SWAT to a small watershed containing rice paddy fields for Total Maximum Daily Load (TMDL) programs. In their study, the researchers used SWAT to calculate nutrient loads that originated from animals and the application of manure and fertilizer in the rice paddy fields. They compared the results with TMDLs and proposed requirements for decreasing nutrient loads in each subbasin. Bouraoui and Grizzetti (2008) used SWAT to identify the major processes and pathways controlling nutrient losses from agriculture activities. Salvetti et al. (2008) also used SWAT as a tool to determine the rain-driven diffuse load (the load from runoff and erosion processes).

In this study, we applied SWAT in the Grote Nete River Basin (Belgium) where there are pollution problems from nonpoint sources like agriculture and from point sources, which directly discharge wastewater to the river like households, industries and wastewater treatment plants (WWTPs). The effects of pollution from diffuse sources and point sources were estimated and evaluated after sensitivity analysis and model calibration. Moreover, the effects of different routing methods in modeling instream water quality processes were analyzed and compared.

2. Study area

The Grote Nete Basin is situated in the south-eastern part of the Nete Basin. Important tributaries of the Grote Nete Basin are the Mol-Nete, the Wimp and the Grote Laak (Fig. 1).

The region has a temperate climate with an average annual precipitation of 790 mm. Precipitation is relatively equally distributed throughout the year. The mean temperature is 16^{o}C in July and 2^{o}C in January. The topography of the basin is definitively flat, as is most of Flanders. More than 30% of the Grote Nete catchment is covered by forest and 26% by cultivated land (mainly corn). Wetlands and water bodies exist on only 1.35% of the area.

Water quality in the river is affected by diffuse pollution, mostly from agriculture activities, and by point source pollution from households and industries that are not connected to the public sewer system and WWTPs.

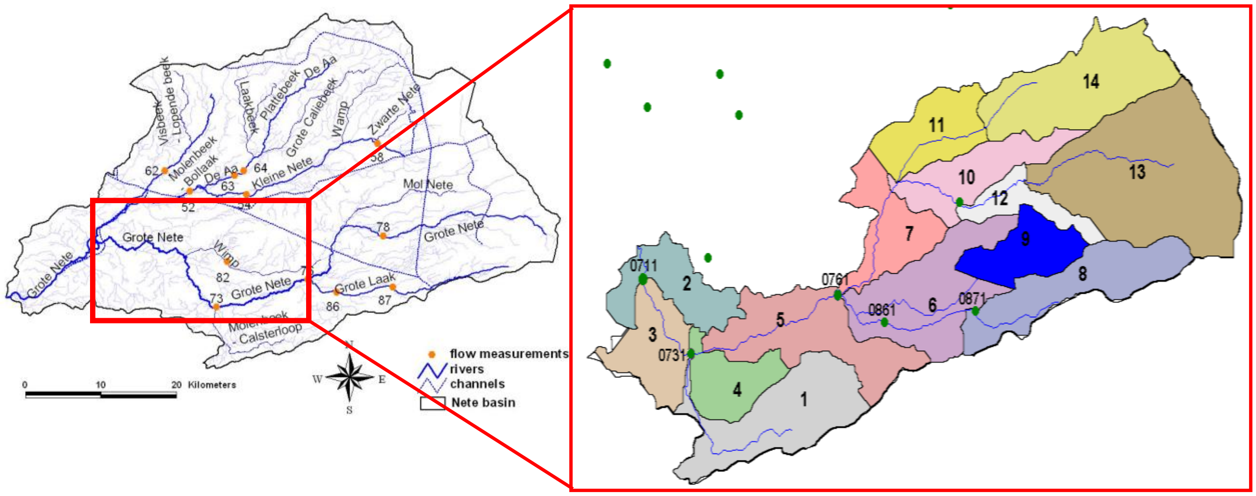


Figure 1. *The study area and its SWAT model*

3. The SWAT model and methodology

3.1. The SWAT model for Grote Nete River Basin and available data

We developed a model of the Grote Nete River Basin in SWAT with 14 subbasins, 71 HRUs, 14 point sources (one per subbasin) and 1 reservoir (situated in subbasin 9 for canal water removal) (Fig. 1). Meteorological data for the basin, including daily maximum and minimum temperature, daily precipitation, daily wind speed, daily humidity and solar radiation, were available from 1998-2006.

Agriculture is the main source of diffuse pollution in the basin due to the use of animal manure and fertilizer. However, a small amount comes from rainfall. It is assumed that the concentration of nitrate in rainfall is one ppm, still this amount is insignificant. Fertilizer application data was available from 2000-2006 and was obtained from the VLM (Flemish Land Agency).

Due to SWAT's inability to model more than one point source per subbasin, 14 point sources were added to corresponding subbasins. Loadings from each point source represented an aggregate of loadings from all point sources in the corresponding subbasin including industry, WWTP, households, small industries and agricultural point sources (greenhouse farming, dairy farms and the rinse-off from yards). The point source data had a yearly time step during 1998-2006. Moreover, monthly water quality data for calibration was available from 2002-2006 at the outlet of subbasin 3 and 4. However, some CBOD and PO_4 data were not accurate, which was ignored in the calibration. Due to the settings in the model and the software, the model does not represent processes related to algae.

3.2 Methodology

From available data, we ran the model with a daily time step from 1998-2006 with the first two years (1998-1999) serving as a warm-up period. For flow calibration, we used the next three years (2000-2002), and the remaining years (2003-2006) were used for validation. For water quality, we completed the sensitivity analysis and calibration with several water quality variables including NH_4, NO_2, NO_3, PO_4, CBOD and DO. For the sensitivity analysis, we chose 40 parameters related to both land phase and instream water quality processes. We used the SWAT sensitivity tool to complete the analysis and chose the most sensitive parameters for the next calibration step. Calibration was then executed by SWAT's auto-calibration tool, using water quality data from 2002-2006. After calibration, we analyzed the SWAT catchment modeling and water quality modeling results to determine the contribution of diffuse sources and point sources and their overall effect on water quality in the river.

4. Model calibration

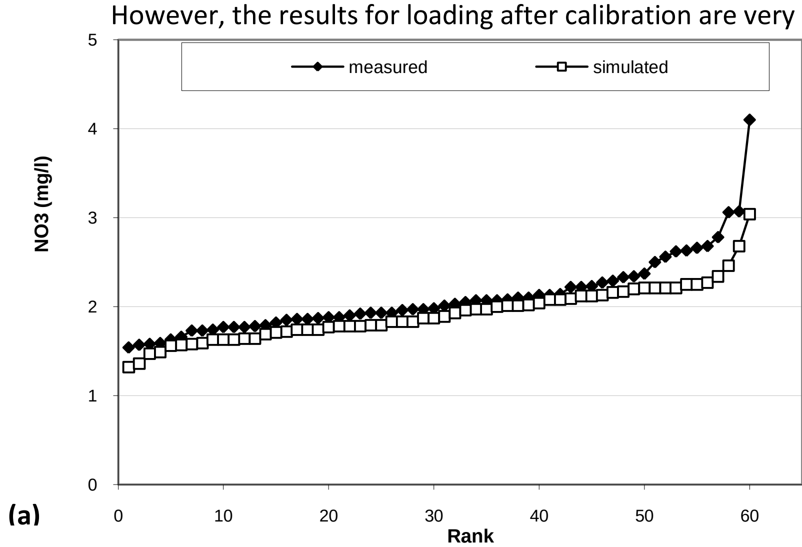
4.1. Flow calibration

Flow calibration was based on a multi-site calibration and validation. The stations considered for calibration and validation were 0871, 0731, and 0711, corresponding to the outlets of subbasins 8, 4 and 3, respectively. Calibration was done by combining manual and auto-calibration (Parasol) techniques. We obtained a satisfactory NSE (Nash-Sutclifffe Efficiency) during the calibration period. The smallest NSE was 0.66 at station 0871 and the maximum NSE was 0.73 at station 0731.

4.2. Water quality calibration

In this study, we used the SWAT auto-calibration tool. The variables involved in water quality calibration include: NH_4, NO_2, NO_3, PO_4, CBOD and DO. We found that NO_3 and PO_4 were the most important variables to focus on because they were assumed to be the only nitrogen and phosphorus components in the fertilizer-animal manure applied.

For nitrate, one can clearly see in Figure 2 that the ranked result for simulated and measured NO_3 is quite close. The simulated concentration is a bit underestimated compared with the measured one. However, the results for loading after calibration are very good.



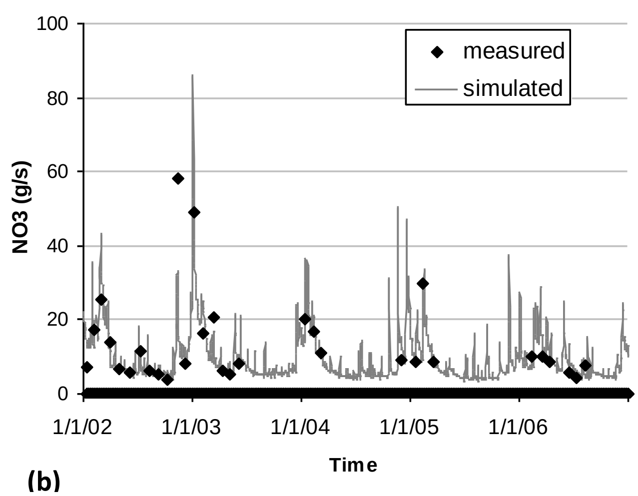


Figure 2. *(a) Ranked plot of simulated and measured NO3 concentrations and (b) a plot of simulated and measured NO_3 loadings*

Unlike NO_3, the calibration for PO_4 was not good. It can be clearly observed in Figure 3 that PO_4 concentration is highly overestimated. Although we tried to reduce PO_4 to the minimum value by changing parameters controlling PO_4, it was still overestimated. The reason is that SWAT lacks equations for phosphorus removal. Therefore, we suggest that equations be added for adsorption of PO_4 to sediments and for this study, coagulation to iron ions coming from groundwater.

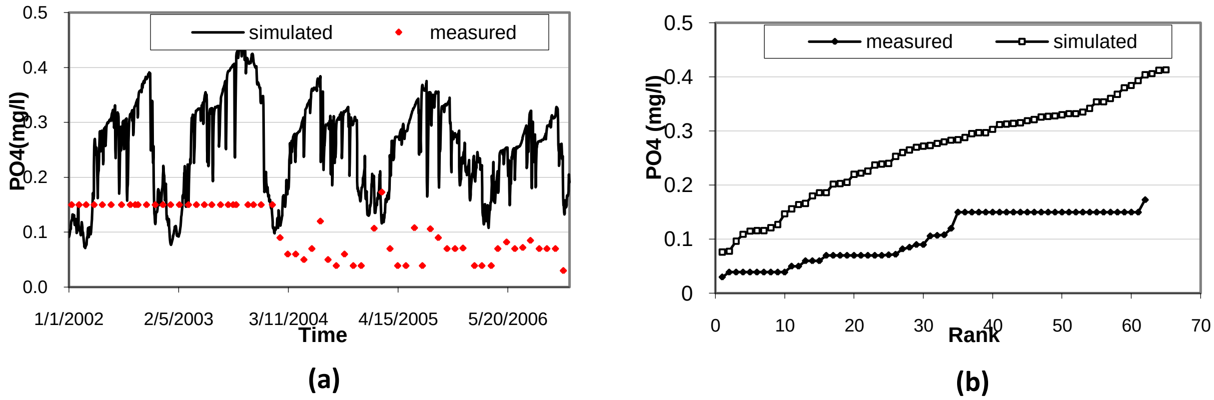


Figure 3. *(a) Plot of simulated and measured NO3 concentrations and (b) a ranked plot of simulated and measured NO_3 loadings*

5. Routing methods in SWAT

5.1 Original routing method

Originally, flow was routed through the canal using the Variable Storage routing method or the Muskingum routing system. These methods are variations of the kinematic wave model. Therefore, SWAT cannot model the backwater effect.

Variable Storage method

In the Variable Storage method, outflow depends on the stored volume in the reach, the inflow and a calculated Storage Coefficient (SC).

$$V_{out,2} = SC \cdot (V_{in} + V_{stored,1}) \tag{1}$$

where SC is the storage coefficient that depends on the travel time (TT) and the time step (Δt), V_{in} is the average inflow at the beginning and the end of the time step in m^3, $V_{out,2}$ is the outflow at the end of the time step in m^3 and $V_{stored,1}$ is the storage volume at the beginning of the time step in m^3.

$$SC = \frac{2 \cdot \Delta t}{2 \cdot TT + \Delta t} \tag{2}$$

$$TT = \frac{V_{stored}}{q_{out}} = \frac{V_{stored,1}}{q_{out,1}} = \frac{V_{stored,2}}{q_{out,2}} \tag{3}$$

where TT is the travel time (s), V_{stored} is the storage volume (m^3) and q_{out} is the discharge rate (m^3/s).

Muskingum method

In the Muskingum method, the outflow is calculated from the inflow, the inflow of a previous time step and the outflow of a previous time step. Thus, storage in the reach is not a required state for this method.

$$q_{out,2} = C_1 \cdot q_{in,2} + C_2 \cdot q_{in,1} + C_3 \cdot q_{out,1} \tag{4}$$

where $q_{in,1}$ is the inflow rate at the beginning of the time step (m^3/s), $q_{in,2}$ is the inflow rate at the end of the time step (m^3/s), $q_{out,1}$ is the outflow rate at the beginning of the time step (m^3/s) and $q_{out,2}$ is the outflow rate at the end of the time step (m^3/s). C_1, C_2 and C_3 depend on the time step (Δt), K (the ratio of storage to discharge having the dimension of time) and X (a weighting factor that controls the relative importance of inflow and outflow in determining the storage in a reach) where

$$C_1 + C_2 + C_3 = 1 \quad (5)$$

Losses through the routing phase

Transmission losses

During periods when a stream receives no groundwater contributions, it is possible for water to be lost from the channel via transmission through its sides and bottom. Transmission losses were estimated with the equation

$$tloss = K_{ch} \cdot TT \cdot P_{ch} \cdot L_{ch} \quad (6)$$

where *tloss* is the channel transmission losses (m^3 H_2O), K_{ch} is the effective hydraulic conductivity of the channel alluvium (mm/hr), *TT* is the flow travel time (hr), *Pch* is the wetted perimeter (m), and L_{ch} is the channel length (km). Transmission losses from the main channel are assumed to enter bank storage or deep aquifer.

Evaporation losses

Evaporation losses from the reach were calculated with the following equation:

$$E_{ch} = coef_{ev} \cdot E_0 \cdot L_{ch} \cdot W\, TT/24 \quad (7)$$

where E_{ch} is the evaporation from the reach for the day (m^3 H_2O), $coef_{ev}$ is an evaporation coefficient, E_0 is potential evaporation (m^3 H_2O), L_{ch} is the channel length (km), W is the channel width at water level (m) and TT is the travel time (hr).

Water balance

Water storage in the reach at the end of the time step was calculated as follows:

$$V_{stored,2} = V_{stored,1} + V_{in} - V_{out} - tloss - E_{ch} + div + V_{bnk} \quad (8)$$

where $V_{stored,2}$ is the volume of water in the reach at the end of the time step (m^3 H_2O), $V_{stored,1}$ is the volume of water in the reach at the beginning of the time step (m^3 H_2O), V_{in} is the volume of water flowing into the reach during the time step (m^3 H_2O), V_{out} is the volume of water flowing out of the reach during the time step (m^3 H_2O), *tloss* is the volume of water lost from the reach via transmission through the bed (m^3 H_2O), E_{ch} is the evaporation from the reach during one day (m^3 H_2O), *div* is the volume of water added or removed through diversions from the reach for a day (m^3 H_2O) and V_{bnk} is the volume of water added to the reach as return flow from bank storage (m^3 H_2O).

The outflow V_{out} can be calculated either by the Muskingum or Variable Storage method.

5.2 Adaptations to river routing methods in SWAT

In order to get stable calculations in SWAT routing, both the Muskingum method and the Variable Storage method had to be applied incorrectly. In both methods, the hydrological state variables such as river flow, depth, wetted perimeter, cross section area and flow velocities are based on a summation of the water volume, the reach and the inflow rather than the volume alone (Van Griensven et al., 2006).

$$A_{ch} = \frac{(V_{in} + V_{stor})}{L_{ch} \cdot 1000.} \qquad (9)$$

where A_{ch} is the cross-sectional area of flow in the channel (m^2) and L_{ch} is the length of the channel (km).

This equation gave stable calculations for small reaches because the inflow acts as a kind of buffer for the storage in the reach, but the stability was based on the wrong underlying calculations. For example, assuming residence time is one hour, the volume times 24 is added to the reach volume. The resulting travel time is strongly underestimated by an order of 24, while the river depth calculation is strongly overestimated. When Muskingum and Variable Storage routing were implemented in the proper way, unstable river volume and hence river depth velocities were obtained in cases with short residence times, creating strong variations in inflow between the two days. Therefore, a new routing module was developed wherein the relation between velocity and flow are calculated by solving the Manning equations in an iterative fashion until an A_{ch} is found (and corresponding R_{ch}) that corresponds to the inflow $q_{in,1}$ in the following equation (Van Griensven et al., 2006):

$$q_{in,1} = \frac{A_{ch} \cdot R_{ch}^{2/3} \cdot slp_{ch}^{1/2}}{n} \qquad (10)$$

A corresponding reach volume can be calculated with the following equation:

$$V_{manning} = 1000 \cdot L_{ch} \cdot A_{ch} \qquad (11)$$

where q_{ch} is the rate of flow in the channel (m^3/s), A_{ch} is the cross-sectional area of flow in the channel (m^2) and R_{ch} is the hydraulic radius for a given depth of flow (m).

The key solution to getting stable calculations for situations where the residence time is either smaller or larger than the calculations is to use distinct equations for these situations. If the residence time γ (days) is smaller than the calculation time step Δt (days), the reach volume at the end of the time step, $V_{stored,2}$ (m^3), will be equal to $V_{manning}$ (m^3):

$$V_{stored,2} = V_{manning} \qquad (12)$$

However, when γ is larger than the time step, only part of $V_{stored,1}$ (m^3) should be replaced by $V_{manning}$:

$$V_{stored,2} = V_{stored,1} - \frac{\Delta t}{\gamma}(V_{stored,1} - V_{manning}) \qquad (13)$$

The routing component needed a final correction: the calculation of transitional losses (infiltration or evaporation) and river bank contributions in the adapted method were modified to be based on the calculation time step instead of residence time, as these factors are also dependent on the wetted perimeter (noted below).

Moreover, Van Griensven et al. (2006) completed the following modifications for channel loss calculations:

1. The channel loss calculation now relies on the time step of the model run rather than residence time since channel losses were heavily influenced by the previous routing corrections as they depend on the wetted perimeter.

2. In the original code, when water losses were abstracted from the river outflow, chemical concentrations remained constant. This resulted in a loss of chemicals or pollutants when loads were calculated. The calculation was adapted so that solids remain in the river during evaporation or infiltration. Thus, their concentration will increase when water is infiltrated or evaporated.

Finally, a new water quality module (IWQ=2) was introduced, whereby processes are computed in the river reach (process rates are multiplied by time step) instead of at the outflow (process rates are multiplied by the residence time).

In this study, two SWAT routing methods were used: the Muskingum routing method (IRTE=1) and the adapted routing method (IRTE=2), to compare the effects of different routing methods on modeling instream water quality processes.

6. Results and discussion

6.1. Effect of instream water quality processes with different routing methods

Figure 4 shows the difference in SWAT-produced water quality variables orgN and orgP in two cases both using the Muskingum routing method: with and without instream water quality processes. The figure shows that there is only a difference during an increase in discharge or when discharge at the current time step is higher than discharge at the previous time step. The reason for this effect is that when the flow decreases, less water is stored in the reach than is further lost via transmission through the side and bottom of the channel or through evaporation. Since there is no storage in the reach, no water quality processes happen. This is the problem in modeling water quality using the Muskingum routing method. The problem is even greater for the variable storage method since no storage at all was computed in our case.

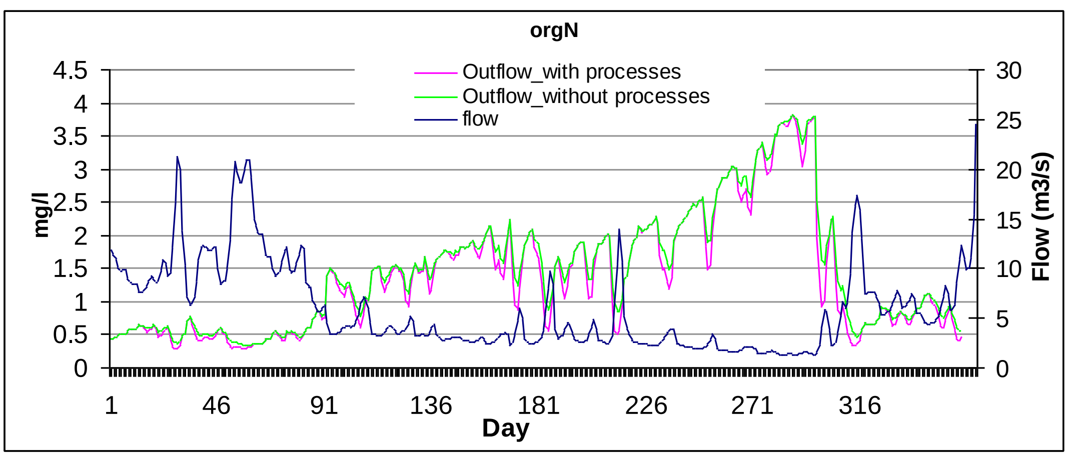


Figure 4. *Comparison of water quality variable values between running SWAT with and without water quality processes using the Muskingum routing method*

Because of the aforementioned problem with using the Muskingum method, the adapted routing method based on the Manning equation was used. Figure 5 represents the differences in concentration between different water quality variables including orgN, orgP, NO_3, PO_4, CBOD and DO in two cases both using the adapted routing method: with and without water quality processes. With the adapted routing method, the differences between the two cases vary more logically. The differences are larger during the dry period when nutrient concentrations are high and lower during the flood period when the concentration is lower because of dilution. In the adapted routing method, the stored volume in the reach is calculated differently when the residence time is smaller or larger than the calculation time step. In this case, there is always water stored in the reach, and thus, water quality processes always happen.

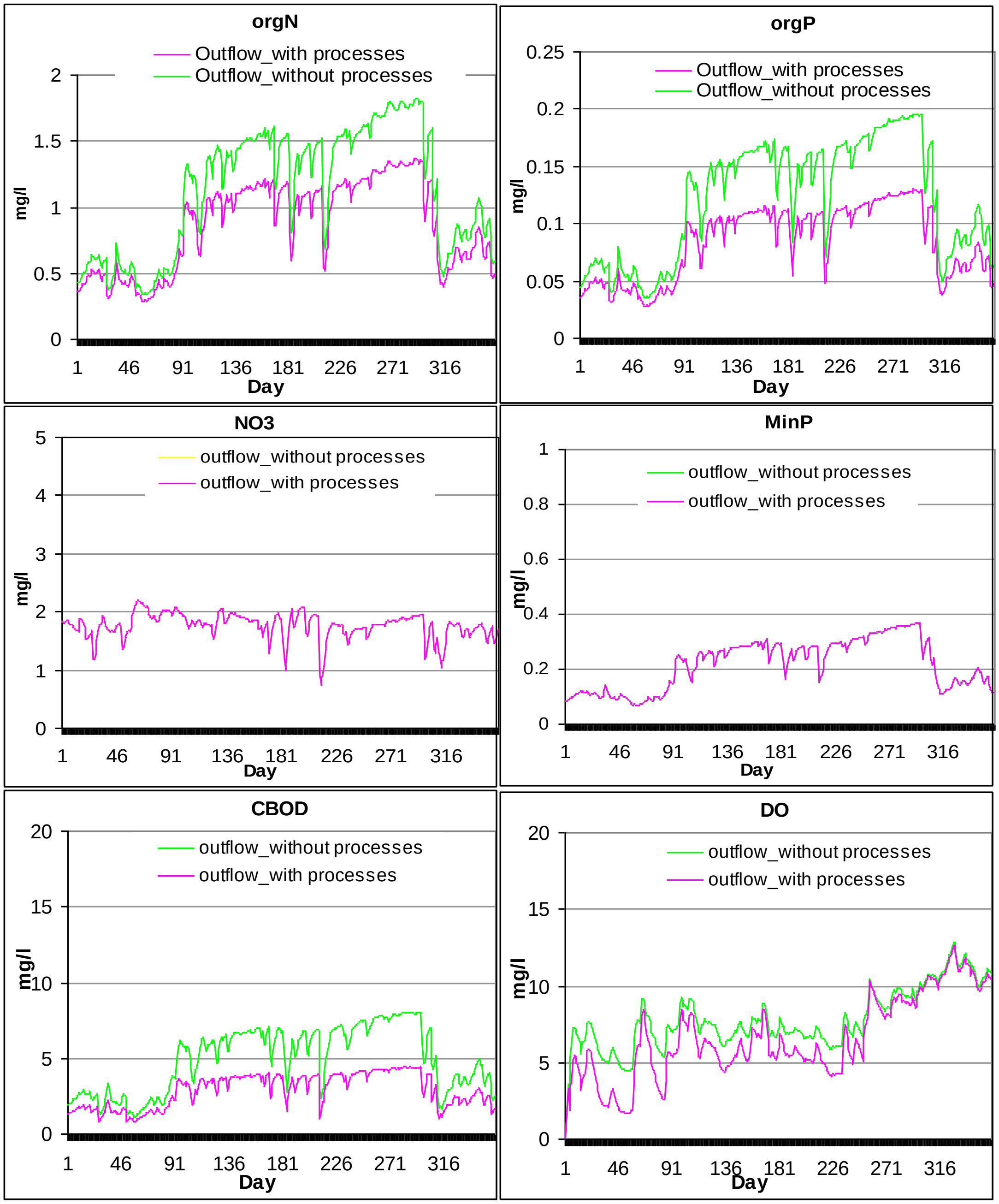


Figure 5. *Comparison of water quality variable values between running SWAT with and without water quality processes using the adapted Manning routing method*

One can clearly observe in the figure above that organic N and organic P concentrations decrease. This is due to two processes: mineralization of organic N into NH_4 and organic P into PO_4 and settling of organic N and organic P. Nitrate retains the same value because the SWAT parameter representing the nitrification rate (NO_2 to NO_3) is very low. This is due to the fact that in SWAT, the only way to reduce the amount of NO_3 is through uptake by algae. But, the denitrification process is not applied in SWAT and algae processes were not available. Thus, the reason for the low nitrification rate (NO_2 to NO_3) was that the nitrate loading from diffuse land sources was nearly the same as the nitrate loading calculated from measured data. Therefore, the auto-calibration tool gave very a low nitrification rate to prevent the increase of NO_3. Similarly, the only process that can reduce PO_4 in SWAT is uptake by algae. Therefore, in this study, PO_4 also could not be decreased, and thus, the auto-calibration tool gave a very low value for the mineralization process from orgP to PO_4. Unlike NO_3, resulting PO_4 values were much higher than measured values. Therefore, it is necessary to give SWAT the ability to reduce PO_4 in order to simulate PO_4 accurately.

Due to water quality processes, CBOD decreased by settling and decomposition. DO was increased through aeration and was reduced through different processes including CBOD decomposition, nitrification and sediment oxygen demand.

For the period 2002-2006, the effects of water quality processes are represented by the percent change in the water quality variables in the following table.

Table 1. *Effects of water quality processes when the adapted routing method is used*

No.	Variables	Percentage change in by water quality processes (%)
1	OrgN	-22
2	OrgP	-30
3	NO_3	0.01
4	NH_4	-1.3
5	NO_2	29
6	PO_4	0.06
7	CBOD	-41

6.2. Contribution of diffuse and point sources to the pollution of Grote Nete River

Using the results achieved through catchment modeling with SWAT, we estimated pollutant loading from diffuse sources, which are mainly attributed to agriculture. On average, 10% of nitrogen and 0.63% of phosphorus in applied fertilizer reached the river. Loadings from diffuse sources were then compared with loadings from point sources calculated from the measured values. The contribution of different pollution sources to the river is shown in Figure 6 for two nutrient variables: total nitrogen and total phosphorus. The figure shows that diffuse source pollution is the largest source of nitrogen, contributing about 39% of the total amount of nitrogen to Grote Nete River. However, households are the largest source of phosphorus, with a contribution of 42%.

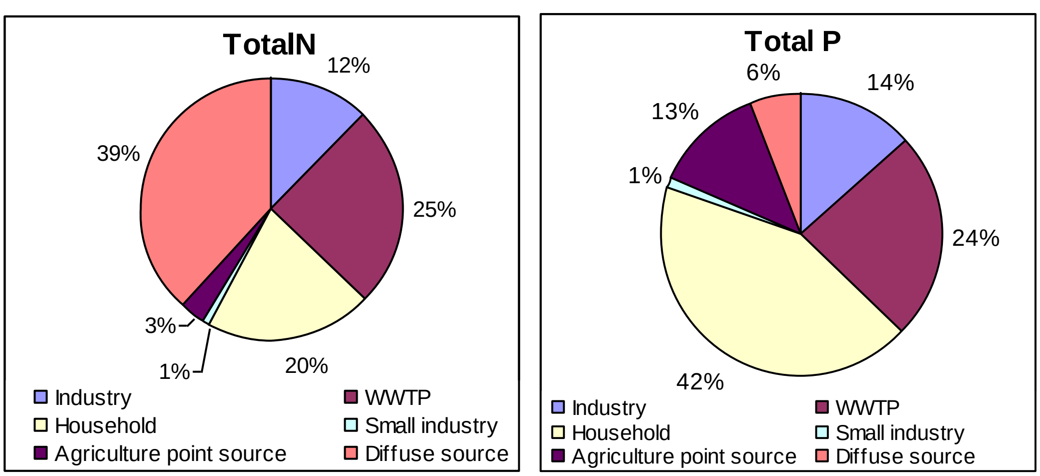


Figure 6. *Percentage of total N and total P flowing to Grote Nete river from different sources*

6.3. Effect of diffuse and point sources on nitrate concentration

The following figure shows the variation in nitrate concentration at the outlet of the whole basin for 3 scenarios: (1) with fertilizer and point sources, (2) with fertilizer and without point sources and (3) without fertilizer and without point sources.

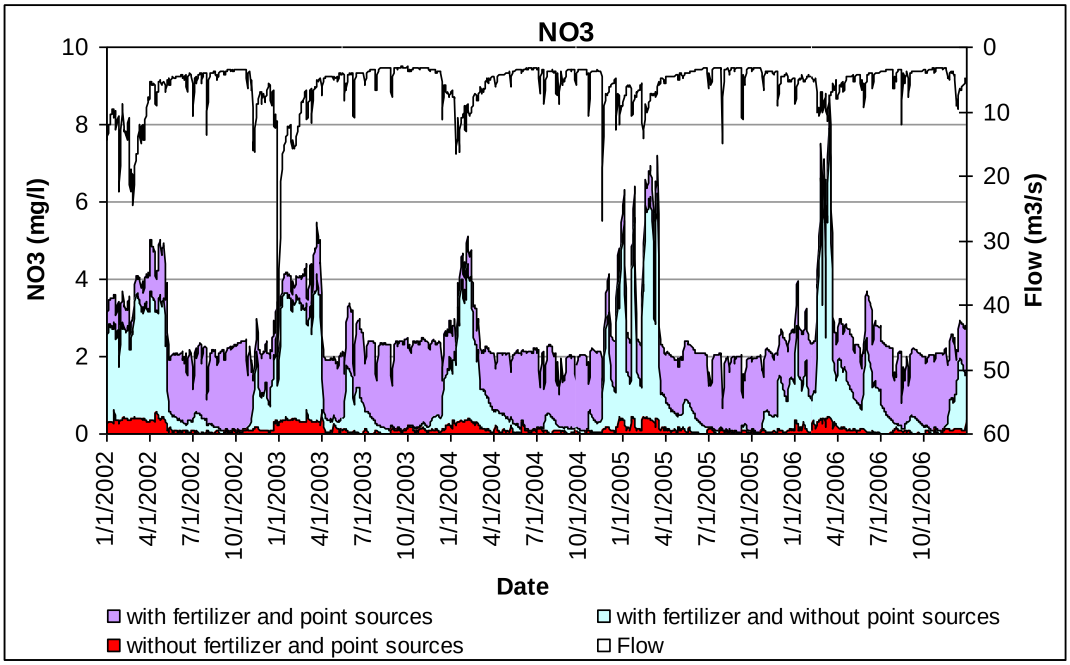


Figure 7. *Variations in nitrate concentrations at the outlet of Grote Nete subbasin*

In the scenario without fertilizer and without point sources, nitrate existing in the soil was still contributing to the river load. The concentration of nitrate was low in the dry period (May to October) and high in the flood period (November to April) because of nitrate in runoff. In the scenario with fertilizer and without point sources, nitrate was very high during the flood period because runoff brings a large amount of nitrate from fertilizer to the river. Moreover, the flood period is also the time when a lot of fertilizer is applied throughout the whole basin. In the dry period, the concentration was also higher than the dry period or the flood period of the first scenario. The last scenario was run with both fertilizer and point sources. One can clearly observe that in the flood period, fertilizer affects nitrate concentration more than point sources while in the dry period point sources contribute most of the nitrate to the river.

7. Conclusion

The integrated SWAT model is a useful tool for studying pollution from both diffuse sources and point sources. However, river water quality modeling in SWAT faces problems in reducing phosphorus concentration since algae is not considered in the model. Therefore, it is necessary to add more phosphorus modeling processes such as adsorption to sediments followed by settling processes or coagulation with iron originating from groundwater, a process that characterizes the Nete River.

The Muskingum routing method is problematic for modeling water quality processes when there is a decrease in inflow and storage in the reach. The adapted routing method (Van Griensven et al., 2006) used in this study gave better results because water is always stored in the system, even if the residence time is larger or smaller than the time step. Thus, water quality processes are always modeled. Therefore, it is necessary to be careful in choosing a routing method when modeling water quality in SWAT. However, running the model with a sub-daily time step can possibly solve the problems created by using the Muskingum method in modeling water quality processes.

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Numerical analyses on seasonal variations of nutrient salts and load discharges in Abashiri River Basin

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Abstract

In recent years, environmental standards involving lacustrine water quality have aimed at improving water quality through control of pollutant loads emitted into lakes and rivers. These standards focus on putting an adequate sewage system in place and developing water quality laws. However, lacustrine water quality has not improved as well as expected. Nonpoint source pollutant loads discharged from agricultural lands are suspected to be one of the main culprits of water quality problems. Thus, we applied the Soil and Water Assessment Tool (SWAT) model to the Abashiri River Basin to obtain information related to river basin hydrology and its effects downstream in Lake Abashiri. The Abashiri river basin is located in the eastern part of the Hokkaido region, Japan. The River basin catchment area is about 1,100 km^2. Forest is dominant in the area. Over 80% of the area is forest and less than 20% of the basin area is used for agriculture. In this stage, we focused on agricultural activities in the basin and tried to estimate seasonal variations of nitrogen and phosphorus with SWAT. First of all, we investigated information about cultivated crops and the timing of plowing and fertilizer application in the basin. Then, we treated that information as model input data. In this basin, we found the majority of nitrogen and phosphorous fertilizers are applied in April and May, the period of snow melting and start of crop cultivation, and September, which is the beginning of winter wheat cultivation. Though SWAT can simulated fluctuations in TN and TP loads relatively well, in the current stage, model performance statistics showed some cases to be unsatisfactory.

Keywords: nitrogen, phosphorus, agricultural activities, Soil and Water Assessment Tool (SWAT)

1. Introduction

Impact assessments of land-use change, population change and watershed development relating to water quantity and quality are the most important topics in a basin. Also, an integrated management approach to the water environment including both the river basin and downstream areas, such as a lake, is very important for conservation and sustainable resources use. In recent years, environmental standards involving lacustrine water quality have aimed at improving water quality through control of pollutant loads emitted into lakes and rivers. These standards focus on putting an adequate sewage system in place and developing water quality laws. However, lacustrine water quality has not improved as well as expected. Nonpoint source pollutant loads discharged from agricultural lands are suspected to be one of the main culprits of water quality problems. In the integrated approach to watershed management and improvement of the lacustrine environment, information about both the lake and rivers will be necessary. Thus, we applied the Soil and Water Assessment Tool (SWAT) model to the Abashiri River Basin to obtain information related to river basin hydrology and its effects downstream in Lake Abashiri.

In this stage, we focused on agricultural activities in the basin and tried to estimate seasonal variations of nitrogen and phosphorus with SWAT. First of all, we investigated information about cultivated crops and the timing of plowing and fertilizer application in the basin. Then, we treated that information as model input data.

2. Study area

The Abashiri River Basin is located in the northeastern part of Hokkaido Region, Japan (Fig. 1). It covers an area of approximately 1,100 km^2. The length of the river from its source to the Hongo river discharge observation station, where the outlet of the whole basin is located, is approximately 120 km. Approximately 80% of the land in the basin is forest and 19% is occupied by agricultural lands, which are mainly fields of upland crops. Average total annual precipitation is approximately 800 mm at the Tsubetsu weather gauge. In addition, average daily wind speed at the Tsubetsu weather gauge and daily humidity at the Abashiri weather gauge are 1.8 m and 74%, respectively. During the winter season,

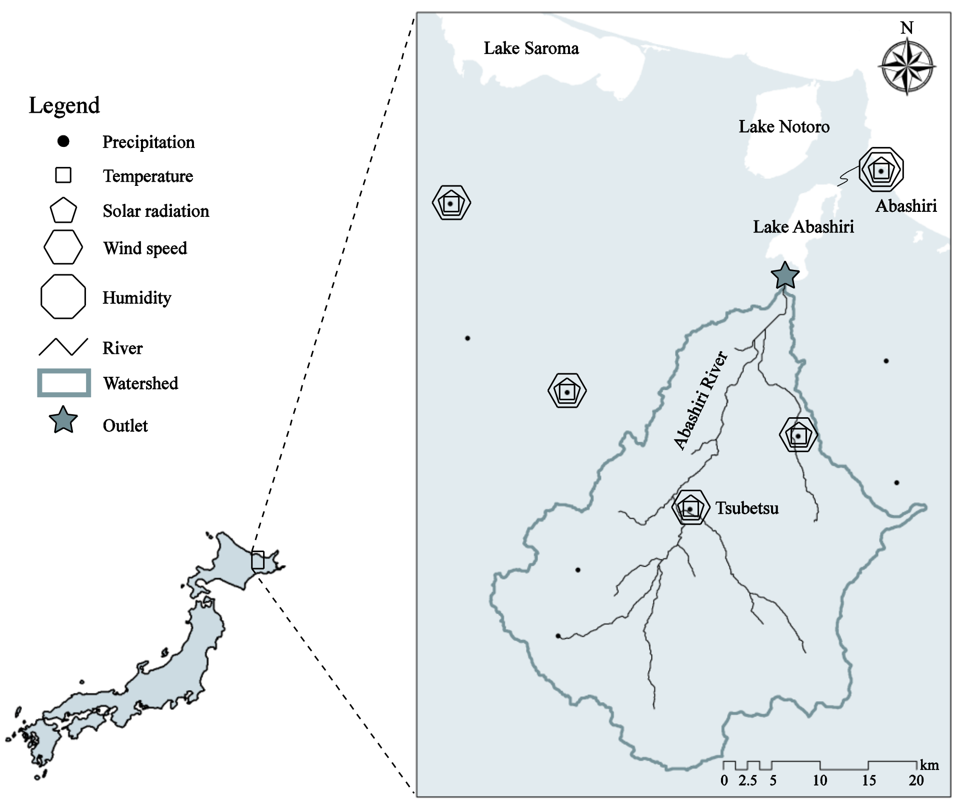


Figure 1. *Location of the study area*

especially from December to February, the average daily minimum temperature is less than -10°C and even the daily maximum temperature falls to below-freezing temperatures.

3. Methodology

We applied The Soil and Water Assessment Tool (SWAT) to the Abashiri River Basin from 1998 to 2007 using a daily time step. We treated 1998 to 2000 as the warm-up period of the model simulation. The parameter values were calibrated from 2001 to 2004 (4 years) and validated from 2005 to 2007 (3 years).

3.1 Brief descriptions of the SWAT model

SWAT is a physically based, continuous-time hydrologic model with an ArcView-GIS interface developed by the Blackland Research and Extension Center and the USDA-ARS (Arnold et al., 1998) to predict the impact of land management practices on water, sediment and agricultural chemical yields in large, complex basins with varying soil type, land use and management conditions over long periods of time. The main driving force behind SWAT is the hydrological component. The hydrological processes are divided into two phases: 1) the land phase, which controls the amount of water, sediment and nutrients received by a water body and 2) the water routing phase, which simulates water movement through the channel network. SWAT considers both natural sources of nutrient inputs (e.g., mineralization of organic matter and N-fixation) and anthropogenic contributions (fertilizers, manures and point sources). SWAT delineates watersheds into subbasins interconnected by a stream network. Each subbasin is further divided into hydrologic response units (HRUs) based upon unique soil and land class characteristics separate from any specified location in the subbasin. SWAT sums the flow, sediment and nutrient loading from each subbasin HRU and the resulting loads are then routed through channels, ponds and reservoirs to the watershed outlet (Arnold et al, 2001). A single growth model in SWAT, based on a simplification of the EPIC crop model, is used for simulating all crops (Williams et al., 1984). Phenological development of the crop is based on daily heat unit accumulation. SWAT also uses the WXGEN weather generator model (Sharpley and Williams, 1990) to generate climate data or to fill gaps in the measured records.

3.2 Input data descriptions

SWAT requires meteorological data such as daily precipitation, maximum and minimum air temperature, wind speed, relative humidity and solar radiation. Furthermore, spatial datasets including a digital elevation model (DEM) as well as land cover and soil maps are required.

Meteorological data was obtained from the Japan Meteorological Agency (JMA: http://www.jma.go.jp/jma/index.html). Gauges measuring precipitation, air temperature and wind speed were located in and around the basin. However, as there were no gauges in the basin to monitor relative humidity data, we used the relative humidity from Abashiri city instead. In addition, solar radiation was calculated with the Angstrom formula (FAO, 1998) using the actual duration of sunlight in the basin observed by the JMA.

Daily discharge data were prepared at one monitoring station in the basin, the Hongo outlet. The data were provided by the Hokkaido Development Agency under the Ministry of Land, Infrastructure, Transport and Tourism (MLIT).

Monthly total nitrogen and phosphorus data were monitored at the Hongo outlet by the Hokkaido Development Agency (HDA).

DEM data were prepared using a digital elevation map with a 50-m grid created from a 1:25,000 topographic map published by the Geographical Survey Institute (GSI).

In this study, we used GIS data based on national digital information that identified land-use categories such as paddy field, upland field, orchard, denuded land, forest, water and others. The data was obtained from the National-Land Information Office in the MLIT (http://nlftp.mlit.go.jp/).

GIS soil data were clipped from a 1:500,000 GIS soil map in the Fundamental Land Classification Survey prepared by the MLIT (http://tochi.mlit.go.jp/tockok/index.htm). Soil types were categorized into ten groups of fourteen soils including Dystric Rhegosols, Fluvic Gleysols, Gleysols, Haplic Andosols, Helvic Acrisols, Humic Cambisols, Lithosols, Ochric Cambisols, Rhodic Acrisols, and Vitric Andosols.

3.3 Model performance evaluation

We used the Nash-Sutcliffe efficiency (NSE), root mean square error (RMSE), observation's standard deviation ratio (RSR) and percent bias (PBIAS) to evaluate model performance. The NSE value indicates how well the plot of observed versus simulated values fits the 1:1 line (Nash and Sutcliffe, 1970). NSE values range from $-\infty$ to one, with values less than or very close to zero indicating unacceptable or poor model performance and values equal to one indicating perfect performance. The NSE value is calculated using the following equation:

$$NSE = 1.0 - \left(\sum_{i=1}^{n} (Y_{obs,i} - Y_{cal,i})^2 \Big/ \sum_{i=1}^{n} (Y_{obs,i} - Y_{obs\_mean})^2 \right) \quad (1)$$

where n is the number of registered data points, $Y_{obs,i}$ is the observed data at time i, $Y_{cal,i}$ is the simulated data at time i and Y_{obs_mean} is the mean of the observed data.

The RSR value is calculated as a ratio of the RMSE and standard deviation of the measured data (Moriasi et al., 2007). RSR incorporates the benefits of error index statistics and includes a scaling/normalization factor. The RSR value varies from the optimal value of zero, which indicates zero RMSE or residual variation, to a large positive value (Moriasi et al., 2007). The RSR value is calculated using the following equation:

$$RSR = RMSE/STDEV_{obs} = \left(\sqrt{\sum_{i=1}^{n} (Y_{obs,i} - Y_{cal,i})^2} \right) \Big/ \left(\sqrt{\sum_{i=1}^{n} (Y_{obs,i} - Y_{obs\_mean})^2} \right) \quad (2)$$

where n is the number of registered data points, $Y_{obs,i}$ is the observed data at time i, $Y_{cal,i}$ is the simulated data at time i and Y_{obs_mean} is the mean of the observed data.

The PBIAS is used to determine if the average tendency of the simulated data is larger or smaller than its observed counterparts (Gupta et al., 1999). The optimal value of PBIAS is zero, with low-magnitude values indicating accurate model simulation. Positive values indicate model underestimation bias, while negative values indicate model overestimation bias (Gupta et al., 1999). PBIAS is calculated using the following equation:

$$PBIAS = \left(\sum_{i=1}^{n} (Y_{obs,i} - Y_{cal,i}) \times 100 \Big/ \sum_{i=1}^{n} (Y_{obs,i}) \right) \quad (3)$$

where n is the number of registered data points, $Y_{obs,i}$ is the observed data at time i and $Y_{cal,i}$ is the simulated data at time i.

4. Results and Discussion

4.1 Major crops and standard fertilizer application schedule in the basin

Cities located in the Abashiri River Basin produce crops such as winter wheat, bean, Irish potato, sugar beet and onion (Fig. 2), with the most popular being winter wheat and sugar beet. In this basin, we found the majority of nitrogen and phosphorous fertilizers are applied in April and May, the period of snow melting and start of crop cultivation, and September, which is the beginning of winter wheat cultivation. Bihoro City is the most urbanized area in the basin (Fig. 3). Figure 4 shows observed water quality variations at Hongo Outlet measured by the HAD during 2007. Although phosphorus is very difficult to distinguish, data indicates that nitrogen and phosphorus increased in April and September. This change coincides with the timing of fertilizer application. Surprisingly, nitrogen concentrations kept increasing during winter.

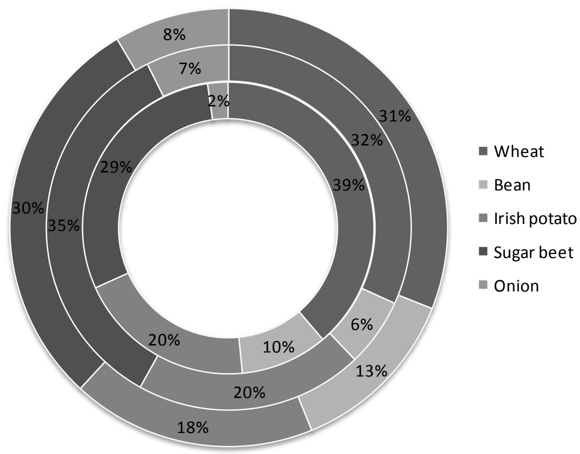


Figure 2. *Major crops in cities located in the Abashiri River Basin (Note: this figure was made from the agriculture statistics data of 2005 and 2007)*

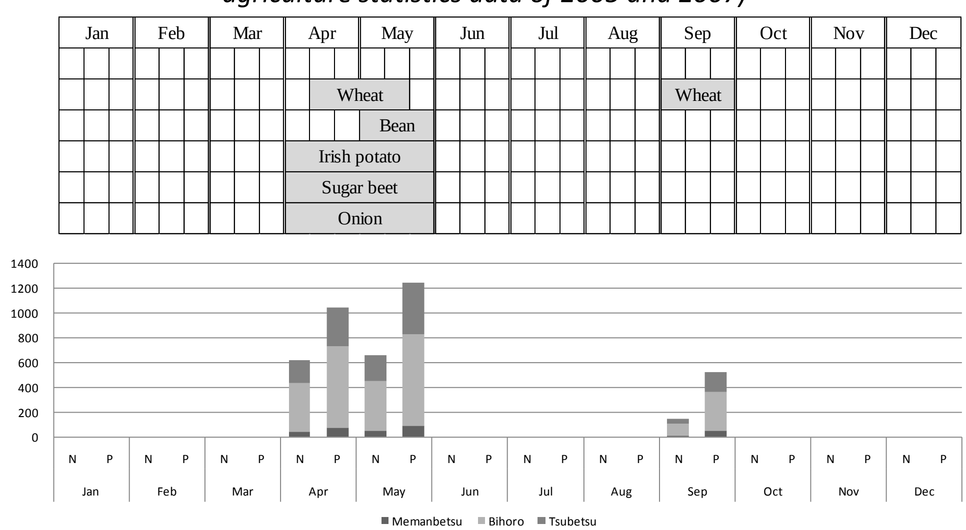


Figure 3. *Agricultural fertilizer schedule and nutrient loads in the basin*

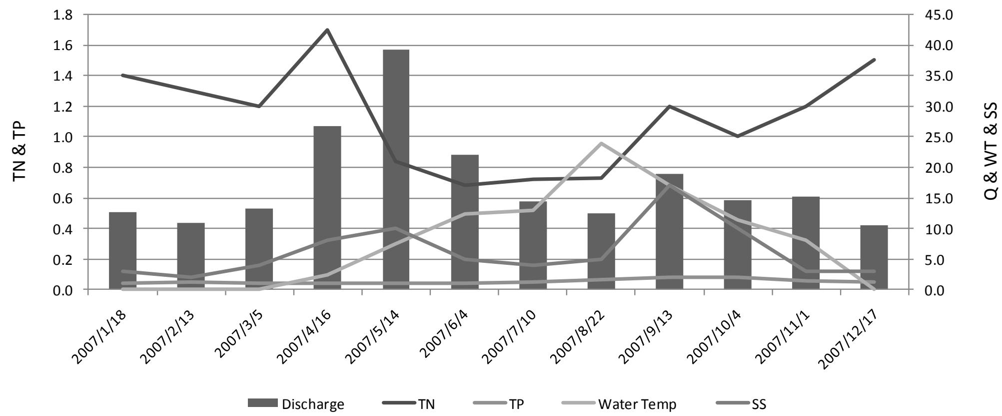


Figure 4. *Observed water quality variations at Hongo Outlet (2007) measured by the Hokkaido Development Agency (TN, TP, SS: mg/L; Q: m^3/s; water temperature: ˚C)*

4.2 Simulated results of river discharge

The simulated and observed daily flow discharge is shown in Figure 5. The results of calibration and validation at the Hongo outlet represented the fluctuations in discharge relatively well. However, reproducibility during winter season was low, particularly from January to March. Specifically, the difference between simulated and observed monthly discharge during these three months was larger than in other months, especially in March (26 mm). During that period, cold weather partially froze the surface of the river, possibly affecting the precision of the observed daily discharge data. The resulting simulated annual discharge was 513 mm, while the observed discharge was 571 mm during the simulation period. In 2003, the different between simulated and observed annual flow discharge was smallest (2.7 mm). On the other hand, the difference was largest in 2004 (165.4 mm).

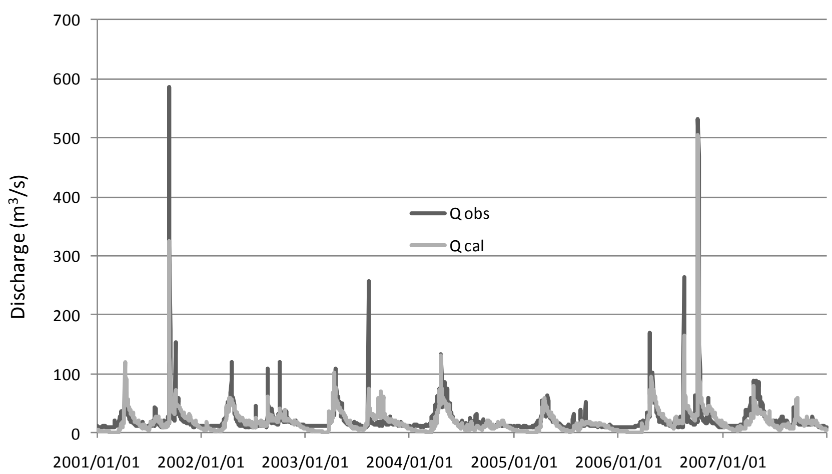
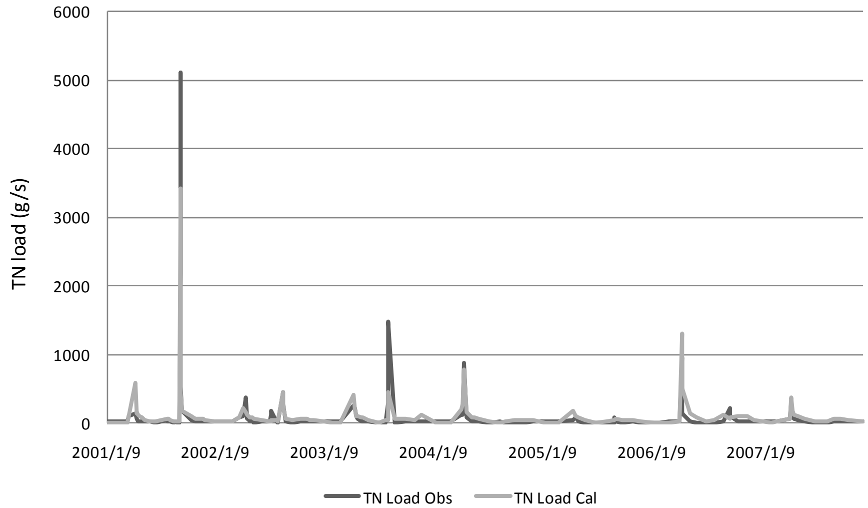


Figure 5. *Simulated river discharge at the Hongo Outlet (Calibration: 2001-2004; Validation: 2005-2007)*

4.3 Simulated results of TN and TP loads

The simulated and observed TN and TP load discharges are shown in Figures 6 and 7. Though almost all TN and TP data were measured monthly, these graphs were drawn using only data for which water quality was observed. From these figures, we concluded that simulated TN and TP load discharges matched the observed discharges relatively well. However, as mentioned in the model performance summary (Table 1), SWAT simulated the observed river discharge values satisfactorily, but in some cases of TN and TP load discharges, the SWAT model has not yet performed satisfactorily.



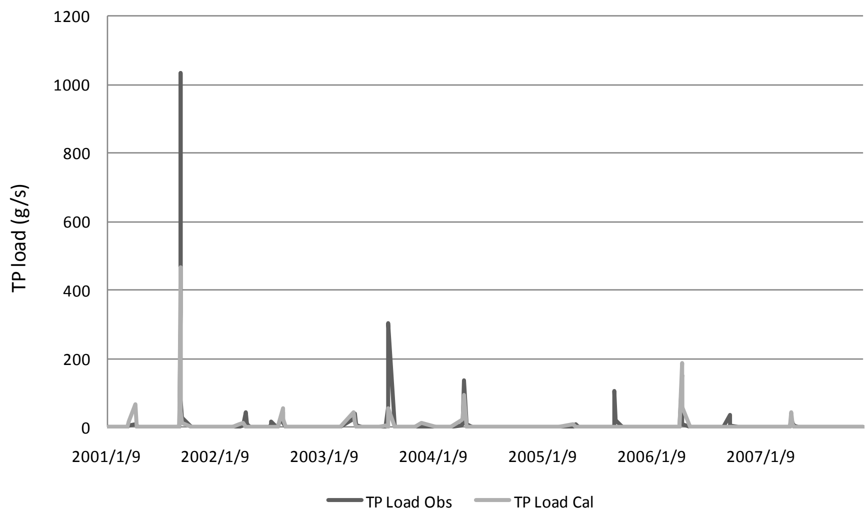


Figure 6. *Simulated TN load discharge (top) and TP load discharge (bottom) at Hongo Outlet*

Table 1. *Summary of model performance*

		NSE	RSR	PBIAS (%)
Flow	Cali.	0.66	0.59	10.25
	Vali.	0.73	0.52	9.99
TN	Cali.	0.74	0.51	5.70
	Vali.	0.49	0.71	-70.48
TP	Cali.	0.58	0.65	42.88
	Vali.	0.35	0.81	8.56

5. Conclusions

Looking at nutrient loads, we found that agricultural activities produced the largest amount of nitrogen and phosphorus in the basin. In addition, differing concentrations coincided with the snowmelt season of April and May, the high rainfall period of September, and periods of intense agricultural activities. It is very important to consider how to reduce nutrient discharged loads from agricultural lands in order to improve river water quality. At this stage, SWAT can reproduce discharge satisfactorily. However, nitrogen and phosphorus load discharges have not been represented satisfactorily in some cases. In order to consider the impact of load discharges from the river basin to the downstream lacustrine environment, more accurate simulations are necessary. As a next step, it may also be necessary to consider livestock and other sources of pollutions.

Acknowledgements

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Integrating APEX Cropland Output with SWAT Watershed Simulations

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Abstract

The Conservation Effects Assessment Project (CEAP) National Assessment is designed to quantify the environmental benefits of conservation programs at the regional and national level, including both on-site and instream water quality benefits. The complexities of nature at this scale suggest modeling as an efficient and necessary method. We simulated a select subset of National Resources Inventory sample points as "representative fields" using the Agricultural Policy Environmental eXtender (APEX) model. The statistical sample weight associated with each sample point was used to aggregate the modeling results to 8-digit watershed outlets. These were then passed to the Hydrologic Unit Model for the United States/Soil and Water Assessment Tool (HUMUS/SWAT) for estimating the offsite effects of conservation practices. Each 8-digit watershed in the United States was treated as a subbasin in HUMUS/SWAT, and the two models were run separately at the 8-digit level. Therefore, two major steps were taken in both models: (1) calibration of water yield at the 8-digit watershed level and (2) development of sediment delivery ratios (SDR) for transporting sediment from cultivated cropland (simulated using APEX) and uncultivated land uses (simulated with SWAT) to the 8-digit outlet. This article seeks to address four points: (1) why use APEX for CEAP field-level cropland modeling; (2) APEX simulation of conservation practices; (3) calibration of APEX for water yield; and (4) SDR development within APEX. Calibration and SDR procedures were developed and applied in the Upper Mississippi River Basin. APEX predicted and observed annual average water yields agreed well as evidenced by an R^2 value of 0.82. The mean SDR varied from 0.30 to 0.46, which is reasonable compared to literature values.

Keywords: APEX model, sediment delivery ratio, conservation practice, water yield, calibration.

1. Introduction

Conservation practices are designed to reduce soil, nutrient, or pesticide losses from farms so that farmlands remain productive and to improve in-stream water quality. Conservation practices also enhance agro-ecosystem quality by establishing wildlife habitat. Conservation practice assessment allows policy-makers to make informed decisions when designing new conservation programs and to improve implementation of existing programs. Both field studies and modeling approaches have been used to evaluate the effects of conservation practices. While extensive literature exists that describes plot- or field-scale conservation practices, research results from plot- and field-scale studies do not capture the complexities and interactions of conservation practices within a watershed. Moreover, the effects of conservation programs have not previously been quantified at the national or regional scale.

The USDA NRCS and ARS are working together on the Conservation Effects Assessment Project (CEAP) to quantify the environmental benefits of conservation practices at the national, regional and the watershed scales. The CEAP involves developing a set of individual farm field simulations based on an extensive farming practices survey developed by NRCS and administered by the National Agricultural Statistics Service to approximately 10,000 different farmers in 2003, 2004, 2005 and 2006. The environmental effects to be estimated include soil changes in carbon content and losses of nitrogen and phosphorus from the farm field and the resulting instream water quality at the regional and national level. The complexities of nature at this scale suggest modeling as an efficient and necessary method.

The Agricultural Policy Environmental eXtender (APEX) model (Williams and Izaurralde, 2006) was used to quantify the on-site benefits obtained from the conservation practices implemented on cropland in the United States. The HUMUS/SWAT (Hydrologic Unit Model for the United States/Soil and Water Assessment Tool) model (Arnold et al., 1998; Srinivasan et al., 1998) was used to quantify the offsite environmental benefits. In HUMUS/SWAT, each major river basin (e.g., the Upper Mississippi) is treated as a watershed and each United States Geological Survey (USGS) delineated 8-digit watershed as a subbasin. At the 8-digit watershed level, two simulation models—APEX for cultivated cropland and SWAT for uncultivated land, were run separately. A delivery ratio procedure was developed within APEX to compute delivery ratios for transporting sediment, nutrient and pesticides to the 8-digit outlet as SWAT input. The APEX outputs, which also included water yield, were aggregated at each 8-digit watershed level and were passed to HUMUS/SWAT. Further routing was conducted in HUMUS/SWAT for estimating the offsite effects of conservation practices at the major river basin output. This article addresses: (1) APEX simulation of conservation practices; (2) calibration of water yield; and (3) delivery ratio development for transporting sediment from cultivated cropland to 8-digit watershed outlets.

2. Modeling framework

For the CEAP study, we simulated a select subset of National Resources Inventory (NRI) sample points as "representative fields" using APEX. Statistical sample weights associated with each sample point (Goebel, 2009) were used to aggregate the APEX modeling results for national reporting of on-site benefits. APEX also provides watershed output to SWAT by using delivery ratios computed within APEX that consider SWAT basin channel lengths and slopes. These APEX outputs for SWAT were also aggregated to the 8-digit watershed level using statistical sample weights. The aggregated results, representing the outputs from cultivated cropland areas, were passed to HUMUS/SWAT. The results were then combined with

HUMUS/SWAT outputs for uncultivated land at the 8-digit watershed outlets for further routing downstream by HUMUS/SWAT to estimate the offsite effects.

2.1 APEX and HUMUS/SWAT

The APEX model is a dynamic, integrated tool that is capable of simulating extensive land management strategies, such as different nutrient management practices, tillage operations, conservation practices and alternative cropping systems on field, farm or small watershed scales. It can be configured to simulate filter strip impacts on pollutant losses from upslope field, intensive rotational grazing scenarios depicting movement of cows between paddocks, impacts of vegetated grassed waterways in combination with filter strips, and land application of manure, removal from livestock feedlots or waste storage ponds (Gassman et al., 2009). APEX operates on a daily time step. A detailed theoretical description of APEX can be found in Williams and Izaurralde (2006).

The APEX model was selected for CEAP field-level cropland modeling due to its flexibility and features including: (1) field units within APEX have spatial relationship and can be routed at the field scale in a specified order, which allows simulation of conservation practices such as filter strips as a physically based process; (2) the APEX crop growth component enables simulation of mixed stands with plant competition for light, water and nutrients; (3) APEX simulates detailed management practices related to farm animal productions, rotational grazing and wind erosion; (4) APEX enables the use of dynamic soil layers associated with soil erosion and the removal of eroded material, and it provides eight options (including RUSLE 2) for estimating water erosion; (5) APEX simulates tillage with the following functions: mixing nutrients and crop residues, converting standing residue to flat residue, changing bulk density and subsequent settling after tillage, speeding mineralization; (6) APEX features an improved soil carbon cycling routine that follows the Century model (Parton et al., 1987, 1993, 1994; Vitousek et al., 1994); and (7) APEX has manure management with automatic application from stockpile or lagoon, and manure erosion from feedlots and application fields.

The SWAT model is a basin-scale, distributed hydrologic model. It was developed to quantify the impact of land management practices in large, complex catchments (Arnold et al., 1993). SWAT operates on a daily time step. It allows a basin to be divided into sub-watersheds based on topography to incorporate spatial detail. Each sub-watershed is further divided into hydrological response units (HRUs), which are unique combinations of soil and land cover. Individual HRUs are simulated independently, area weighted and added for each sub-watershed. They are then routed through a stream network to the basin outlet. HRUs allow SWAT to include more spatial detail by representing more landscape land use and soil classifications in a computationally efficient manner. The HUMUS project (Srinivasan et al., 1998) used SWAT to model 350 USGS six-digit watersheds in the 18 major river basins in the United States. The revised HUMUS/SWAT modeling framework with updated databases for the 18 major river basins was used for the CEAP project.

The combination of APEX and HUMUS/SWAT was used in the CEAP National Assessment. Two major steps were conducted to integrate APEX outputs with SWAT simulations: the water yield calibration of APEX and development of sediment delivery ratios for transporting sediment, nutrients and pesticides from APEX sites to the 8-digit outlet.

2.2 Modeling Conservation Practices in CEAP

APEX requires weather, soil, site, and field management information. The available data and sources for CEAP cropland field-level modeling are summarized in Table 1. In the CEAP National Assessment, conservation practices are classified into cultural practices and structural practices. Cultural practices are those that a farmer or land manager implements, usually based on annual decisions, by changing the way cropland is managed to achieve production or conservation goals. Some examples of cultural practices include reducing tillage intensity through practices such as conservation tillage and improved vegetative cover with the use of cover crops, conservation crop rotations or mulch applications. Managing nutrient applications with a nutrient management plan and pest problems using integrated pest management are other cultural techniques. APEX management capabilities include processes built to simulate these practices as physically and realistically as possible. For example, tillage simulation is designed for mixing nutrients and crop residues, changing surface roughness and bulk density and subsequent settling. Crop growth simulates the growth of plants (which vary from vegetables), field crops (cover crops, crop rotations), annual and perennial grasses, brush, trees and mixed stands. And during the plant growth cycle, the crop management factor (USLE c factor) is updated daily to reflect changes in plant cover.

Structural practices are considered permanent, requiring more than annual management decisions. These practices are often considered permanent because implementation usually requires engineering design, surveying and contracting with a vendor. Planting of perennial grasses, trees or herbaceous cover to achieve desired conservation effects are considered structural practices. Practices like contour farming and strip cropping tend to “support” cultural management practices. Structural practices such as terraces and diversions work by intercepting and diverting surface runoff to stable outlets. Other structural practices, including field borders, buffer strips and riparian buffers, filter surface runoff and allow contaminated water to infiltrate the soil. To capture combined effects and eliminate duplicate functions, practices were assigned into one of the following functional categories: managed in-field flow interceptor, engineered in-field flow interceptor, riparian buffer and wind erosion control (Table 2).

APEX provides considerable flexibility in simulating conservation practice effects. The model allows one to simulate effects using empirically based techniques, theoretical techniques or a combination of both. Several common techniques used for the CEAP National Assessment are briefly summarized in Table 2. Detailed documentation for modeling CEAP conservation practices can be found in Potter et al. (2009).

Table 1. *Available data and sources*

Data Type	Source	Date	Description
Landscape	NRI	1997 or 2003	NRI point attribute data, including links to soil attribute data, slope and slope length, use indicators of conservation practices, land-use history
Crop management	NRI-CEAP cropland survey	2003 - 2006	Crop rotation, including cover crops, fallow, multiple crops and CRP vegetative cover; Tillage, planting, and harvesting operations; Fertilizer and manure management; Pesticide management
Structural conservation practices	NRI CEAP surveyed farmers NRCS field office Farm Service Administration (CREP)	1997 or 2003 NRI 2003 – 2006 CEAP survey	See Table 2, structural conservation practices column
Soils	NASIS (USDA-NRCS 2007) Pre-NASIS Soils_5 database NSSL NCSS laboratories	-	Layer depth, bulk density, organic carbon content, sand content, silt content, coarse fragment content, soil pH, soil albedo, soil hydrologic group, soil water content at wilting point, soil water content at field capacity, initial organic N and P concentration, initial soluble N and P concentrations, saturated conductivity, lateral hydraulic conductivity

Weather	Eischeid et al. (2000) Daly et al. (1997 and 2002) Di Luzio et al. (2008)	1960 - 2006	Daily precipitation and maximum and minimum temperature
Streamflow	Gebert et al. (1987)	1951-1980	Annual average water yield by 8-digit watersheds obtained by overlaying interpolated runoff contours representing average annual runoff for the conterminous United States with the 8-digit watershed map
Basin channel length/slope	HUMUS/SWAT database	-	SWAT basin channel length and slope for each 8-digit watershed in the United States, used for estimating the times of concentration in APEX for the purpose of calculating the sediment delivery ratio from APEX site to 8-digit outlet

CEAP: Conservation Effects Assessment Project
CREP: Conservation Reserve Enhancement Program
NCSS: National Cooperative Soil Survey
NASIS: National Soil Information System
NRI: National Resources Inventory
NRCS: Natural Resources Conservation Service
NSSL: National Soil Survey Laboratory
PRISM: Parameter-elevation Regressions on Independent Slopes Model
USGS: United States Geological Survey

Table 2. *Structural conservation practices simulated in CEAP*

Structural conservation practices	Simulated by modifying APEX parameters[‡]			Field configuration
Managed in-field flow interceptor	**P factor:**	**LUN:**		
Contour farming	0.6 - 0.9 (vary with upland slope)	+2		Within field (one subarea)
Strip cropping	0.5 - 0.9 (vary with upland slope)	+4		
Contour buffer strips	0.25 - 0.45 (vary with upland slope)	+4		
Engineered flow interceptors	**P factor:**	**LUN:**	**Slope length:**	
Terraces	0.45 - 0.75 (vary with upland slope)	+2		
Grass terraces	0.25 - 0.45 (vary with upland slope)	+4		
Vegetative barrier	0.45 - 0.75 (vary with upland slope)	+2		
Diversions			0.5*NRI reported	
Riparian buffers	**P factor:**	**LUN:**	RCHC=0.001; RCHN=0.2	Two or three subareas: an upland subarea, a grass filter strip, a forest buffer. Runoff and pollutants are routed through filter, buffer.
Filter strips	0.6	26 (grass filter)	Grass filter: FFPQ=0.95	
Riparian herbaceous or forest buffers	0.6	Simulated as a grass filter (**LUN=26**) and a forest buffer (**LUN=29**)	RCHS=.25*NRI reported Forest buffer: FFPQ=0.85 RCHS=.1*NRI reported	
Wind erosion control	**Unsheltered field length*width[†]**	**Unsheltered distance with strip cropping:**		Within field (one subarea)
Hedgerows	0.06 km*0.06 km	0.03 km		
Cross wind practices	0.04 km*0.04 km	0.03 km		
Windbreak/shelterbelt	0.03 km*0.03 km	0.02 km		
Herbaceous wind barrier	0.04 km*0.04 km	0.03 km		
Field borders	**P factor:** 0.95			Within field (one subarea)
Grass waterway		RCHC=0.001 RCHN=0.25	**Slope:** 0.52*NRI reported slope	Two subareas: an upland subarea and a grass waterway
Grade stabilization structures			**Slope:** 0.1*NRI reported slope	Two subareas: an upland subarea and a routing area

[‡] Parameter changes for combinations between different groups or within group are not listed here, see Potter et al. (2009) for more detail
[†] Without practices the field was assumed to be 0.4 km*0.4 km
FFPQ: Fraction floodplain flow (e.g., FFPQ=0.95 means that 95% is overland flow in the floodplain and 5% channel flow)
NRI: National Resources Inventory
LUN: Land use number for looking up curve number
RCHC: Channel USLE C factor of routing reach
RCHN: Channel Mannings N of routing reach
RCHS: Channel slope of routing reach

2.3 Calibration of Water Yield

Gebert et al. (1987) created runoff contours using streamflow data collected from 5,951 gauging stations during the period 1951 to 1980. The runoff contours represent average annual runoff for the conterminous United States. Annual average water yield by 8-digit watershed is obtained by overlaying interpolated runoff contours with the 8-digit watershed maps. Average annual runoff from each 8-digit watershed was used for model calibration. Figure 1 illustrates the average annual water yield calibration at the 8-digit watershed level using criteria listed in Table 3. Four parameters were used for APEX water yield calibration (Table 4). (1) The curve number index coefficient is used to calculate the retention coefficient in the curve number method for daily curve number calculations based on plant evapotranspiration (Wang et al., 2009). (2) The Hargreaves PET equation exponent is a coefficient used to adjust water yield and Hargreaves estimated evapotranspiration (ET) (Hargreaves and Samani, 1985). (3) The return flow ratio is the ratio of flow returning to the channel and the total percolation flow. (4) The tile drainage saturated hydraulic conductivity coefficient is used to control the upper limit of tile drainage flow. The adjustable ranges of these parameters (Table 4) were based on the APEX user manual (Williams et al., 2003), literature (Wang et al., 2006) and expert opinion (the model developer, Jimmy Williams, Blackland Research and Extension Center, Temple, TX).

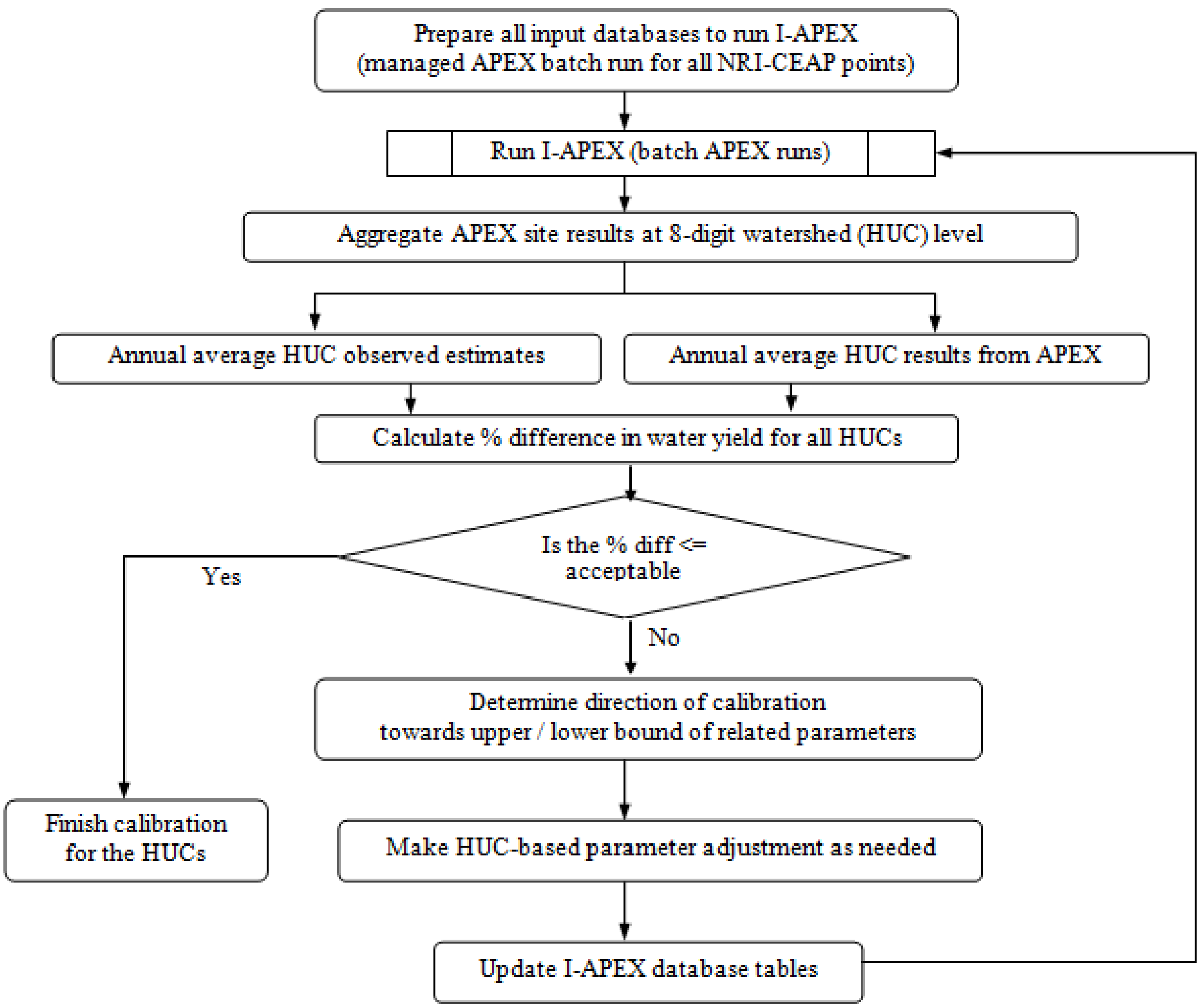

Figure 1. *APEX calibration procedure for water yield from cultivated cropland aggregated at the 8-digit watershed level*

***Table 3.** Criteria for APEX water yield calibration at the 8-digit watershed level*

% Ag+CRP Area	<10	10-20	20-30	30-40	40-50	50-60	60 & above
% Difference between APEX and USGS water yields	within 50	within 45	within 40	within 35	within 30	within 25	within 20

***Table 4.** Parameters used in the APEX calibration procedure, their range and their effect on different components of runoff*

Parameter	**Changes**			**Range Used**	
	Surface Runoff	**Sub-Surface Runoff**	**Water Yield**	**Minimum**	**Maximum**
Curve number index coefficient	x	x	x	0.5	1.50
Hargreaves PET equation exponent	x	x	x	0.5	0.6
Return flow ratio	x		x	0.05	0.95
Tile drainage saturated hydraulic conductivity coefficient	Tile Drain Flow		x	0.8	3.0

2.4 Delivery Ratio

There are typically 20 plus NRI-CEAP points (APEX simulation sites) in each 8-digit watershed. Each NRI-CEAP point is assumed to be 16 ha. These sample points provide statistical samples representing the diversity of soils and other conditions in the landscape. Since each APEX simulation represents a fraction of the cultivated areas within an 8-digit watershed, the actual locations are not known and are assumed to be randomly distributed. Faced with this limitation, the development of sediment delivery ratio (SDR) in this study depended on the efficiency of the algorithm with modest input parameter requirements. The SDR can be estimated as:

$$SDR = \frac{Y_B}{\sum Y_S} \tag{1}$$

where Y_B is the sediment yield at the basin outlet and Y_S is the sediment yield at the outlet of the APEX sites. Sediment yield can be estimated using a variation of MUSLE called MUST (Williams, 1995):

$$Y = 2.5 \times \left(Q \times q_p\right)^{\alpha} \times K \times C \times P \times LS \tag{2}$$

where Q is the runoff volume (mm), q_p is the peak runoff rate (mm h^{-1}), K, C, P and LS are the linear USLE factors and α is the peak runoff rate exponent set as 0.5 in the original MUST equation (Williams, 1995). The α can be smaller than 0.5 in developing the delivery ratio. Y_B can be calculated with Eq. 2 by area weighting the linear USLE factors and Q, and estimating q_p at the basin outlet. Y_S can be estimated for each of the APEX sites using appropriate values of the linear USLE factors Q and q_p. Since the linear USLE factors and Q cancel, the delivery ratio for each APEX site can be estimated with the equation:

$$SDR_S = \left(\frac{q_{pB}}{q_{pS}}\right)^{\alpha} \tag{3}$$

where SDR_S is the delivery ratio for the APEX site s, q_{pB} is the peak runoff rate at the basin outlet (mm h^{-1}) and q_{pS} is the peak runoff rate at the outlet of the APEX site s (mm h^{-1}). Since the APEX simulation results are passed to SWAT at the 8-digit outlet, q_{pB} is not known when APEX simulations are being made. However, the peak runoff rate is a function of runoff volume and watershed time of concentration:

$$q_p = f\left(\frac{Q}{t_c}\right) \tag{4}$$

Substituting the inverse of t_c for q_p (Q cancels) in Eq. 3 yields:

$$SDR_S = \left(\frac{t_{cS}}{t_{cB}}\right)^{\alpha} \tag{5}$$

where t_{cS} is the time of concentration of the APEX site and t_{cB} is the time of concentration of the basin. The times of concentration can be estimated with the Kirpich equation in the metric form:

$$t_c = 0.0663 \times \frac{L^{0.77}}{S^{0.385}} \tag{6}$$

where L is the watershed length along the main stem from the outlet to the most distant point (km) and S is the main stem slope (m/m). Substituting t_{cS} and t_{cB} calculated from Eq. 6 in Eq. 5 yields:

$$SDR_S = \left(\left(\frac{L_S}{L_B}\right)^{0.77} \times \left(\frac{S_B}{S_S}\right)^{0.385}\right)^{\alpha} \tag{7}$$

where L_B and S_B are the 8-digit watershed basin channel length (km) and basin channel slope (m/m), respectively; L_S and S_S are the APEX watershed length (km) and slope (m/m), respectively.

3. Application

The water yield calibration procedure and the delivery ratio developed within APEX have been applied to the CEAP study for the Upper Mississippi River Basin (UMRB) (Figure 2), where a total of 3703 NRI-CEAP points were simulated. Nine out of 131 8-digit watersheds in the UMRB have no NRI-CEAP points.

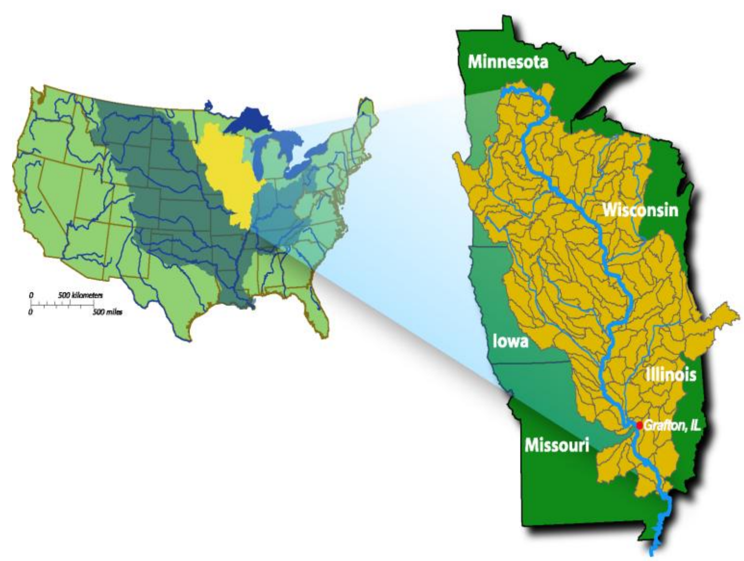

Figure 2. *Location of the Upper Mississippi River Basin (adapted from Jha et al., 2006)*

3.2 Water Yield

A comparison of APEX predicted and observed annual average water yield for the remaining 122 8-digit watersheds in the UMRB is shown in Figure 3. Observed and simulated runoff patterns are in concurrence with the precipitation patterns of this basin. The model prediction is satisfactory as indicated by the R^2 value of 0.82 and the Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970) of 0.78.

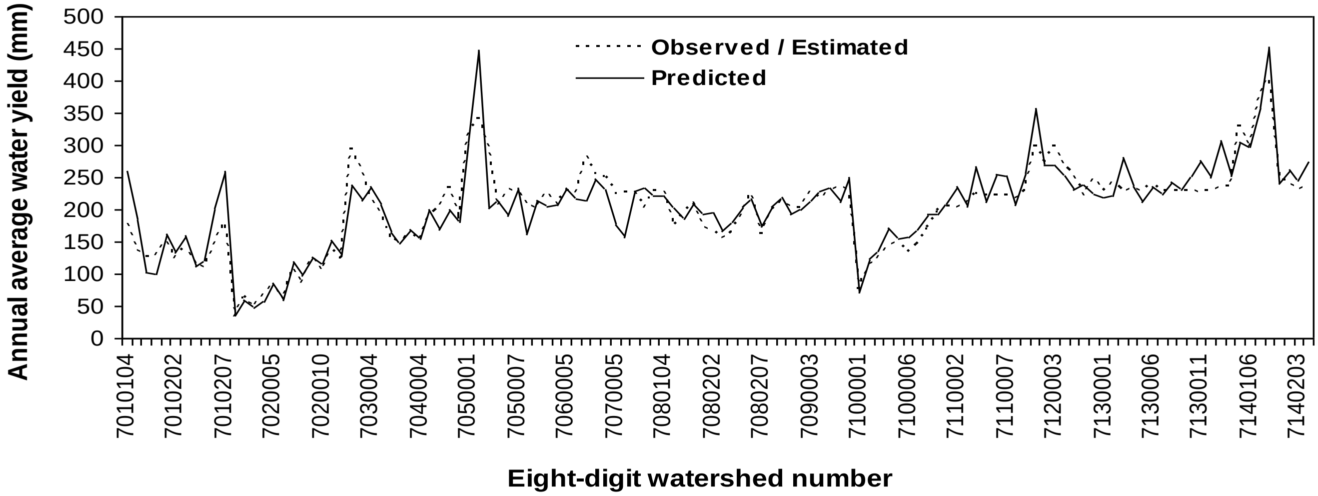

Figure 3. *APEX predicted vs. observed annual average water yield for 8-digit watersheds in the Upper Mississippi River Basin*

3.1 Sediment Delivery Ratio

The delivery ratios vary for each NRI-CEAP point simulated in an 8-digit watershed. Examples of delivery ratio distributions at the 8-digit watershed level are shown in Figure 4. Figure 5 shows the mean, 10th percentile and 90th percentile of sediment delivery ratios for cultivated cropland in all 8-digit watersheds within the UMRB. Spatial variation of mean sediment delivery ratios is shown in Figure 6. The UMRB mean SDR varied from 0.30 to 0.46. Meade et al. (1990) developed relationships for sediment yields in the Upper Mississippi Basin as a function of drainage area and land use based on a study conducted before 1950. Based on Meade's relationships, the sediment delivery ratio from the edge-of-fields to the 8-digit watershed outlets is approximately 0.4. The SDR estimated for the current conservation conditions in the CEAP National Assessment study are reasonable compared to the delivery ratio suggested by Meade et al. (1990).

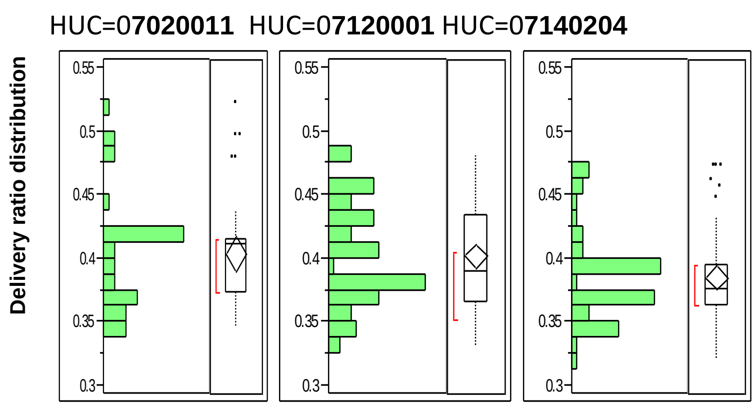

Figure 4. *Examples of delivery ratio distributions at the study area*

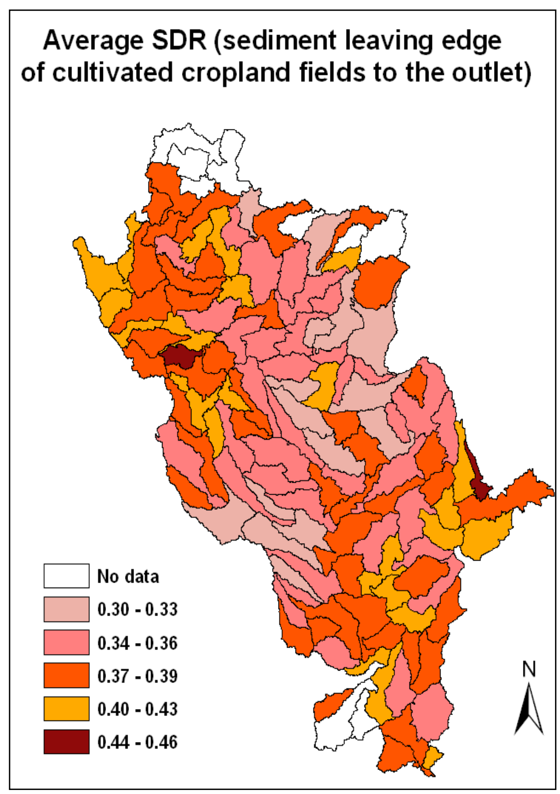

Figure 6. *Average sediment delivery ratios for the Upper Mississippi River Basin*

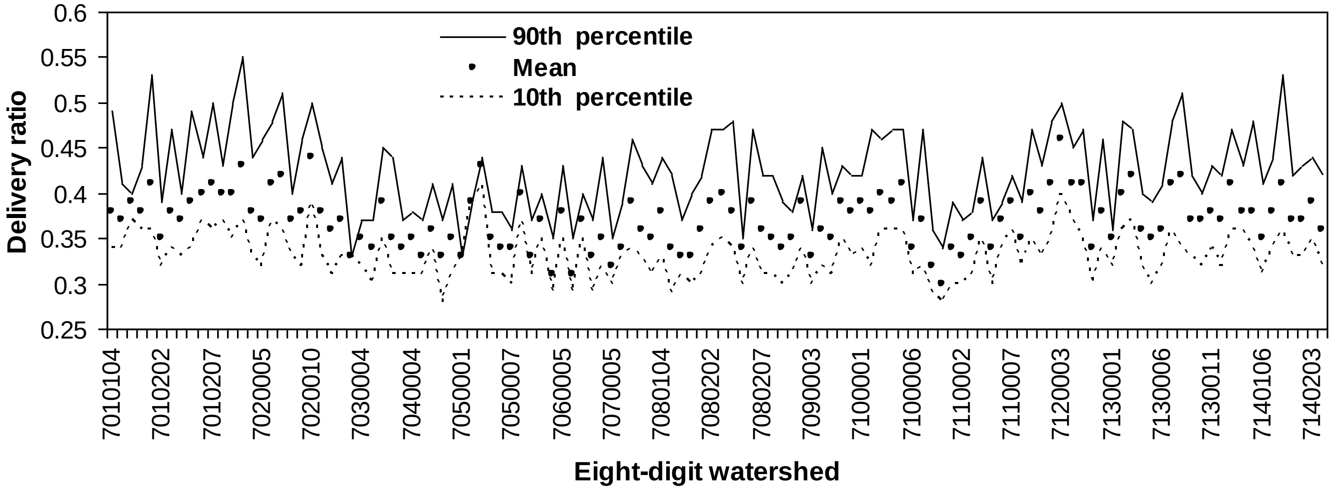

Figure 5. *The mean, 10th and 90th percentile of delivery ratios for cultivated cropland by 8-digit watershed in the Upper Mississippi River Basin*

4. Conclusion

The CEAP National Assessment project was created to quantify the environmental effects of Farm Bill sponsored conservation programs. We used a combination of APEX and HUMUS/SWAT for simulating cultivated cropland and non-cultivated land uses, respectively. APEX conservation practice simulations were briefly summarized in this study. The water yield calibration procedure of APEX and the development of sediment delivery ratios within APEX were described and demonstrated using the Upper Mississippi River Basin as an example. APEX predicted and observed annual average water yields agreed well as evidenced by the R^2 value of 0.82 and the Nash-Sutcliffe efficiency of 0.78. The mean sediment delivery ratios from the edge-of-fields to the 8-digit watershed outlets varied from 0.30 to 0.46, which is reasonable compared to the delivery ratio suggested by Meade et al. (1990). Test results are promising, showing that these procedures have potential application in other river basins of the United States for the CEAP project or similar large-scale studies.

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SWAT application in small flysch catchments in Slovenia

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Abstract

Geology, soil and topology characteristics in combination with the changing social structure of research areas have led to changes in agricultural land use (e.g., abandonment of agricultural land, afforestation, intensive vineyarding, agro-melioration). Together with climate change, changing land uses have also led to altered physical and chemical processes connected with water (e.g., river flow, erosion, infiltration, evapotranspiration, leaching of nutrients). Typical flysch geology for these areas consists of repeated sedimentary layers of sandstone, marl, slate and limestone, which can quickly crumble under the influence of precipitation and temperature changes. This kind of geology also accelerates surface runoff. Therefore, inappropriate land management can result in very strong erosion processes. The main objective of this research is to identify the long-term effects of changing agricultural land use on surface flow in the flysch-type catchments of the Dragonja River in Slovenian Istria and the Reka River in Goriška Brda. We hope to thereby contribute to the understanding of hydrological processes in flysch catchments and to suggest guidelines for reaching or preserving good water quality during catchment development. This paper presents hydrology sensitivity analysis, calibration and validation for the base scenarios. Further work will concentrate on future agricultural land use scenarios to show the kind of long-term environmental responses that can be expected with changes in climate and agri-environmental policy.

Keywords: flysch, hydrology, SWAT, Dragonja, Reka, Water Framework Directive

1. Introduction

Geology, soil and topology characteristics in combination with the changing social structure of research areas have led to changes in agricultural land use (e.g., abandonment of agricultural land, afforestation, intensive vineyarding, agro-melioration). Together with climate change, changing land uses have also led to altered physical and chemical processes connected with water (e.g., river flow, erosion, infiltration, evapotranspiration, leaching of nutrients).

For the purpose of this research, SWAT was used for the first time in Slovenia. However, it is expected to be used much more widely in the future due to the European Union Water Framework Directive (WFD), which requires member states to enhance the ecological and chemical state of surface waters by 2015. In recent years, awareness of climate change has been attached to the WFD because water quality is in close connection with water quantities. Kajfež-Bogataj (2008) states that the average annual air temperature in Slovenia has increased by 1.4 ± 0.6°C over the last 50 years (from 1956 to 2005). In addition, a 1°C increase in the average annual temperature can be expected over the next 20 years. Expected declines in medium and low flow rates and higher temperatures may result in reduced self-purifying capacity, restrictions on discharges from wastewater treatment plants, less water available for abstraction and lower recharge of aquifers. For these reasons, the safety of the quality drinking water supply is in question. Biotopes, like the Dragonja and Reka rivers, which discharge into the Adriatic Sea, are already adapted to dry periods without water in the riverbed. Thus, adjustment to new climatic conditions by natural processes will be minimal.

Flysch bedrock in Slovenia mostly consists of alternating layers of sediments with predominating marl and sandstone. Flysch is a highly erodible material that quickly decomposes under wet, warm climatic conditions and can be accelerated by agricultural activities. Various future-use studies have implemented SWAT in areas with flysch geology (Di Carlo et al., 2008; Panagopolous, 2007). However, these studies did not concentrate on soil characteristics and their state in regard to land use and management changes. Differences in past and current land use categories and crop management are important, as they can change the hydrological characteristics of the rivers and influence the ecosystem.

SWAT-2005 operates as extension in ArcGIS 9.1. The Soil and Water Assessment Tool (SWAT) is a complex, conceptual, continuous-time hydrologic model specially developed to assist water resource managers in assessing the impact of management decisions on water supplies and nonpoint source pollution in river catchments (Arnold et al., 1998). For the purpose of this research, version 1.0.7 was used. SWAT was developed for use in ungauged catchments to predict the impacts of land management on water, sediment and agricultural chemical yields (Arnold and Fohrer, 2005). However, calibration of the model, necessary for viable representation of the area, is not possible in ungauged catchments. It is a spatially semi-distributed hydrologic model, meaning that the impact of changes in land use can easily be modelled (Romanovicz et al., 2005). Major model components are hydrology, weather, soil, temperature, plant growth, nutrients, pesticides and land management. SWAT operates on a daily time step and allows the catchment to be subdivided into natural sub-catchments and then into combinations of unique soil, land use and slope characteristics called Hydrologic Response Units (HRUs) (Arnold et al., 1998; Shepard, 1999; Di Luzio, 2004). Data gathered from governmental institutions enabled us to model these research areas on daily time step.

2. Materials and methods

Typical flysch geology for these areas consists of repeated sedimentary layers of sandstone, marl, slate and limestone, which can quickly crumble under the influence of precipitation and temperature changes. This kind of geology also accelerates surface runoff. Therefore, inappropriate land management can result in very strong erosion processes.

The Reka River catchment (30 km^2) in the Goriška Brda region (72 km^2) is situated on the Slovenian-Italian border (Figure 1). The most visible topography characteristics are ridges with steep slopes, orientated from north-east to south-west along the Friulian lowlands and the Adriatic Sea, only 20 kilometres apart. This area is characterized by a warm and sunny sub-Mediterranean climate, favourable for agriculture. The upper parts of the valleys are much deeper, narrower and steeper; while the lower part of the area is open and suitable for intensive agricultural practices other than vine or fruit-growing. The average slope inclination of Brda is 16.1° (Ažman Momirski et al., 2008). Consequently, land owners have constructed terraces, covering 29% of the total area, for easier cultivation and to prevent erosion (Ažman Momirski et al., 2008). Nearly 70% of these terraces are used for vineyards. Winters in the Brda region are mild with an average January air temperature of 3.4°C as measured at Vedrijan in central Brda. Climate changes have been observed, shifting from 2.9°C (1961-1971) to 3.4°C (1963 -1990) (Ažman Momirski et al. 2008; ARSO, 2008). From 1963 – 1990, average annual observed precipitation was 1482 mm. In spring, the quantity of precipitation rises steadily from February (100 mm) to June, saturating agricultural soils with water before summer. Summers are hot, with average July air temperatures over 21°C. Goriška Brda has a dense network of streams and rivers. The river has a stormy character due to the flysch geology and high precipitation rates. Average annual discharge of the Reka River tributary Kožbanjšček at Neblo station is 0.32 m^3/s (1998-2005).

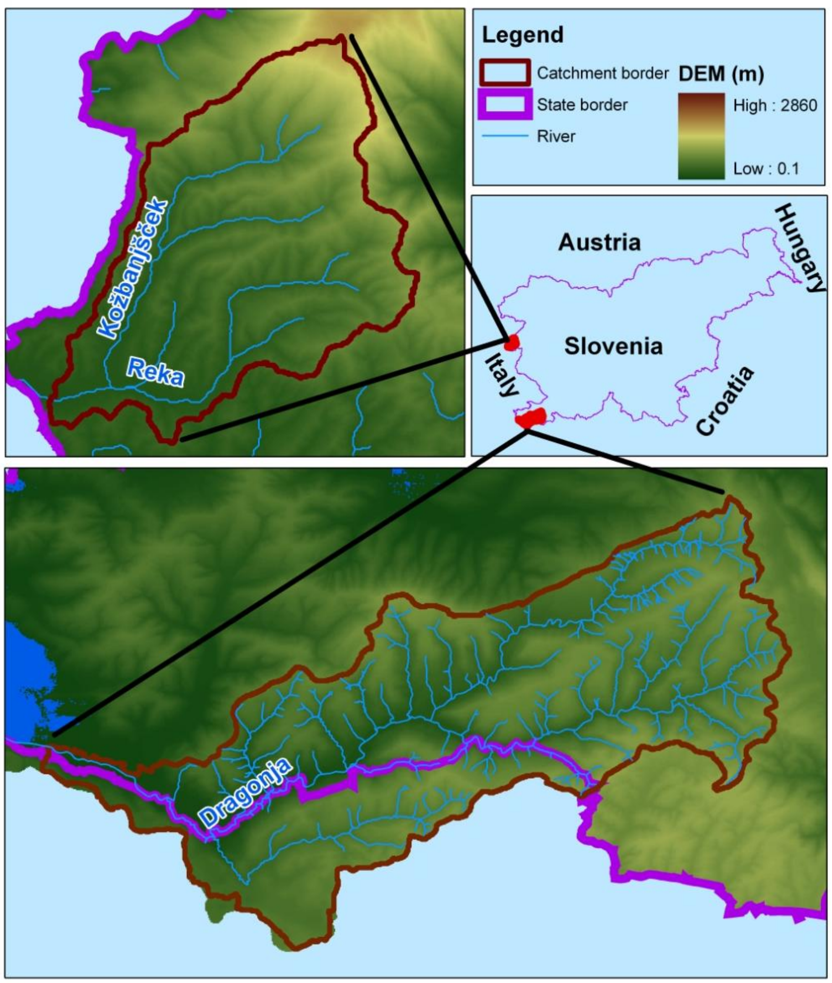

Figure 1. *The Reka River and Dragonja River research areas with major tributaries*

The Dragonja River catchment (91 km^2) in Slovenian Istria is situated on both sides of the Slovenian-Croatian border (Figure 1). The topography of the area is characterized by steep slopes and flat but narrow valleys orientated in the south-west direction. The Dragonja River flows into the Adriatic Sea. More than half of the river basin is situated at an altitude between 200 and 300 m above sea level and has a slope between 5° and 15° (Zorn and Petan, 2008). The climate can be described as sub-Mediterranean with no strong seasonality in rainfall distribution (Petkovšek and Mikoš, 2004). The seasons are almost equal in regard to precipitation except for autumn, which contains 30% of the annual precipitation. The total annual precipitation increases with distance from the sea, ranging from 1000 mm at the coast to 1300 mm in the upper area. Snow is extremely rare and moderate. The mean annual temperatures at the coast are around 14°C and are approximately 2–3°C lower further inland (Šraj et al., 2008; ARSO, 2008). Agriculture is practiced at the bottom of the valleys or on the hill ridges. In the past, steep slopes were cultivated as vineyards, pastures or fields. However, due to altered socio-economic conditions, a majority of terraced land was abandoned and overgrown by bushes and forests. Before natural afforestation of the area, the river had a stormy character that is now weaker. Average annual discharge of the Dragonja River at Podkaštel station is 0.8 m^3/s (1998-2005).

With the exception of sediments, water quality is not seriously impaired in these two areas. However, nutrient pollution is noticeable in certain sections near STW.

We used different maps for spatial data representation including the digital elevation model with resolution 25×25 m, a map of the actual river network and the Digital Soil Map of Slovenia (1990) at a scale of 1:25.000 with defined soil types and properties. Also, the land use map was made from an ortho-photo image with fine spatial distribution of major land cover classes derived from GERK agriculture subsidy payments and CORINE 2000. Temporal data was represented by weather data obtained from the Environmental Agency of the Republic of Slovenia. Farmers and the Agricultural Chamber provided the original baseline land use management scenarios for these catchments. Special attention was given to the representation of vineyards, forests and orchards as they cover the majority of the research areas. Afterward, land use, soil and slope characterizations were determined, their combinations forming delineated catchment Hydrological Response Units (HRUs). The Reka River catchment threshold for HRU formation was land use (0%), soil (10%) and slope (5%). For the Dragonja River catchment the thresholds were land use (5%), soil (10%) and slope (5%). In the end, we obtained 618 HRUs for the Reka River and 531 for the Dragonja River study area.

The base models for both catchments run for a period of 17 years (April 1, 1991 to December 31, 2007). The study period was divided into: warm up (April 1991 to December 1992), calibration (January 1998 to December 2002) and two validation periods (Reka: January 1993 – December 1994 and January 2003 – December 2005; Dragonja: January 1993 – December 1996 and 2003 to December 2005).

3. Results

This section presents the sensitivity analysis, calibration and validation for the Reka and Dragonja Rivers base scenarios.

3.1 Sensitivity analysis

First of all, in SWAT sensitivity analyses of both study areas, we used observed river discharge data from 1998-2005. After 270 runs, hydrological parameters were ranked by their sensitivity (Table 1). We found that the most sensitive parameters were Alpha_Bf, Cn2, Ch_K2, Blai and Surlag among others.

Table 1. *SWAT parameters (10) ranked by the sensitivity analysis for the research areas*

	River Reka		River Dragonja	
RANK	With observed	Without observed	With observed	Without observed
1	Alpha_Bf	Esco	Blai	Esco
2	Cn2	Cn2	Ch_K2	Alpha_Bf
3	Ch_K2	Canmx	Cn2	Gwqmn
4	Surlag	Gwqmn	Alpha_Bf	Cn2
5	Esco	Sol_Z	Canmx	Canmx
6	Sol_Awc	Revapmin	Esco	Sol_Awc
7	Ch_N	Alpha_Bf	Sol_Awc	Sol_Z
8	Canmx	Sol_Awc	Sol_Z	Revapmin
9	Go_Delay	Blai	Surlag	Go_Revap
10	Sol_Z	Sol_K	Ch_N	Blai

The parameters identified in the sensitivity analysis and corresponding mean values were used in calibration of the models. All these parameters have important influences on the hydrological properties of soil, groundwater, surface runoff and river flow.

3.2 Calibration

The Reka River catchment model was calibrated against daily discharge data from the Kožbanjšček tributary at Neblo and the river Dragonja against daily discharge data from Podkaštel, both for the period 1998-2002. For the calibration, we used the first 10 parameters identified in the sensitivity analysis. Calibration was performed manually with the purpose of investigating and observing the impacts of SWAT parameters on simulation results. Both base models for the Reka and Dragonja Rivers were run for several simulations. SWAT's hydrologic calibration must to be performed to fit the measured daily streamflow data to the simulated daily streamflow. SWAT runs were performed on a daily time step and output files were also generated on a daily basis. Model parameters were varied in stepwise fashion, within a reasonable range, during numerous calibration runs until reaching a satisfactory agreement between measured and simulated streamflow. The calibration was processed entirely at the catchment scale (one value for entire catchment). All parameters used were varied within a reasonable range of values for the research areas until finally resulting in improved performance of the models.

After changing the parameters, the correlation between measured and calibrated simulated daily flow is moderate, as shown in Table 2.

Table 2. *Daily time step streamflow model performance statistics for the Reka and Dragonja catchments for the calibration period (1998 – 2002)*

Statistical test	Units	Optimal values	Reka Base	Dragonja Base
R^2	-	1	0.53	0.35
E_{NS}	-	1	0.51	0.34
RMSE	-	0	0.44	1.61
PBIAS	%	0 (+ values = underestimate; - values = overestimate)	-9.89	1.56

The simulation results reflect the quality of the obtained discharge data, especially for the Reka catchment, whose gauging station has been redesigned several times and still operates as an analogue station. There were also a lot of problems with soil parameters from the digital soil map, which is lacking hydraulic and soil available water capacity data. Thus, Sol_Awc and Sol_K parameters had to be calculated with the Saxton et al. (1986) method, which was developed based on different soil types. Meteorological data is also very poor, especially for the Dragonja study area. There were only two rainfall gauging stations near the catchment area, yet none of them were situated in the catchment. Certain gauges measured high discharge rates but were not in correlation with rainfall station data. Due to very poor meteorological gauging, net local storms are not presented very well in model outputs. Nash-Sutcliff efficiencies (E_{NS}) for the base models of the Reka and Dragonja Rivers were 0.50 and 0.34, respectively. Overall, performance statistics show that simulated streamflow was underestimated relative to the measured flow in the Dragonja model and overestimated in the Reka model (Figure 2). Due to these results, further work on calibration is required, concentrating on soil parameters, crop growth and meteorological data.

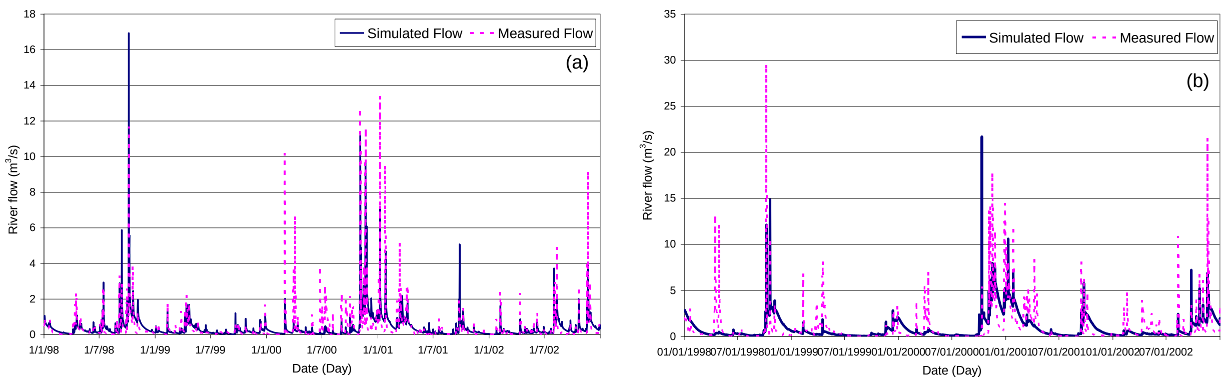

Figure 2. *Comparison between simulated and measured flow for the Reka (a) and Dragonja (b) catchment for the calibration period (1998-2002)*

Before calibrating sediments and water quality parameters, it is important to look at model performance indicators. Three main parameters are crop growth, evapotranspiration and soil water content, as all of them greatly affect the water balance. The daily HRU time series can be extracted from the SWAT output files.

3.3 Validation

The calibrated Reka River model was validated for the period ranging from January 1, 1993 - December 31, 1994 and January 1, 2003 - December 31, 2005. The Dragonja River model was validated for the period ranging from January 1, 1993 - December 31, 1996 and January 1, 2003 - December 31, 2005 (Table 3).

Table 3. *Daily time step streamflow model performance statistics for the Reka and Dragonja catchments for the validation periods*

			Reka Base		Dragonja Base	
Statistical test	**Units**	**Optimal values**	**1991-1994**	**2003-2005**	**1993-1996**	**2003-2005**
R^2	-	1	0.53	0.48	0.46	0.28
E_{NS}	-	1	0.53	0.48	0.35	0.28
RMSE	-	0	0.69	0.27	2.69	1.26
PBIAS	%	0 (+ values = underestimate; - values = overestimate)	9.80	-11.65	17.93	-3.81

Nash-Sutcliff efficiencies and R^2 values (0.53 and 0.48) for the Reka River model are similar to the calibrated values. PBIAS values show underestimation of the flow for the first period (9.80) and overestimation for the second period (-11.65). The Dragonja River Nash-Sutcliff efficiencies for both periods are in agreement with calibration; however, results for the second period are lower. PBIAS shows underestimation of river flow for the first period (17.93) and overestimation for the second period (-3.81).

4. Conclusions

The Soil and Water Assessment Tool was applied in Slovenia for the first time. For this purpose, two flysh catchments in the western part of the country with sub-Mediterranean climate were selected.

For the calibration, we used the first 10 parameters identified by sensitivity analysis. The most sensitive parameters were identified as Alpha_Bf, Cn2, Ch_K2, Blai and Surlag among others. Calibration was performed manually in order to investigate and observe the impacts of SWAT parameters on simulation results. All parameters used were varied within a reasonable range of values for the research areas until finally resulting in improved model performance.

The base scenario's simulation performance statistics reflect the quality of the obtained discharge data. Gauging stations and river channels were redesigned several times in the past three decades, which was observed in the rivers' hydrographs. Problems with statistics indicating low performance originated in soil parameters from a digital soil map that was lacking hydraulic and available soil water capacity data (Sol_K and Sol_Awc); thus, these parameters had to be estimated. To overcome this problem, we are already in the process of completing in-field soil profile sampling. This will enable us to compare whether soil hydrological parameters estimated from texture in the digital soil map can serve modelers as well as field sampling data. Meteorological data is also very poor. Although, observed data for the Reka River catchment is more readily available, as a precipitation gauging station is situated in the middle of the study area. Low density of meteorological stations in Slovenia causes serious problems for modelers, as topography and strong local storms can lead to discrepancies in measured river flow and measured precipitation at official state stations. In recent years, private digital climate stations are spreading. However, their periods of data measurement are short and insufficient for modeling long-term effects.

Further work will concentrate on future agricultural land use, agri-environmental and climate scenarios to show the type of long-term environmental responses expected. This work will contribute to the understanding of hydrological processes in flysch catchments. Furthermore, it will suggest guidelines for reaching or preserving good water quality in order to fulfil Water Framework Directive demands.

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Application of SWAT in Hydrologic and Nutrient Transport Modeling of the Lake Winnipeg Watershed

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Abstract

The quality of water in Lake Winnipeg, Canada, has deteriorated during past three decades as a result of excess nutrient loading from nonpoint sources in the watershed. While nutrient transport from nonpoint sources to the lakes is driven by complex hydrologic and biochemical processes, snowmelt-driven hydrologic response plays a key role in nutrient delivery to the lakes. This paper presents the first part of a study on the application of SWAT (Soil & Water Assessment Tool) for hydrologic modeling of two representative sub-catchments of the Lake Winnipeg watershed: the upper Assiniboine catchment (13500 km^2) in the province of Saskatchewan and the Morris catchment (4300 km^2) in the adjacent province of Manitoba. Both catchments are dominated by agricultural land use and are considered particularly suitable for understanding the impacts of climate variability and change on nonpoint nutrient loadings to the lake. We analyzed the effects of two gridded precipitation inputs: North America Regional Reanalysis (NARR) data and Gridded Climate Dataset for Canada (GCDC) in discharge simulations of both catchments. Although SWAT is able to simulate overall discharge reasonably well for both datasets, the calibrated model results indicate that the GCDC precipitation inputs resulted in a better simulation of discharge dynamics compared to NARR. The results of the models suggest that the type of precipitation input has an important influence on SWAT model simulation results, even in a snowmelt dominated catchment.

Keywords: Gridded precipitation input, Lake Winnipeg watershed, model calibration, model performance, snowmelt hydrologic response

1. Introduction

The quality of water in Lake Winnipeg has deteriorated due to excess nutrient loading from nonpoint sources in the watershed. According to an investigation by Jones and Armstrong (2001), total nitrogen (N) and total phosphorus (P) loads in Lake Winnipeg have increased by 13% and 10%, respectively, over the last three decades. The increases in N and P in the lake are likely due to changes in agricultural practices, including expansion of the livestock and food processing sectors and increases in human population in the watershed (Chambers et al., 2001). Therefore, in order to control nutrient pollution in the lake, it is important to be able to quantify the mobilization and transport mechanism of nutrients in the source watersheds.

While nutrient transport from nonpoint sources to the lakes is driven by complex hydrologic and biochemical processes, previous studies on catchment-scale nitrate transport processes indicate that rainfall and snowmelt driven hydrologic processes play a key role in nitrate loss from catchments (Creed et al., 1996; Quinn, 2004; Shrestha et al., 2007). Phosphorus transport is also influenced by hydrologic processes that are dominated by snowmelt-driven runoff over nearly level landscapes and frozen soils in the Canadian prairies (Salvano and Flaten, 2006). Therefore, modelling of the hydrologic response to rainfall and snowmelt is the first step in understanding and modeling N and P transport in the Lake Winnipeg watershed. In addition, climate change is expected to influence the hydro-meteorological regime in the Prairies region, which will also affect the nutrient transport processes.

The main objective of this study was to assess the impacts of climate variability and changes in hydrologic and nutrient regimes in the Lake Winnipeg watershed. This paper reports on the first part of the study, which focuses on hydrologic modeling of the two representative sub-catchments of the Red and Assiniboine basins in the Lake Winnipeg watershed. We employed the SWAT model (Soil & Water Assessment Tool; Arnold et al., 1998), which is a river basin scale model developed for assessing the impacts of management and climate on water supplies, sediment and agricultural chemical yields in watersheds and large river basins. SWAT is considered appropriate for the Lake Winnipeg watershed, as it has been extensively and successfully used in snowmelt dominated regions for simulating hydrologic response (Abbaspour et al., 2007; Ahl et al., 2008; Levesque et al., 2008) and nutrient transport (Grizzetti et al., 2003; Gollamudi et al., 2007; Panagopoulos et al., 2007). We analyzed the effects of two gridded precipitation inputs: North America Regional Reanalysis (NARR) data and Gridded Climate Dataset for Canada (GCDC) in discharge simulations of both catchments.

2. Study Area

Previous studies on nutrient loading in the Lake Winnipeg Watershed indicate that Red and Assiniboine River Basins are the major source of nitrogen and phosphorus loading to Lake Winnipeg (Bourne et al., 2002). Therefore, we selected two representative sub-catchments: Morris catchment in the Red River basin and upper Assiniboine catchment in the Assiniboine River Basin (Figure 1). Both catchments are dominated by agricultural land use and are considered appropriate for understanding climate impacts on nonpoint nutrient loadings.

The upper Assiniboine catchment covers an area of about 13,500 km^2, upstream of the Lake of Prairies (Shellmouth reservoir) in the province of Saskatchewan. The topography is gently to moderately undulating with elevations ranging from 427 to 723 m. Average annual precipitation from 1979 to 2003 is about 390 mm. Major tributaries of the Assiniboine River include the Whitesand River, Shell River, Lilian

River and Yorkton Creek. The catchment is dominated by agricultural land use (about 55%) with mixed grain and wheat as primary crops (Environment Canada, 2000).

The Morris River, with a catchment area of about 4300 m^2, is a tributary of the international trans-boundary Red River. Located in southern Manitoba with headwaters in the north-eastern edge of the Pembina Hills region (Jones and Armstrong, 2001), its relief varies from 228 to 535 m. Average annual precipitation in the catchment from 1979 to 2003 is about 440 mm. The Boyne River and Tobacco Creek are the major tributaries, which drain into a network of man-made channels before flowing into Morris River. The catchment is dominated by agricultural land use (about 80%) for which river water is used extensively for irrigation.

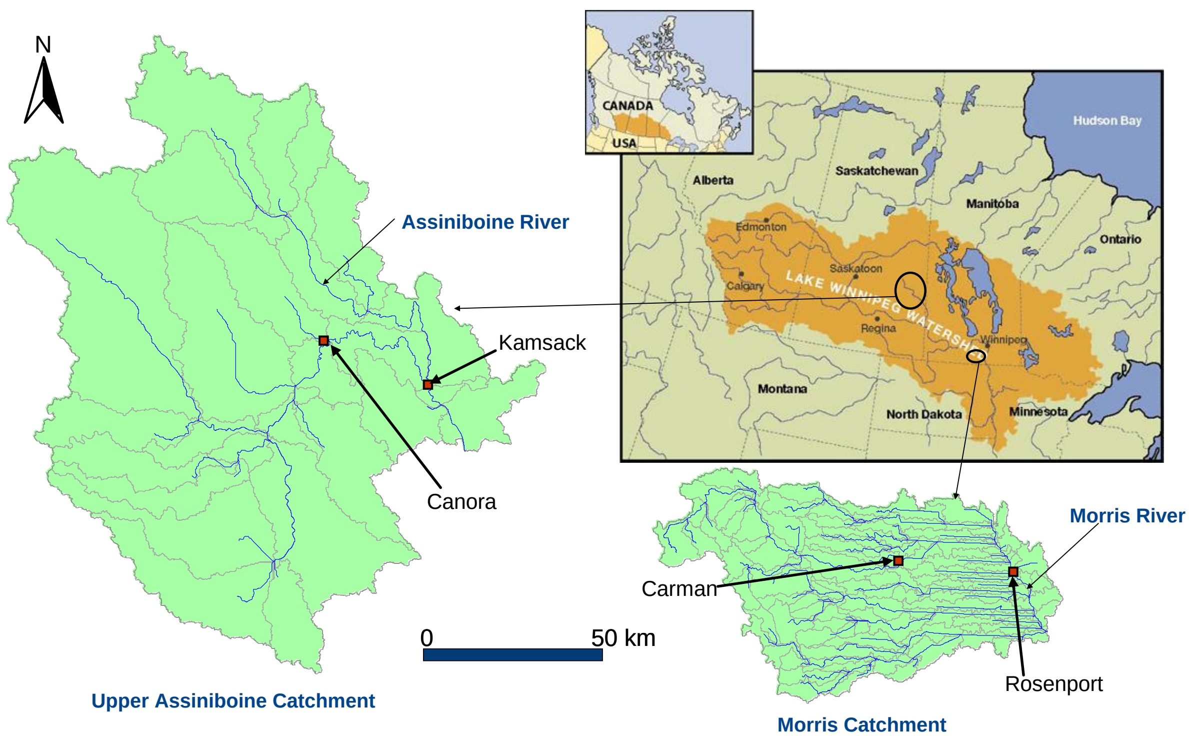

Figure 1. *Location Map of Upper Assiniboine and Morris Catchments*

3. Model set-up and calibration

The hydrologic and nutrient transport models for both catchments were set up using SWAT2005 (Neitsch et al., 2005) and ArcSWAT (Winchell et al., 2008) interface. We also employed a digital elevation model with 90-m resolution obtained from the Consultative Group for International Agriculture Research-Consortium for Spatial Information, CGIAR-CSI (Jarvis et al., 2008). Digital land use and soil data were obtained from the Land Cover of Canada, LCC (Cihlar and Beaubien, 1998) database (1 km resolution) and Soil Landscapes of Canada, SLC (SLC Working Group, 2007) version 3.1.1 (1: 1 million resolution), respectively. The LCC and SLC databases were reclassified to match with the SWAT database requirements.

We used gridded daily precipitation, maximum and minimum air temperature, solar radiation, wind speed and relative humidity (45 km resolution) from North America Regional Reanalysis, NARR (Mesinger et al., 2006) datasets as meteorological inputs to the SWAT model. The NARR is a long-term, consistent, high-resolution climate dataset for the North American domain. In addition to the National Centers for

Environmental Prediction (NCEP) Eta Model and its Data Assimilation System (at 32 km/45 layer resolution with output every three hours), the hallmarks of the NARR are incorporation of hourly assimilation of high quality and detailed precipitation observations, the use of a recent version of the Noah land surface model, and the use of numerous datasets that are new or improved compared those of the Global Reanalysis. The NARR datasets were employed instead of the relatively sparse data from climate observation stations because of their more detailed spatial coverage and because the model will be later coupled with GCM/RCMs having similar spatial resolution and gridded format. This will help in maintaining the consistency of the inputs for model calibration and validation and climate change scenario analysis using GCM/RCM. Additional SWAT models for both catchments were set up by replacing the NARR precipitation with daily precipitation data of 10-km spatial resolution from the Gridded Climate Dataset for Canada (GCDC). The GCDC is an interpolated dataset based on daily Environment Canada climate station observations using a thin-plate smoothing spline-surface fitting method (Agriculture and Agri-Food Canada, 2008).

The SWAT models for both the catchments were calibrated using ParaSol (Parameter Solutions; van Griensven and Meixner, 2003), a procedure available in the SWAT-CUP2 toolbox (Abbaspour et al., 2007). Parasol is a global optimization algorithm based on Shuffled Complex Evolution (SCE-UA; Duan et al., 1992) and uses a threshold value defined by χ^2-statistics to define confidence regions or Bayesian statistics. Based on previous research in snow dominated catchments (Abbaspour et al., 2007; Ahl et al., 2008; Levesque et al,. 2008), a set of 13 parameters were chosen for calibration of the hydrologic response. This included the seven parameters controlling for snowpack accumulation and melt: snowpack temperature lag factor (TIMP), snowmelt base temperature (SMTMP), maximum melt factor (SMFMX), minimum melt factor (SMFMN), areal snow coverage threshold at 50% (SNO50COV), areal snow coverage threshold at 100% (SNOCOVMX) and snowfall temperature threshold (SFTMP). In addition, six other parameters affecting runoff generation and surface and subsurface runoff were chosen including: SCS runoff curve number (CN2), surface runoff lag coefficient (SURLAG), baseflow factor for bank storage (ALPHA_BF), groundwater delay time (GW_DELAY), Manning coefficient for the main channel (CH_N) and effective hydraulic conductivity in the main channel (CH_K2).

Ten years of data (1986-1995) were used for model calibration and eight years of data (1996-2003) for model validation. A warm-up period of one year was employed so initial conditions would not affect the model calibration. Five independent calibration runs between 5000-10000 simulations were performed for the SWAT model with NARR inputs and NARR climate + GCDC precipitation inputs. We used observed discharge data from the Canora and Kamsack gauging stations in the upper Assiniboine catchment and Carman and Rosenport gauging stations in Morris catchment (Figure 1) in parameter optimization. However, in the Assiniboine catchment, discharge data at the Canora station were missing during winter (November-February), and in the Morris catchment, discharge data during winter were missing from both hydrometric stations. Such missing data were excluded from model calibration and validation. The sum of the squares of the residuals between observed and simulated discharge were used as an objective function for model optimization. Discharge simulations from two gauging stations were combined to form a single objective for optimization. In addition, Nash-Sutcliffe coefficient of efficiency (NSCE), coefficient of determination (R^2) and mean absolute error (MAE) were used for independent evaluation of model performance.

4. Results and Discussion

Tables 1 and 2 summarize results obtained from the upper Assiniboine and Morris catchments using NARR inputs and NARR climate + GCDC precipitation inputs. The results of the SWAT model calibration using the ParaSol procedure shows that the method provides an effective tool for automatic calibration of SWAT. A statistical analysis of the results indicate that the SWAT model with GCDC precipitation data produces better overall results than with the NARR precipitation. This could be due to the NARR datasets' coarser spatial resolution (45 km) and representation of temporal dynamics. The NARR precipitation datasets are based on NCEP Eta Model and incorporation of assimilated observed precipitation (Mesinger et al., 2006). Therefore, it may not fully represent the temporal dynamics of rainfall patterns at a sub-catchment scale, which are required for the SWAT model. The GCDC is a gridded observation dataset of 10-km spatial resolution, so it provides a better representation of the rainfall patterns at the sub-catchment scale. The difference in SWAT model performance is especially evident in model validation, where the model driven by GCDC precipitation shows far better results for all three model-performance criteria considered.

The results of the model simulation at Kamsack and Canora gauging stations using GCDC precipitation inputs are shown in Figures 2 and 3. The runoff dynamics for both catchments in the Lake Winnipeg watershed are represented adequately in the calibration and validation datasets. The peaks in the discharge hydrographs occur during the snowmelt season of April-May, which is reproduced reasonably well for most events. While the SWAT model driven by NARR precipitation misses the secondary peaks after initial snowmelt (not shown in Figures 2 and 3), the model driven by GCDC precipitation is able to better reproduce the secondary peaks.

Similar results are obtained in the Morris catchment (Figures 4 and 5). The overall statistical performance was better in the Rosenport gauging station (Morris River) compared to the Carman station. The SWAT model calibrated with GCDC precipitation inputs had a better overall statistical performance. The model with GCDC inputs was also able to better represent the runoff dynamics. Therefore, based on statistical performance and graphical representation of the results in both catchments, we found that precipitation inputs have an important influence on SWAT model performance, even in a snowmelt-driven catchment.

The results of the SWAT model calibration may have been affected by a number of factors such as river ice formation, which influenced the discharge data in both catchments. The presence of river ice leads to considerable uncertainty in discharge data, especially during ice break up (Pelletier, 1990; Hamilton, 2008). The discharge uncertainties also influenced the model calibration and validation results. For example, no discharge peaks were present in the observation data for both discharge stations in the upper Assiniboine catchment during the 2002 snowmelt. However, the SWAT simulation at both stations produced discharge peaks of about 100 m^3/s. This discrepancy may be due to problems in the observation data, which can also affect the statistical performance of model validation. In the Morris catchment, an additional source of uncertainty in the discharge values was the lack of accounting for irrigation water withdrawals.

Table 1. *SWAT statistical performance for the upper Assiniboine catchment*

Input dataset	Station	Calibration			Validation		
		MAE	R^2	NSCE	MAE	R^2	NSCE
NARR+GCDC	Kamsack	3.89	0.86	0.79	3.80	0.79	0.73
	Canora	3.34	0.85	0.82	4.56	0.72	-0.49
NARR	Kamsack	3.80	0.84	0.75	5.79	0.69	0.10
	Canora	6.91	0.81	0.80	7.67	0.65	-6.46

Table 2. *SWAT statistical performance for the Morris catchment*

Input dataset	Station	Calibration			Validation		
		MAE	R^2	NSCE	MAE	R^2	NSCE
NARR+GCDC	Rosenport	3.12	0.70	0.70	6.09	0.56	0.56
	Carman	0.87	0.65	0.62	2.62	0.40	0.39
NARR	Rosenport	3.08	0.67	0.66	6.28	0.58	0.49
	Carman	0.87	0.67	0.65	3.12	0.42	0.16

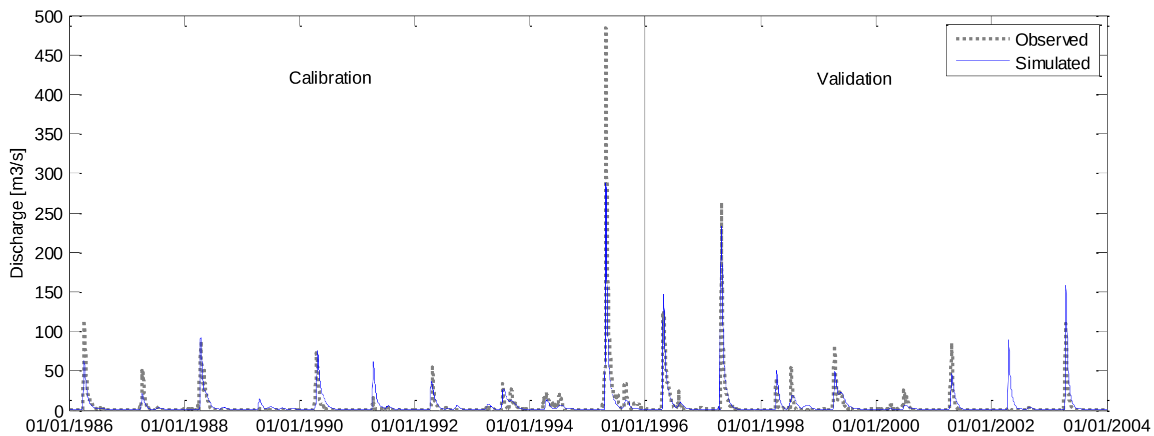

Figure 2. *Comparison of observed and simulated discharge at the Kamsack gauge in Assiniboine River (NARR meteorological + GCDC precipitation inputs)*

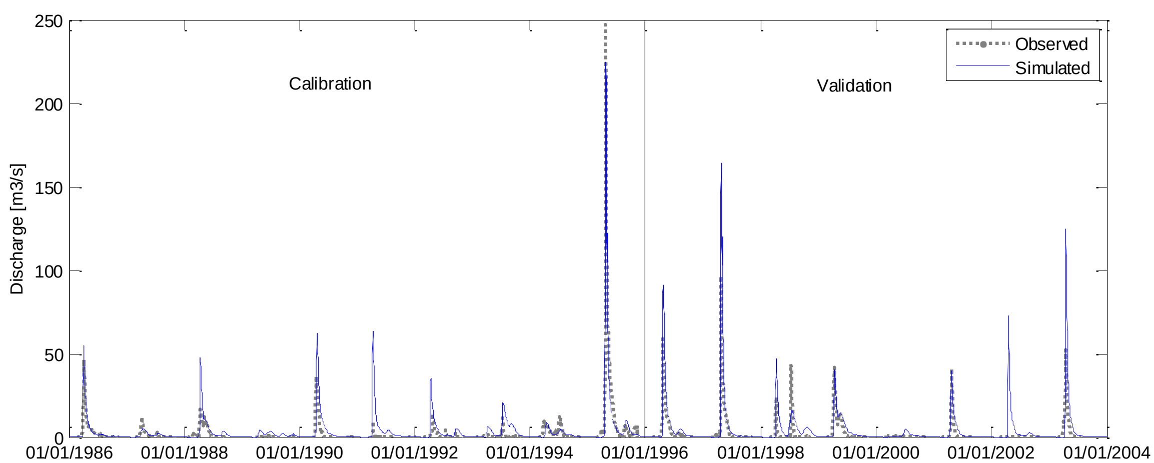

Figure 3. *Comparison of observed and simulated discharge at the Canora gauge in Whitesand River (NARR meteorological + GCDC precipitation inputs)*

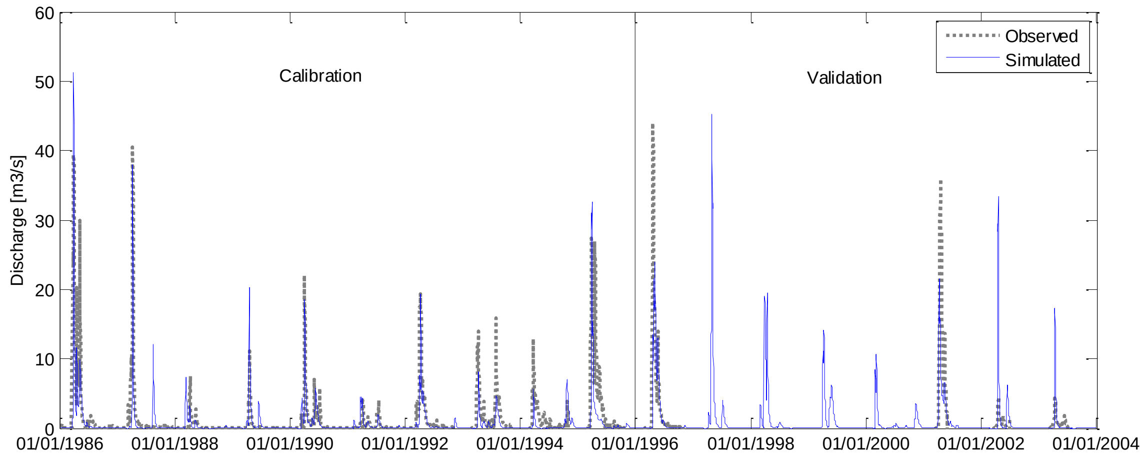

Figure 4. *Comparison of observed and simulated discharge at the Carman gauge in Boyne River (NARR meteorological + GCDC precipitation inputs)*

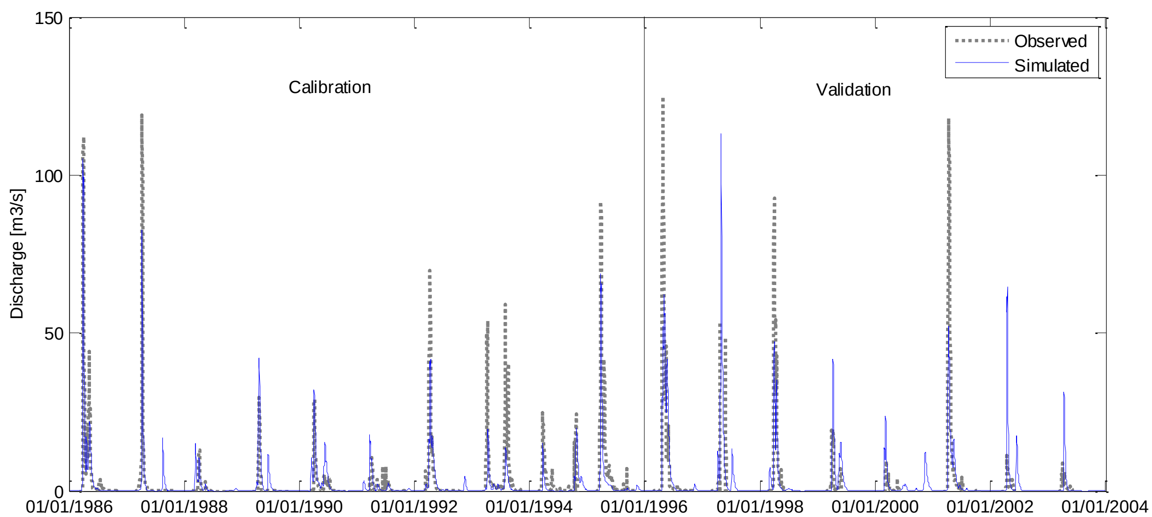

Figure 5. *Comparison of observed and simulated discharge at the Rosenport gauge in Morris River (NARR meteorological + GCDC precipitation inputs)*

5. Conclusions

We investigated hydrologic response in two snowmelt-driven catchments in the Lake Winnipeg watershed was using the SWAT hydrologic model. The results of our SWAT model calibration using the ParaSol procedure show that the method provides an effective tool for automatic calibration of SWAT in snowmelt-driven catchments. The results also show that the calibrated SWAT model is able to produce a reasonable match between the observed and simulated discharge hydrographs. Moreover, the model with GCDC precipitation data is able to better reproduce the discharge dynamics compared to the one using NARR precipitation data in both catchments. This is due to the GCDC dataset having higher spatial resolution as well as a better representation of temporal variability at the sub-catchment scale. This suggests that the quality of precipitation inputs can influence SWAT model performance, even in a snowmelt-driven catchment. Future research will involve the calibration of nutrient (nitrogen and phosphorus) release from the catchment and predictions regarding the impacts of future climate scenarios by combining GCM/RCM outputs with SWAT.

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Spatio-temporal variation of surface-groundwater interactions in a small watershed, South Korea

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Abstract

The intensity and direction of groundwater–surface water exchange flux are controlled by the groundwater head gradient, hydraulic conductivity and riverbed geometry. The spatial heterogeneity of these factors and the subsequent variability in the impact of these interaction processes affect the watershed water balance. However, detailed studies concerning the spatio-temporal variability of the extent and intensity of surface-groundwater interactions have been extremely limited. In this study, we carried out an assessment to quantify the water exchange flux by applying the integrated SWAT-MODFLOW model to the upper-mid stream of Anyangcheon, a representative urban stream that runs through Anyang City, South Korea. Effluent stream characteristics were found in this watershed; namely, baseflow was annually discharged except during heavy rain periods. The intensity and the spatial extent of surface-groundwater interactions in different sub-watersheds were simulated on a daily basis.

Keywords: surface-groundwater interactions, SWAT-MODFLOW, spatial-temporal variability, intensity and spatial extent of interactions

1. Introduction

Recent studies analyzing surface water-groundwater interactions have been actively conducted in the U.S.A, Germany and Switzerland. The standard for hydrologic and chemical changes in a river is determined by the groundwater flow percolating and flowing into the watershed. Groundwater flow into streams takes place during the dry season, so in terms of the hydrology, it accounts for most of the annual baseflow in many rivers. On the contrary, during the rainy season, river water penetrates into the river bank with surface runoff and interflow increasing steadily (Matthess, 1983). With increasing interest in flow characteristics as well as pollution in the hyporheic zone, we also analyzed the relationship between the water quality in the hyporheic zone, surface water and groundwater (Rassam and Knight, 2007). According to Krause et al. (2007), stream stage and groundwater level show the spatio-temporal variation and conductance of the riverbed. These measurements are reliant on geometric characteristics of a river, which also show spatial variations. This plays an important role in terms of ecohydrology in the watershed. In this study, we carried out an assessment to quantify the water exchange flux by applying the integrated SWAT-MODFLOW model to the upper-mid stream of Anyangcheon, a representative urban stream that runs through Anyang City, South Korea.

2. Status of the Watershed

The watershed is in the upper to middle area of the Anayangcheon with its outlet point at Siheung Bridge as shown in Figure 1. It is also located in the southeast portion of Seoul and is at a longitude of 126° 52′–127° 03′ east and latitude of 37°19′–37°27′ north. The subject area covers 140.72 km^2 and contains 56 km of stream length. Anyang Observatory Station and Nam-Myeon Observatory Station exist within the watershed, and Naksaeng Observatory Station is outside the area. Weather observation data used in this study comes from Seoul and Suwon Observatory Stations. We also used Anyang and Siheung Water Level Observatory Stations for observation of surface water and Goonpo-Dangjeong and Anyang-Bisan Observation Stations for groundwater data within the watershed.

The average annual rainfall (2002–2006) is 1,587.5 mm in Seoul and 1,349.1 mm in Suwon. The average temperature is 12.8°C in Seoul and 12.3°C in Suwon. The annual evaporation is 1,099.8 mm in Seoul and 1,080.5 mm in Suwon. The average annual relative humidity is 61.9% in Seoul and 63.2 % in Suwon, and the monthly relative humidity records are highest in July. The constant amount of sewage discharged from urban areas is found instream. Both graywater and sewage from the Bagdal and Seoksu sewage treatment plants are discharged into the stream. Bakdal sewage treatment plant was established in 1995, and Seoksu sewage treatment plant has been in operation since 2003. Therefore, this study takes into consideration the volume of sewage (the annual average of 360,000 m^3/day) and the volume of graywater (the annual average of 32,000 m^3/day).

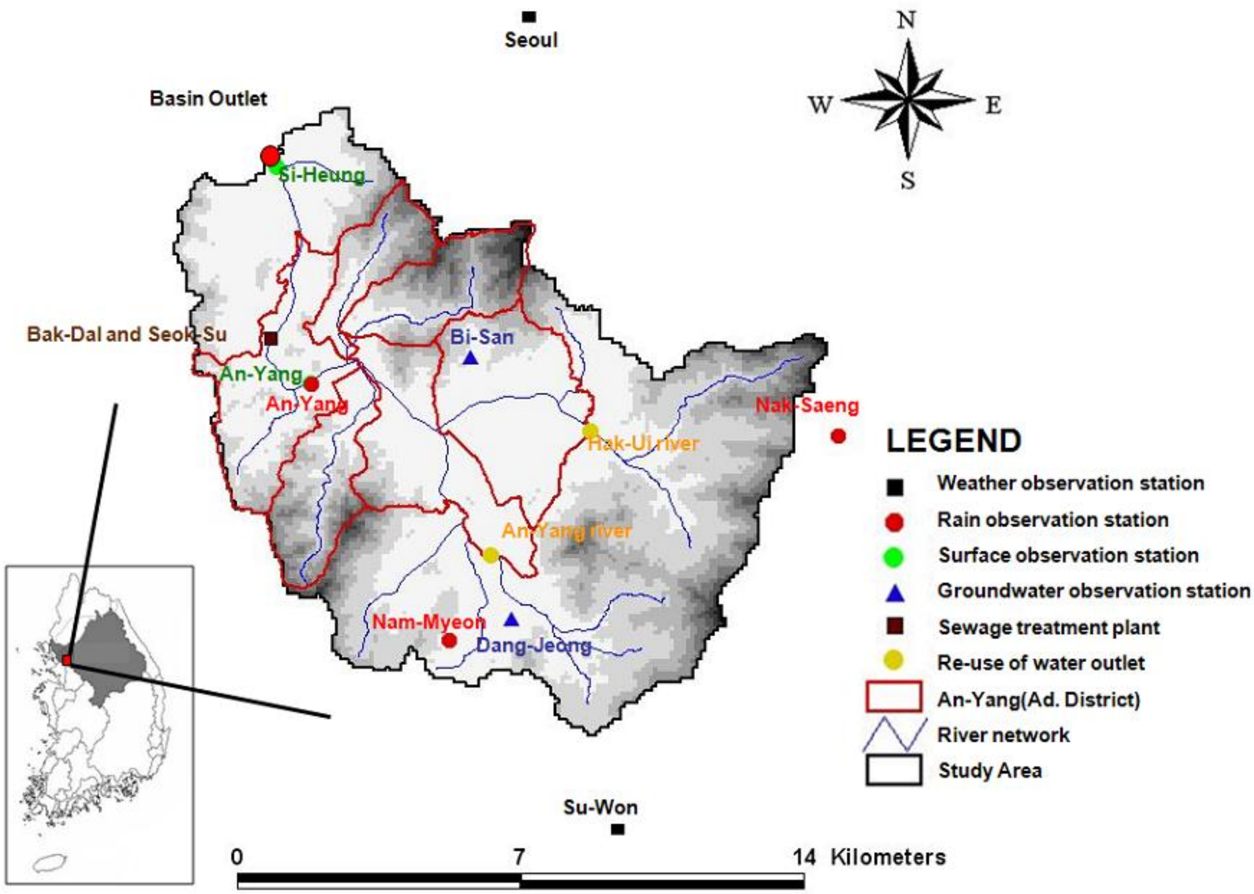


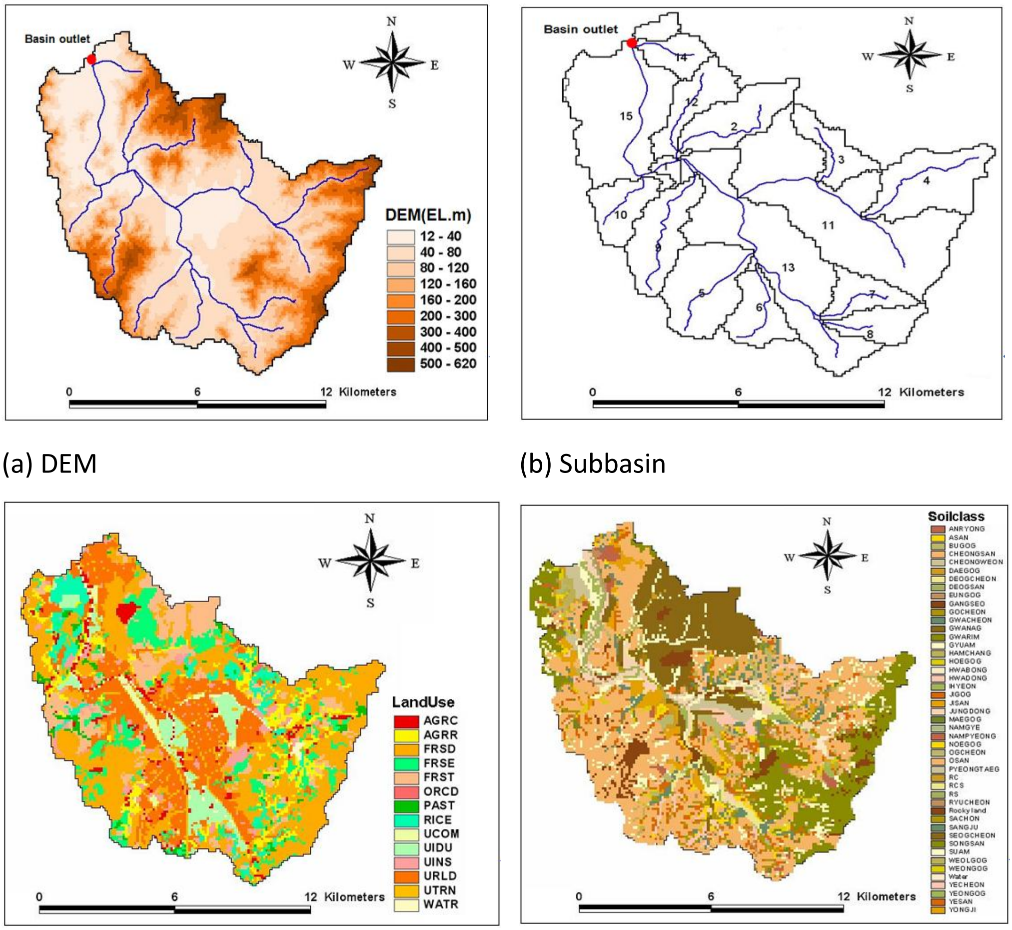
Figure 1. Description of the study watershed (Anyangcheon stream)

2. Methodology

SWAT-K is a modified version of the SWAT model (Arnold et al., 1993), which is better adapted to the features of South Korea. SWAT-MODFLOW in SWAT-K is an integrated model that combines MODFLOW as a subroutine in SWAT (Kim et al., 2008). It is an integrated model that can calculate the amount of groundwater–surface water exchange with MODFLOW's river package as well as cell-based recharge from HRU-based groundwater recharge MODFLOW's RECHARGE package. SWAT-MODFLOW has proven its worth as an integrated surface-ground water model in various trial applications within basins of various sizes (Kim et al., 2008).

2.1 The input data of SWAT

The basic input requirements of SWAT are: a Digital Elevation Model, land use map and soil type map. A DEM of the basin was built up by resampling 100-m grid shape from a 1:25,000 topographical map, and with this, the basin was divided into 15 subbasins (Figs. 2(a) and 2(b)). Mid-classification of land cover was applied for the land use map, which was provided by the Ministry of Environment (Fig. 2(c)). Using a detailed soil map provided by the National Institute of Agricultural Science and Technology, we determined soil classes by using soil series classifications (Fig. 2(d)).



(a) DEM (b) Subbasin

(c) Land use (d) Soil class

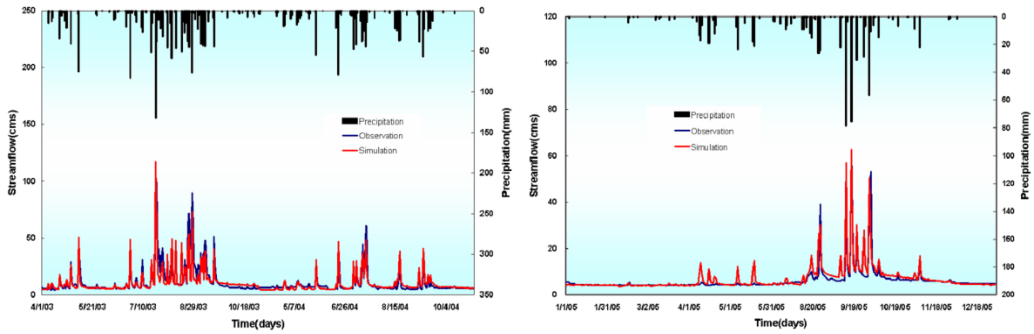
Figure 2. *SWAT Input Data*

2.3 The Input Data for MODFLOW

The hydrogeologic setting of the basin was simplified to a single alluvial layer and two permeable bedrock layers. The alluvial layer was configured as unconfined aquifer, and bedrock layers were configured as a confined/unconfined transformation layer. The spatial distribution of the alluvial layer and bedrock layers was generated by the Kriging technique, which is based on a linear model that uses the geostatistical method. The model grids are composed of 155 columns, 161 rows and 3 layers. The size of a horizontal cell is 100 m × 100 m. The boundary of the watershed was established as a no-flow boundary.

3. Results

We used data from 2003–2004 for the calibration, except for dry season months (January-March and November-December) when no observational data were available. Validity of the model was evaluated with the coefficient of determination (R^2) and Nash-Sutcliffe efficiency (NSE). Parameters used for the calibration include CN2, SOL_AWC, ESCO and GW_DEALY in SWAT, storage coefficient S and conductance of riverbed in MODFLOW. A comparison between the observed and simulated values at the outlet point, located at the water level observation station in Siheung, revealed that R^2 (0.7) and NSE (0.69) were both satisfactory. The model was verified with the streamflow data in 2005, producing an R^2 of 0.74 and an NSE of 0.68 (Figs. 3(a) and 3(b)). As explained earlier, the water level in the mid to upper areas of the Anyangcheon basin is well matched with the model during the dry seasons, as it is provided with treated wastewater in order to prevent drying up the riverbed. However, in the rainy seasons, it appears the simulation values are slightly lower than observed values. The major hydraulic characteristics that define groundwater flow include the hydraulic conductivity of an aquifer, the storage coefficient, conductance of the riverbed, thickness of the aquifer and boundary conditions. The calibration of the groundwater level was conducted by modifying the delay time for recharge (GW_DELAY), the storage coefficient (S) and the conductance of the riverbed.



(a) Calibration results from 2003 and 2004 (b) Validation results from 2005

Figure 3. *Results of the SWAT-K simulation*

3.1 Analysis of the water exchange between surface and groundwater

Characteristics of water exchange between surface and ground waters were examined by quantifying the spatial and temporal variation in water exchange flux. The MODFLOW river package determines the water exchange flux using the difference in water levels between the river and groundwater. The flux is influenced by various physical factors of river.

3.1.1 Temporal changes in water exchange flux between surface and ground waters

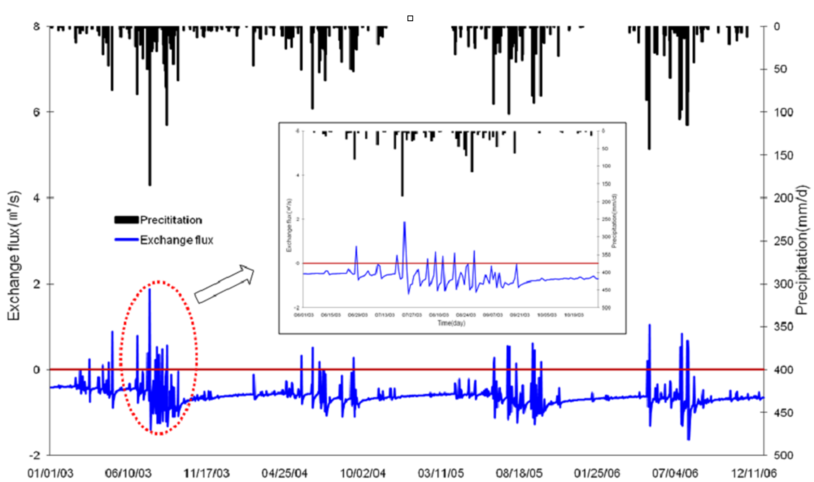


Figure 4. *Simulated results of the river-groundwater exchange flux on the basin river cells during the years 2003 to 2006*

SWAT-MODFLOW can describe the water exchange flux between surface and ground waters in each river cell. Figure 4 shows the total daily surface-ground water exchange flux in the entire river basin. The positive values refer to cases where surface water moves to groundwater, and the opposite flow, from ground to surface water, results in the negative values. The comparison between precipitation and exchange flux during the year 2003–2006 is illustrated in Figure 4. The overall water flux shows a slight negative value because the monitored river basin is originally a gaining stream in which the river stage is lower than groundwater level so water flows from the aquifer to the river.

3.1.2 Spatial variations of the surface- groundwater exchange flux

In order to assess the exchange flux in each subbasin, the spatial changes in exchange flux at each different location were investigated. A simple comparison of exchange flux would be meaningless because physical characteristics such as the length and width of the river and fluctuations in surface and ground water level are all different depending on each subbasin. Therefore, for rivers with the same length and width, the exchange flux per unit area in the upper, middle and downstream portions of the river were compared to find out how spatial location affects the exchange flux in the of representative subbasins. Figure 5 shows the comparison of the exchange flux per unit area in No.3, No.11 and No.15 subbasins, which are located in the upper, middle and downstream portions of the river, respectively. As shown in the figure, the changes in exchange flux between each subbasin are similar to those of the entire area, but there are significant differences among the exchange fluxes of each subbasin. In the No.15 subbasin, located downstream, the exchange flux ranges from 0.7 to 1.3×10^{-3} $m^3/mon/km^2$ while the flux in upper subbasin No.3 ranges from 8.2 to 12.6×10^{-3} $m^3/mon/km^2$, differing almost 10-fold. This is due to the larger gap between surface and ground water heads in the upper stream compared to those downstream. The volume of the exchange flux differs in individual water basins with changes in time and space and is influenced by hydrological components such as streamflow and recharge rate.

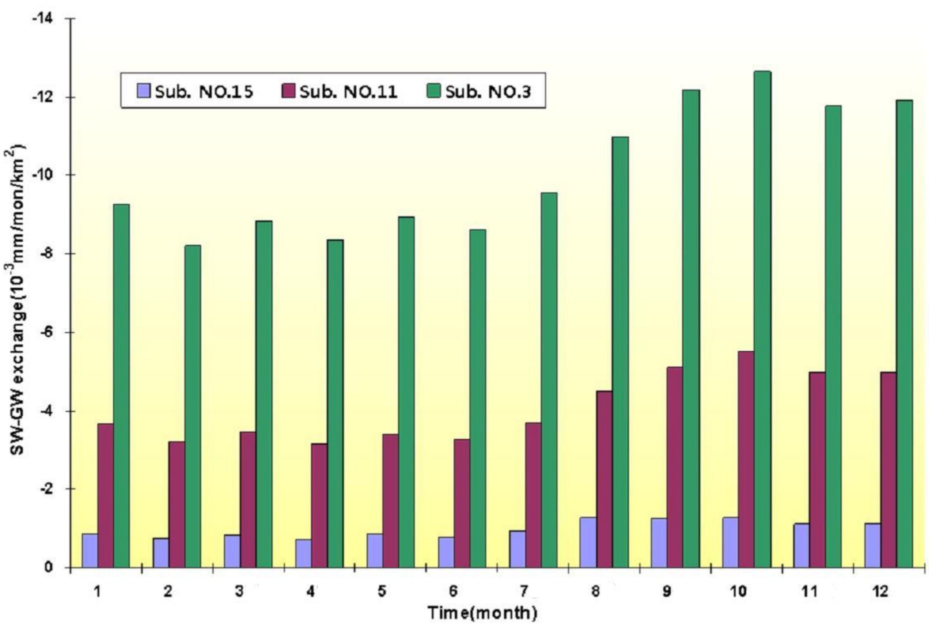


Figure 5. *Comparison of monthly average exchange fluxes for the subbasins*

4. Conclusion

In order to evaluate the spatio-temporal variability of surface-ground water interactions, SWAT-MODFLOW was applied to the Anyangcheon watershed, our research subject area. The results can be summarized as follows.

1) As a result of analysis on groundwater exchange flux, the research area was found to be a gaining stream, a river into which groundwater flows. River water inflow to groundwater takes place only during the rainy season.

2) The highest average annual exchange flux in the surrounding rivers is 51.79 m^3/sec during September rather than July when the average annual precipitation is highest. Deviation in the average annual exchange flux is smaller than that of the average annual precipitation in the area due to the effect of the time gap between recharge and groundwater discharge.
3) Regarding the exchange flux in the upper, middle and downstream areas, in lower altitudes the exchange flux affects a larger area but has a smaller range.

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Assessing the benefit of improved precipitation input in SWAT model simulations

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Abstract

The importance of better input data, model structure and parameterization for good process-based predictions are well recognized in hydrological modeling. Although the Soil Water Assessment Tool (SWAT), a physically based, distributed model, offers a range of possibilities for defining model structure and input data, the input of climatic data is still very simple. SWAT uses data from the gauge located nearest to the centroid of the catchment, which may not always represent overall catchment climatic conditions. This eventually influences the model parameterization process and quality of the predicted results. In this study, we used areal precipitation obtained through interpolation and compared the model performance (observed versus simulated hydrographs) using the normal SWAT precipitation input procedure (station precipitation). The model was applied to mountainous, semi-arid catchments in the Karkheh basin, Iran. Daily time series data from October 1987 to September 2001 were used in model calibration (1987-94) and validation (1994-01). The model performance was evaluated at daily, monthly and annual time scales by using a number of performance indicators. The comparison suggests that the use of areal precipitation is likely to improve model performance at smaller spatial scales, such as sub-catchments representing tertiary level streams, having drainage area in the range of 600 to 2,300 km^2. Whereas reasonably good simulations can be achieved for larger scales representing the Karkheh River and its major tributaries (drainage area of greater than 5,000 km^2) under both precipitation scenarios.

Keywords: hydrological modeling, precipitation, SWAT, water balance, input data uncertainty, Karkheh basin

1. Introduction

The use of hydrological models in the planning and management of water resources is increasing given the advances in the model development and the ever increasing need to address complex water issues. However, despite immense progress, hydrological predictions still involve uncertainties, which can be the result of uncertainties in data, model structure and parameters, boundary conditions and randomness in the natural processes (e.g., Beven, 1993 and 2001; Uhlenbrook et al., 1999; Wagener et al., 2004; Maskey et al., 2004). Addressing these uncertainties is very important for ensuring better decision making. This essentially requires more progress on various aspects such as improving existing models, searching new theories and reducing uncertainties in input data.

Among the wide array of models, the Soil Water Assessment Tool (SWAT) has gained international acceptance as a robust (interdisciplinary) model suitable for application in large river basins (Arnold et al., 1998; Neitsch et al., 2005; Gassman et al., 2007; Faramarzi et al., 2009). SWAT has been used successfully in many countries for studying issues related to hydrology, pollution and water resource management. SWAT offers a range of possibilities for defining model structure and input data. But, the input of climatic data is still very simple. SWAT uses climatic data from the gauge located nearest to the centroid of each sub-catchment, which may not always represent overall catchment climatic conditions. This is particularly true in mountainous terrains, where spatial heterogeneity is high. This in turn has an impact on the model formulation process (e.g., parameterization) and quality of the results. The main objective of this paper is to evaluate how improved precipitation input influences SWAT's hydrological simulations. In this study, we used areal precipitation and compared the model performance (observed versus simulated streamflow hydrograph) under current SWAT precipitation input possibilities. The model is applied to the mountainous, semi-arid Karkheh basin, Iran.

2. Materials and Methods

2.1 Brief description of the study area

The Karkheh basin (Figure 1) is located in the western part of Iran, between 30° to 35° northern latitude and 46° to 49° eastern longitude. The basin is characterized by a Mediterranean climate, having cool, wet winters and hot, dry summers. The total drainage area of the basin is 50,764 km^2 of which 80% is part of the Zagros Mountains. The Karkheh River has four major tributaries: Gamasiab, Qarasou, Saymareh and Kashkan. It starts after the confluence of Saymareh and Kashkan and extends towards the Khuzestan plains where it eventually terminates in the Hoor-Al-Azim swamp. The Hoor-Al-Azim swamp is a large transboundary wetland shared between Iran and Iraq, which is connected to the Euphrates-Tigris system. SWAT was applied to the upper Karkheh basin (42,620 km^2). The modeled area is located in the Zagros mountain range where all the major rivers and their tributaries originate, generating almost all of the Karkheh basin's runoff. Further details on the study area can be found at Sutcliffe and Carpenter (1968), Masih et al. (2009), Ahmad et al. (2009) and Muthuwatta et al. (2009).

2.2 The model set-up and performance evaluation

The SWAT 2005 modeling system, version ARCSWAT 2.0 (Winchell et al., 2008) was used for the project set-up. The Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) of 90-m was used for sub-catchment delineation. The study area was divided into 71 sub-catchments (Figure 1) using a threshold value of 300 km^2 for sub-catchment delineation. The hydrological response units (HRUs) were defined based on land cover, soil and slope. The land cover map we used was prepared with field data, GIS coverage and NDVI images based on remote sensing data from Moderate Resolution Imaging Spectroradiometer (MODIS) for one cropping year (Ahmad et al., 2009). A soil texture classification map was available from the relevant Iranian department, and the slopes were derived from the selected DEM. Daily climatic data for the period January 1, 1987 to September 30, 2001 were used for the model simulations. The study period was divided into calibration (1987-94) and validation (1994-01). Daily precipitation data from 41 stations and temperature from 11 climatic stations were used. The location of climatic gauges used in our study is shown in Figure 1. Missing data were filled by using data from other stations based on regression analysis. Finally, the Hargreaves' method was used to estimate potential evapotranspiration (Hargreaves et al., 1985).

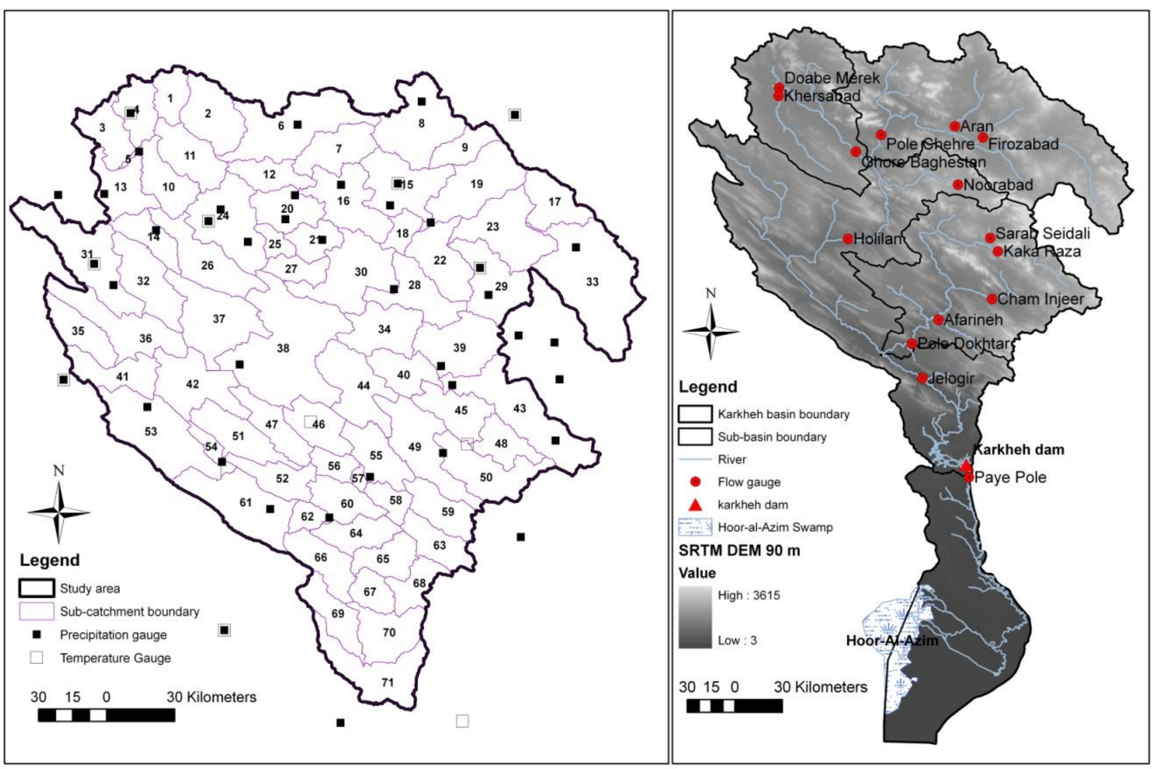

Figure 1. *Salient features of the Karkheh basin (right) and location of study sub-catchments with used climatic data stations (left)*

For the baseline scenario, climatic data from a station nearest the centroid of one of the sub-catchments was used in the model simulations. This scenario is referred to as the point precipitation scenario. In the second scenario, daily station precipitation data were interpolated and aggregated at the sub-catchment level outside of the SWAT environment by using inverse distance technique. We then assigned a virtual precipitation gauge with the interpolated catchment precipitation for each of the 71 sub-catchments. In this scenario, the model simulations were performed by changing only the precipitation data and keeping the rest of the data and calibrated parameters the same, as in the first scenario. This scenario is referred to as the areal precipitation scenario. Finally, we made a comparison between performance achieved by point and areal precipitation scenarios. The hydrological performance was evaluated at 15 streamflow gauges (Figure 1) using Coefficient of Determination (r^2) and Nash-Sutcliffe efficiency (NSE) at daily and monthly time scales. The observed and simulated annual volume balances were also compared.

3. Results and Discussions

3.1 Calibration and validation results based on the point precipitation scenario

A summary of calibration and validation results is presented in Table 1, showing the evaluated performance measures at daily, monthly and annual time scales for the 15 streamflow gauges across the Karkheh River system. In general, observed and simulated streamflow corresponded well with each other at most of the streamflow gauges, both for the calibration and validation periods. For instance, a monthly R^2 value of greater than 0.7 was achieved for 11 out of 15 streamflow gauges. These results suggest that the dynamics of the streamflow hydrographs were modeled reasonably well during calibration and validation periods for most of the study gauges. Similar patterns were observed for daily and monthly Nash-Sutcliffe efficiency (NSE) values, with the exception of a few sub-catchments showing poor NSE. Spatial comparison of the study gauges suggested that the modeling results were superior for the Karkheh River and all of its major tributaries. This is evident from the higher R^2 and NSE values and lower volume error for the gauges located on these rivers (e.g., Paye Pole and Jelogir at the Karkheh River; Holilan at the Saymareh River; Pole Dokhtar at the Kashkan River; Ghore Baghestan at the Qarasou River; and Pole Chehre at the Gamasiab River). However, minor tributaries (tertiary level streams) depicted variable results. In some cases, poor performance could be the result of various limitations such as precipitation and discharge data uncertainties, inappropriate model structure and lack of information included about the various water-use purposes.

3.2 Impact of the areal precipitation input on the model simulations

A comparison of point and areal precipitation scenarios (Table 1) indicates both increases and decreases in the assessed performance indicators. However, a clear spatial difference was identified from the results, with considerable improvement shown by using areal precipitation inputs for most of the tributaries of the Qarasou, Saymarey and Kashkan Rivers (indicated by the gauges: Doabe Merek, Noorabad, Sarab Seidali and Kaka Raza).

Table 1. *Summary of calibration and validation results for the point and areal precipitation scenarios*

ID	*Gauge Name*	*Drainage area (km^2)*	*Calibration (October 1987 to September 1994)*							*Validation (October 1994 to September 2001)*						
			Daily		Monthly		Mean annual flow (m^3/s)			Daily		Monthly		Mean annual flow (m^3/s)		
			R^2	NSE	R^2	NSE	Obs. (m^3/s)	Sim. (m^3/s)	Diff. (%)	R^2	NSE	R^2	NSE	Obs. (m^3/s)	Sim. (m^3/s)	Diff. (%)
Point Precipitation Scenario																
1.1	Aran	2320	0.68	0.66	0.85	0.80	5.0	4.0	-20	0.75	0.59	0.84	0.61	3.7	5.4	45
1.2	Firozabad	844	0.44	0.30	0.67	0.65	1.9	2.1	8	0.50	-0.95	0.64	-0.65	1.4	2.1	54
1.3	Pole Chehre	10860	0.77	0.75	0.91	0.90	41.5	39.4	-5	0.70	0.70	0.87	0.86	28.3	31.0	10
2.1	Doabe Merek	1260	0.69	0.57	0.83	0.72	6.7	7.0	5	0.22	0.11	0.26	0.11	4.7	3.7	-22
2.2	Khersabad	1460	0.38	-3.21	0.64	-6.66	1.8	4.6	160	0.44	-2.50	0.73	-5.16	1.3	3.9	192
2.3	Ghore Baghestan	5370	0.76	0.61	0.90	0.74	25.3	27.1	7	0.54	0.46	0.81	0.78	17.0	17.2	1
3.1	Kaka Raza	1130	0.56	0.32	0.62	0.30	14.7	7.5	-49	0.54	0.43	0.75	0.54	10.7	6.8	-36
3.2	Sarab Seidali	776	0.67	0.13	0.85	0.67	9.6	10.2	5	0.67	-0.04	0.75	0.03	7.3	8.8	19
3.3	Cham Injeer	1590	0.72	0.72	0.86	0.85	12.6	12.8	1	0.57	0.12	0.70	0.02	9.9	13.2	34
3.4	Afarineh	800	0.48	-0.76	0.77	-5.94	4.7	13.8	191	0.39	-2.46	0.69	-6.83	3.4	12.2	260
3.5	Pole Dokhtar	9140	0.75	0.73	0.88	0.83	64.7	74.0	14	0.66	0.48	0.83	0.46	47.1	69.5	47
4.1	Noorabad	590	0.27	-0.01	0.42	0.19	4.5	3.2	-29	0.45	0.45	0.61	0.58	3.0	3.3	7
4.2	Holilan	20863	0.79	0.78	0.91	0.91	86.7	80.5	-7	0.81	0.81	0.92	0.92	63.7	61.1	-4
4.3	Jelogir	39940	0.80	0.75	0.91	0.86	184.5	206.1	12	0.83	0.73	0.93	0.80	140.1	174.3	24
4.4	Paye Pole	42620	0.70	0.69	0.90	0.89	209.6	211.4	1	0.71	0.70	0.92	0.90	210.5	211.5	0.5
Areal Precipitation Scenario																
1.1	Aran	2320	0.75	0.58	0.91	0.82	5.0	6.0	20	0.65	0.19	0.78	0.17	3.7	6.2	65
1.2	Firozabad	844	0.56	-0.32	0.73	-0.01	1.9	3.0	56	0.57	-2.97	0.64	-0.65	1.4	3.0	116
1.3	Pole Chehre	10860	0.76	0.55	0.90	0.75	41.5	51.1	23	0.61	0.52	0.76	0.59	28.3	39.7	40
2.1	Doabe Merek	1260	0.73	0.72	0.87	0.85	6.7	6.2	-7	0.53	0.51	0.68	0.66	4.7	4.0	-17
2.2	Khersabad	1460	0.36	-3.91	0.68	-7.78	1.8	4.9	172	0.38	-1.93	0.61	-5.22	1.3	4.0	195
2.3	Ghore Baghestan	5370	0.78	0.64	0.90	0.74	25.3	26.9	6	0.62	0.52	0.83	0.71	17.0	19.3	14
3.1	Kaka Raza	1130	0.75	0.59	0.84	0.63	14.7	10.6	-28	0.71	0.61	0.83	0.74	10.7	9.5	-11
3.2	Sarab Seidali	776	0.74	0.58	0.83	0.72	10	9.0	-6	0.70	0.49	0.74	0.46	7.3	7.8	6
3.3	Cham Injeer	1590	0.74	0.65	0.88	0.72	12.6	15.3	22	0.62	-0.04	0.76	-0.27	9.9	14.5	46
3.4	Afarineh	800	0.29	-0.17	0.70	-2.03	4.7	10.6	125	0.26	-1.09	0.57	-3.31	3.4	9.9	192
3.5	Pole Dokhtar	9140	0.74	0.72	0.91	0.86	64.7	74.8	16	0.65	0.51	0.82	0.49	47.1	68.7	46
4.1	Noorabad	590	0.47	0.44	0.77	0.67	4.5	4.5	-1	0.49	0.43	0.66	0.49	3.0	3.9	29
4.2	Holilan	20863	0.79	0.70	0.91	0.83	86.7	99.3	15	0.80	0.75	0.88	0.80	63.7	76.8	21
4.3	Jelogir	39940	0.79	0.62	0.91	0.70	184.5	231.3	25	0.79	0.60	0.89	0.59	140.1	192.7	38
4.4	Paye Pole	42620	0.68	0.62	0.90	0.79	209.6	239.4	14	0.66	0.62	0.86	0.76	210.5	234.4	11

[a]Validation period for Firozabad and Paye Pole refer to October 1994 to September 1999.
[b]Obs., Sim., and Diff., refers to observed, simulated and difference, respectively.

On the contrary, Gamasiab River and its tributaries showed poor performance in terms of Nash-Sutcliffe efficiency despite improvements in the coefficient of determination (gauges: Aran, Firozabad and Pole Chehre). In the case of the Gamasiab basin, the decrease in NSE is attributed to high volume error as a result of significantly higher areal precipitation compared to the point precipitation in its sub-catchments. However, it should be noted that these results were obtained by keeping same model parameters as those used in the point precipitation scenario. We also tested whether or not recalibrating some of the model parameters for the areal precipitation scenario would improve the model performance. The results showed performance similar to the point precipitation scenario could be achieved for this region using areal precipitation inputs with some changes in the model parameters. In general, the streamflow regime for the Karkheh River and its major tributaries was modeled reasonably well under both scenarios. For example, daily Nash-Sutcliffe efficiency for the selected gauges on these Rivers ranged from 0.46-0.82 and 0.52-0.75 under point and areal precipitation scenarios, respectively.

Furthermore, the comparison also revealed that areal precipitation could not improve performances for three of the poorly performing smaller tributaries (represented by gauges: Afarineh, Khersabad and Firozabad). Therefore, we stress the need for accumulating more data on different aspects such as soil properties, precipitation and temperature lapse rates, snow fall and snowmelt dynamics, water abstractions for different uses and groundwater and surface water interactions including the influence of the karst formations in these areas. It is also worth acknowledging that acquiring more refined datasets is always difficult, particularly for mountainous regions because of factors like the cost of installing and monitoring data networks, high spatial heterogeneity and difficult and inhospitable terrain. Nonetheless, it would be prudent to revisit the modeling structure and parameter ranges for such cases in light of available information. This could help in improving the model results. In this study, after screening the impact of precipitation, we attempted to revise the model parameter ranges for these low-performing sub-catchments in light of (limited) available information. For instance, during the calibration strategy, the global values were defined based on available information for most of the parameters such as soil depth of different soil types and lapse rates of temperature and precipitation. For these sub-catchments, changes in the global values of soil depth, soil available water capacity and lapse rate were tested. For instance, the maximum soil depth for the rock outcrop soil was defined as 1 meter under global calibration settings but was revised to 1.5 meters for forest and agricultural land use categories. This exercise produced reasonable improvements in the annual water balance simulations, but only marginal improvements in the Nash-Sutcliffe efficiency and coefficient of determination were observed. Finally, while modeling large river basins it is important to acknowledge the modeling limitations and uncertainties for poorly modeled areas representing certain smaller regions or sub-catchments of a larger basin. These limitations must be considered in interpreting and using the results in decision making processes.

4. Conclusions

This study compared the SWAT model performance under point and areal precipitation input scenarios for the Karkheh basin, Iran. The model performance was assessed by using coefficient of determination, Nash-Sutcliffe efficiency at daily and monthly time scales and an annual volume balance at the 15 selected streamflow gauges located within the main and tributary rivers.

The comparison of model simulations under point and areal precipitation input showed variable performance across the basin. Better results were obtained in the case of areal precipitation for most of the studied gauges located on the minor tributaries of the Kashkan, Qarasou and Saymareh Rivers.

However, comparable results were found for the gauges located on the Karkheh River and its major tributaries, indicating similar performance at higher spatial scales under both precipitation input scenarios due to the averaging-out effect of the precipitation input. In general, we concluded that the use of areal precipitation helps in improving SWAT model formulation and consequently improves the reliability of the model results, particularly at finer spatial and temporal resolutions. Development of an additional (optional) component for the interpolation of climatic data within the existing SWAT model framework is recommended. Considering the profound historic development of SWAT over the last 30 years, attention towards this addition would be in line with the overall (ongoing) development of other components of the model.

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Modeling Environmental Benefits of Conservation Practices in Richland-Chambers Watershed, Texas

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Abstract

The effectiveness of conservation practices (CPs) is site specific due to variations in soil, topography, land use and climate. Although CPs are widely known to preserve and enhance water quality and conservation of natural resources, further studies are necessary to quantify their environmental benefits at different spatial scales and geographic locations. This is crucial in terms of time, technical and financial resources. Simulation models offer promise as tools for assessing the environmental benefits of CPs, but no clear guidelines exist on representing them. The objective of this study was to demonstrate a modeling methodology for determining the long-term effectiveness of CPs on sediment, total nitrogen (TN) and total phosphorus (TP) loads at the field and watershed levels. We studied Richland-Chambers Watershed (RCW) (5,157 km^2) in the upper Trinity River Basin, Texas. The Soil and Water Assessment Tool (SWAT) model was calibrated and validated for the pre- and post-BMP periods for flow, sediment and nutrients. The CPs simulated include terraces, contour farming, conservation cropping, conversion of agricultural land to pasture, prescribed grazing, range management, brush management and critical area planting. The ‘critical area planting’ practice produced the greatest reduction in sediment and TN. Also highly effective in reducing (98%) sediment yield at the field level were agricultural land converted to pasture and the practice of brush removal (followed by pasture planting with prescribed grazing) combined with nutrient management. Collectively, the BMPs resulted in 0.9%, 2.4% and 2.5% reductions in sediment, TN and TP, respectively, at the watershed outlet. This study provides guidance in simulating the various CPs within SWAT and systematic quantification of how the suite of BMPs reduces sediment and nutrient loadings in a watershed from field level to watershed outlet.

Keywords: Conservation practices, SWAT, terrace, conservation cropping, brush management, prescribed grazing

1. Introduction

The government invests substantially in conservation programs (or best management practices [BMPs]), especially through the 2002 Farm Bill. There are government programs that subsidize BMP expenditures based on the type. However, BMP implementation by farmers is voluntary for the most part. Although conservation practices are widely known to preserve and enhance water quality and conservation of natural resources, further studies are necessary to quantify their environmental benefits at different spatial scales and geographic locations. It is important to estimate the pollution reduction efficiency of these BMPs in order to help policy makers make decisions on future resource allocations. Published literature values exist for some BMPs studied in specific locations. However, their effectiveness varies with the geographic setting because of variability in landscape characteristics, soils and weather. A comprehensive watershed modeling tool can more effectively capture this variability and simulate the impacts of BMPs in a broader context, limiting labor, time and financial expenses associated with intensive field studies. No clear guidelines exist on how several BMPs should be represented in the simulation models. Moreover, non-availability of long-term and continuous monitoring data limits BMP field validation efforts. The overall objective of this study was to apply the SWAT model to simulate various BMPs and assess their long-term impacts on sediment and nutrient loads at field (or Hydrologic Response Unit [HRU]) and watershed levels.

2. Methods

2.1 Soil and Water Assessment Tool (SWAT)

SWAT is a nonproprietary hydrologic/water quality model developed by the United States Department of Agriculture-Agriculture Research Service (USDA-ARS) (Arnold et al., 1998 http://www.brc.tamus.edu/swat/). SWAT is also available within the U.S. Environmental Protection Agency's Better Assessment Science for Integrated Point and Nonpoint Sources (USEPA's BASINS) as one of the models the USEPA supports and recommends for state and federal agencies to address point and nonpoint source pollution. The SWAT model is a distributed-parameter, continuous-scale model that operates on a daily time-step. It has the capability to simulate a variety of land management practices and has been used as a tool to assess water resource and water quality issues across a wide range of spatial and temporal scales (Gassman et al., 2007). The SWAT model divides the watershed into a number of sub-watersheds based on topography and user-defined threshold drainage area (minimum area required to begin a stream). Each sub-watershed is further divided into Hydrologic Response Units (HRUs), which are defined by unique combinations of soil, land use and land management. HRUs are the smallest landscape component of SWAT used for computing hydrologic processes. The model first determines the overland loadings of flow (runoff), sediment and nutrients and then routes these loadings through the stream network. The present study used SWAT2005 and the ArcGIS (ArcSWAT) interface tool (Olivera et al., 2006) designed to use ArcGIS 9.x GIS platform to generate model inputs and execute SWAT2005.

2.2 Model Setup

We applied the SWAT model to the 5,157 km^2 Richland-Chambers Watershed (RCW) (figure 1). The major land uses in RCW are pasture (51%) followed by cropland (20%), forest (14%), range (6%) and others, including water and urban uses. Daily rainfall and minimum and maximum temperature data were collected from 11 National Weather Service COOP rainfall stations in and around the watershed for the time period ranging from 1975 to 2006. Missing rainfall or temperature data were replaced by data from the nearest stations. Solar radiation, wind speed and relative humidity data were generated with SWAT's built-in weather generator. Using a DEM with 30-m resolution, SSURGO soils, and NLCD 2001 land use/land cover merged with the BMP areas, the RCW was delineated into 156 sub-watersheds and further subdivided into 3,687 HRUs. Grazing was simulated on 75% of the pastureland, and the rest was simulated as hay with three cuttings per year. Winterwheat (32%) was the dominant crop followed by corn (30%), sorghum (22%) and cotton (16%). We used typical management inputs related to type and dates of tillage and type, rates and dates of fertilizer use. Also, 307 PL-566 reservoirs were incorporated into the simulation. The pertinent reservoir data (i.e., surface area and storage at principal and emergency spillways) was lumped within a sub-watershed because there was more than one PL-566 reservoir in a sub-watershed. These PL-566 reservoirs were modeled as ponds in SWAT and were considered in the pre-BMP condition because of their existence during the model calibration period. Reservoir data, including locations and dimensions, were obtained from the U.S. Army Corps of Engineers National Inventory of Dams (NID) dataset (USACE, 1982).

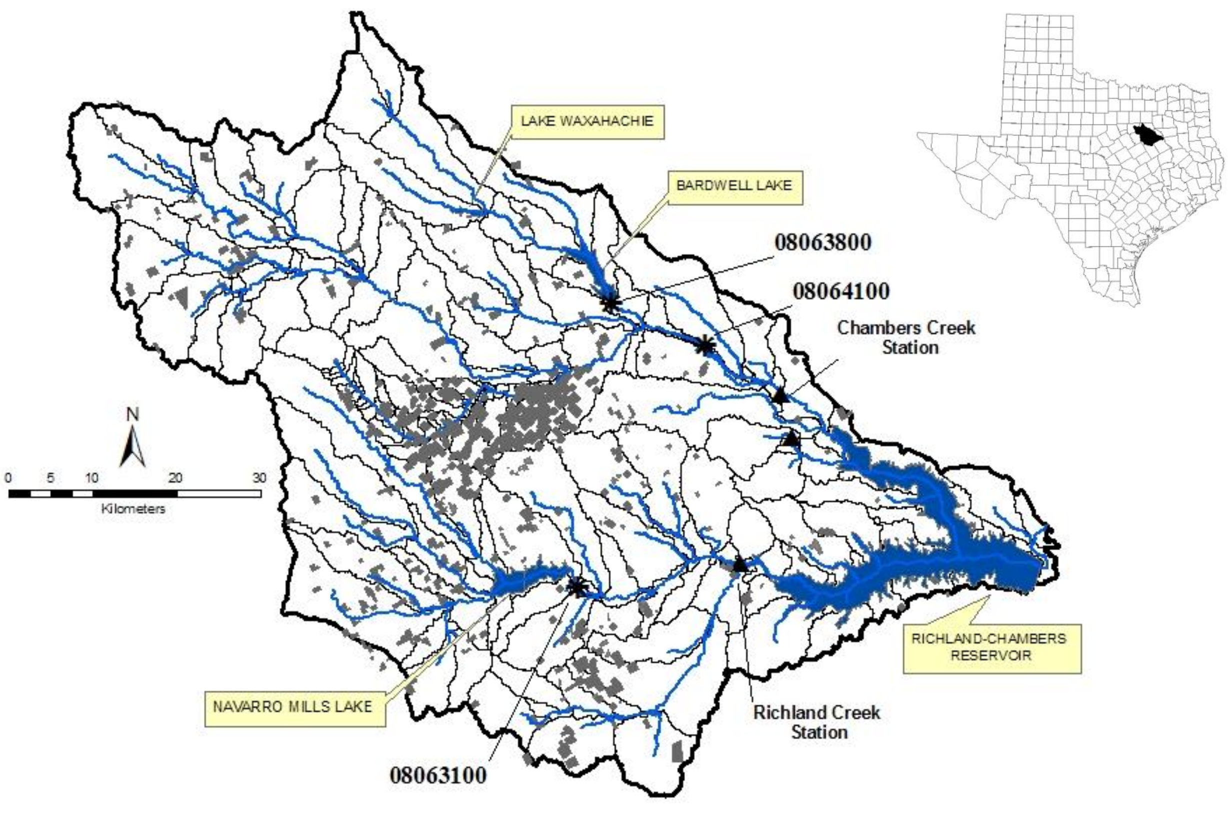


Figure 1. *SWAT delineated sub-watersheds, monitoring stations (Richland Creek station, Chambers Creek station, 08063800, 08064100 and 08063100) and the best management practices implemented in Richland-Chambers Watershed*

2.3 Calibration and validation

Flow and water quality data from USGS gauging stations (08064100, 08063100 and 08063800) and the monitoring stations managed by Tarrant Regional Water District (TRWD) (Richland Creek and Chambers Creek stations) were used to calibrate the SWAT model for flow, sediment and nutrients (figure 1). All three

USGS gauging stations had long-term, continuous records of observed streamflow data. Continuous monitoring data records for sediment and nutrients were not available for this watershed. However, grab-sample data were available (usually 2-5 samples per year with few years missing in some cases) at USGS station 08604100 and all three TRWD monitoring stations. We found that land owners began to implement conservation practices (CPs) throughout the watershed in 1996. Therefore, the model calibration and validation approach was modified to reflect this change in land use and land management. The model was calibrated during the pre-BMP period (up to 1996). The flow calibration was done at annual and monthly time steps at three USGS gauging stations from 1982 to 1995 with the first two years serving as a model warm-up period. This was the pre-BMP calibration, which considered no BMPs. During calibration, care was also given to matching the proportions of surface flow and base flow contribution to streamflow. Base flow contribution to streamflow was analyzed using the base flow filter program (Arnold and Allen, 1999; Arnold et al., 1995; Nathan and McMahon, 1990). A rigorous calibration of sediment and nutrients could not be performed due to limited sampling data. However, certain model parameters were adjusted, giving careful consideration to the key upland and channel processes influencing model simulated pollutant loads.

For validation, estimates on the inflow to Bardwell Lake and Navarro Mills Lake were obtained from the Corps of Engineers hydrologic data website (USACE, 2007), and TRWD provided the Richland-Chambers Reservoir observed data against which the simulated model streamflow values were compared. This is considered spatial validation, where model simulations are validated for the same period as calibration but at a different location(s).

Mean, standard deviation, coefficient of determination (R2) and Nash-Sutcliffe modeling efficiency (NSE) (Nash and Sutcliffe, 1970) were used to evaluate model predicted streamflow during calibration and validation. We compared mean simulated flow, and sediment and nutrient loadings for days with available grab-sample data with mean observed data. Tuppad et al. (2009) presents the type, range, actual value and a brief description of the variables used for calibration along with the component(s) the variable influences.

2.4 BMP simulation and post-BMP model performance

The pre-BMP calibrated model is the starting setup. The BMPs simulated include terraces, contour farming, conservation cropping, conversion of agricultural land to pasture, prescribed grazing, range management, brush management, and critical area planting. Considering the hydrologic/water quality processes simulated by SWAT and the watershed subdivision pertaining to this study, the parameters and their values selected (table 1) were based on published literature and expert opinion. A brief description of the BMPs can be found in Tuppad et al. (2009). For more details, refer to USDA National Handbook of Conservation Practices (USDA-NRCS, 2007). As in the pre-BMP calibration and validation, the SWAT model performance was evaluated during the post-BMP analysis for long-term flow from 1996 through 2006 at three USGS gaging stations. Simulated sediment and nutrient values at the USGS 08064100, Richland Creek, and Chambers Creek stations were compared against the observed grab sample data at these station in terms of median, 25th, and 75th percentile.

Table 13. *Model parameters used to represent pre-BMP and post-BMP conditions in SWAT*

BMP	Variable name	Pre-BMP (from calibration)	Post-BMP
Terrace + Contour	CN2 P-factor SLSUBBSN	Varies 1.0 Assigned by SWAT	CN2 reduced by 6 from calibration values 0.12, if slope = 1 to 2% 0.10, if slope = 3 to 8% ----[a]
Terrace + Contour + Conservation tillage+ nutrient management	EFFMIX CN2 P-factor SLSUBBSN	0.70 – 0.75 varies 1.0 Assigned by SWAT	0.25 CN2 reduced by 7 from the calibration values 0.12, if slope = 1 to 2% 0.10, if slope = 3 to 8% ----[a]
Contour + Conservation tillage+ nutrient management	EFFMIX CN2 P-factor	0.70 – 0.75 varies 1.0	0.25 CN2 reduced by 7 from the calibration values 0.6, if slope = 1 to 2% 0.5, if slope = 3 to 8%
Agriculture to pasture with prescribed grazing	 CN2 BIO_MIN	Cotton-corn rotation Varies 500	Pasture with grazing CN2 reduced by 8 from the calibration values 3000
Improved pasture with prescribed grazing + Nutrient management	CN2 BIO_MIN	Varies 500	CN2 reduced by 10 from the calibration values 3000 Auto fertilization
Prescribed grazing + Nutrient management	CN2 BIO_MIN	Varies 500	CN2 reduced by 6 from the calibration values 3000 Auto fertilization
Range with prescribed grazing	CN2 BIO_MIN	Varies 500	CN2 reduced by 6 from the calibration values 3000
Brush management	Land management CN2 BIO_MIN	Mesquite Varies 500	Pasture CN2 reduced by 10 from the calibration values 3000
Brush management + Nutrient management	Land management CN2 BIO_MIN	Mesquite Varies 500	Pasture CN2 reduced by 10 from the calibration values 3000 Autofertilization
Critical area planting + Nutrient management	Land management CN2	Barren Varies	Pasture CN2 reduced by 20 from the calibration values Autofertilization

BIO_MIN: Minimum biomass required to allow grazing
CN2: Initial SCS runoff curve number for moisture condition II
EFFMIX: Mixing efficiency of tillage operation
P-factor: Conservation support practice factor
SLSUBBSN: Slope length
[a]: Estimated for each terrace based on SWAT assigned overland slope of the HRU where it is installed
SLSUBBSN = (x * S + y) * 100/S, where S is the average slope of the HRU, x = 0.15 and y = 0.9 (ASAE Standards, 2003)

2.5 BMP Evaluation

In order to assess the long-term impacts of the BMPs, the calibrated model of the pre-BMP setup was run for 32 years (1975–2006, including the first two years of warm-up for parameter initialization) to establish a baseline condition. The post-BMP model setup was run for the same 32-year period, and the post-BMP outputs were compared with those from the baseline model setup. The effects of BMP implementation on water quality are presented as percent reductions in average annual sediment, TN and TP loadings at the HRU level and at the watershed outlet. The HRU-level percent reductions represent overland load reductions due to BMP implementation. Load reductions at the watershed outlet include cumulative load reductions considering overland transport and routing through the stream network. The percent reduction was calculated as:

$$reduction,\% = \frac{100(preBMP - postBMP)}{preBMP} \qquad \text{Eq. (1)}$$

3. Results and Discussion

3.1 Model Calibration and Validation

Calibration results for measured and simulated annual and monthly flow data for the three USGS gauging stations is presented in table 2. Based on the rating scale of Moriasi et al. (2007), model performance was considered very good with both R2 and NSE being ≥0.90 at USGS gauging stations 08064100 and 08063100 and was satisfactory at the USGS gauging station 08063800. Due to non-availability of water quality data at USGS stations 08063100 and 08063800, only data from station 08064100 was used to calibrate the model for sediment and nutrients. At the USGS station 08064100, model simulated sediment, organic nitrogen and mineral nitrogen were close to observed values (within 4%) whereas simulated mineral and total phosphorus were higher because of a large overprediction by the model on a few days (table 3). Due to the limited sampling data, matching the daily simulated values with the observed values considering only those days of observation was tedious. Additional monitoring data would have been very helpful in adequately calibrating and validating the model predicted loadings.

Table 2. *Summary of model performance statistics for flow at the USGS gauging stations during calibration in the pre-BMP period (1984-1995)*

Station	Time-step	Mean (m^3/s)		Std. Dev (m^3/s)		R2	NSE
		Measured	Simulated	Measured	Simulated		
08064100							
	Annual	14.66	14.3	5.87	5.95	0.94	0.93
	Monthly	14.69	14.33	19.85	16.66	0.91	0.90
08063100							
	Annual	5.73	5.79	2.96	3.22	0.99	0.98
	Monthly	5.74	5.83	7.97	8.14	0.98	0.98
08063800							
	Annual	3.39	3.54	1.70	1.81	0.63	0.55
	Monthly	3.40	3.54	5.21	4.07	0.67	0.44

Table 3. *Summary of model performance statistics for water quality at the USGS gauging station 08064100 during calibration in the pre-BMP period (1984-1995)*

Component (unit)	# of samples	Mean		Std. dev.	
		Measured	Predicted	Measured	Predicted
Sediment (t)	37	1541.50	1487.00	3249.40	1865.38
Organic N (kg)	91	1762.30	1735.00	5354.30	14276.00
Mineral N (kg)	41	3367.00	3256.00	7488.00	3.38
Mineral P (kg)	41	50.00	64.31	104.70	135.45
Total P (kg)	91	443.00	800.00	2041.00	4482.00

The model simulated cumulative inflow to Richland-Chambers was less than the TRWD estimated value by 1.3%. The simulated sediment load into the RC reservoir was less than the estimated value by 14%.

3.2 Post-BMP model performance analysis

The absolute percent difference between measured and simulated flows at annual and monthly time steps was up to 11%. The model performance was considered very good with both R2 and NSE being ≥0.81 at USGS gauging stations 08064100 and 08063100 and was satisfactory at the USGS gauging station 08063800 (table 4). The model simulated cumulative inflow to Richland-Chambers was less than the TRWD estimated value by 3.6%.

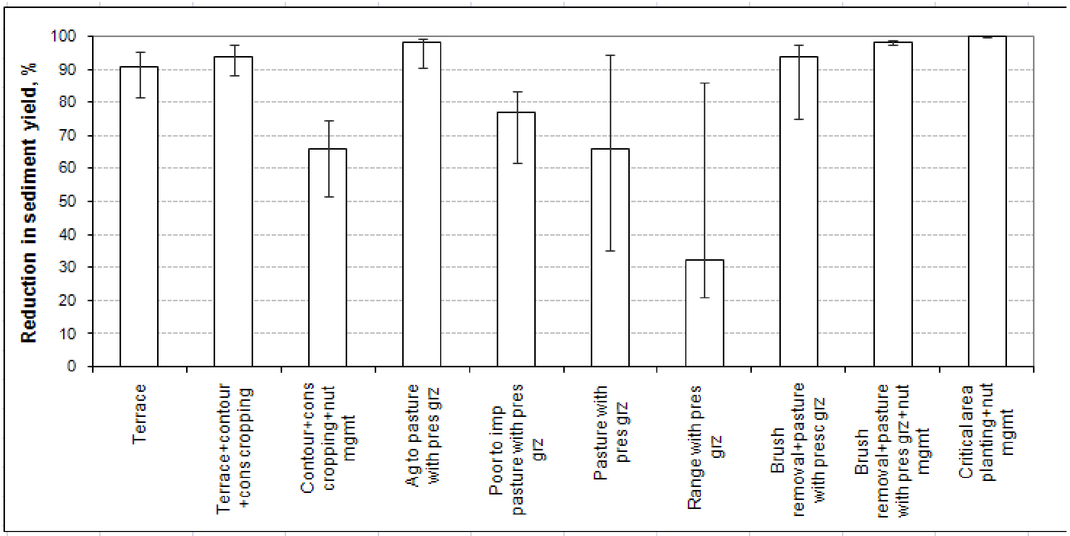
Contrary to the modeled results during the pre-BMP calibration at USGS station 08064100, during the post BMP period, model simulated mineral and total phosphorus mean values were close to the observed values whereas simulated sediment and mineral nitrogen means were higher and the simulated organic nitrogen mean was lower than observed values.

Table 4. *Summary of model performance statistics for flow at the USGS gauging stations during post-BMP period (1996-2006)*

Station	Time-step	Mean		SD		R2	NSE
		Measured	Simulated	Measured	Simulated		
08064100							
	Annual	10.30	11.51	8.32	7.03	0.84	0.81
	Monthly	10.35	11.56	17.18	14.88	0.85	0.84
08063100							
	Annual	3.95	3.63	3.44	3.12	0.99	0.97
	Monthly	3.97	3.68	7.87	7.33	0.99	0.98
08063800							
	Annual	2.54	2.81	1.93	1.42	0.67	0.64
	Monthly	2.54	2.82	4.71	3.31	0.64	0.40

3.3 BMP evaluation

Each of the BMPs simulated were implemented in more than one HRU. A wide range in pollutant reduction was observed when comparing all HRUs with the same type of BMP because of the variability in soils, slope and weather. The distribution (mean, minimum and maximum) in pollutant (sediment, TN and TP) reduction due to each type of BMP is illustrated in figures 2a, 2b, and 2c. Among all the BMPs simulated, the practice of planting pasture on critically eroded and exposed area known as 'critical area planting' produced the greatest reduction in sediment (99.8%) and total nitrogen (96.7%). The following BMPs were also highly effective in reducing sediment, TN and TP at the HRU level: agricultural land converted to pasture and brush removal (followed by pasture planting with prescribed grazing) combined nutrient management. Without field data on production practices for nutrient management, the practices were simulated by using the automatic fertilization option in SWAT wherein amount of each application and maximum amount that could be applied in a given year. Notice in figure 2 that there is a significant difference between the effectiveness of the brush removal practice (followed by pasture planting with prescribed grazing) with and without nutrient management. With nutrient management, reductions in TN increased from 41% to 91% and reductions in TP increased from 20% to 61%. Range management with prescribed grazing produced modest, nevertheless significant, reductions in sediment (32%), TN (33%) and TP (30%). Collectively, these BMPs resulted in 1%, 2% and 3% reductions in sediment, total nitrogen and total phosphorus, respectively, at the watershed level.



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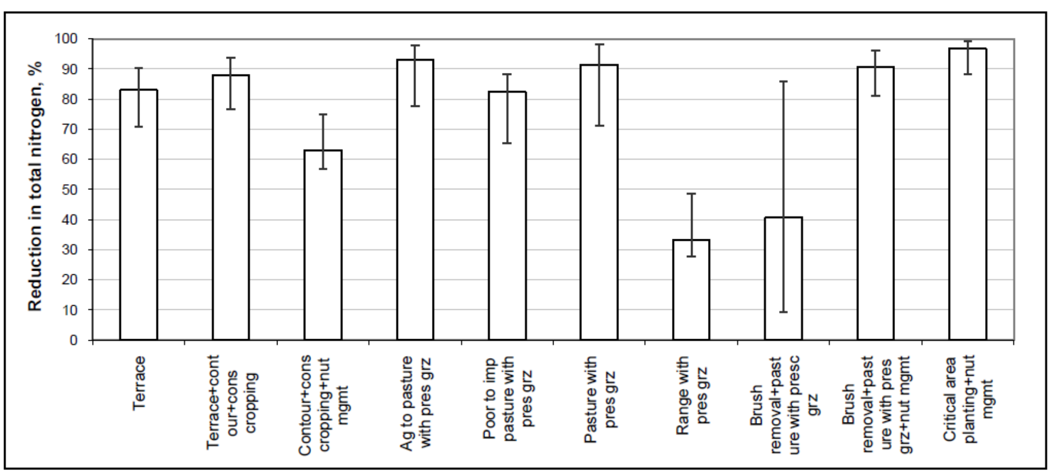

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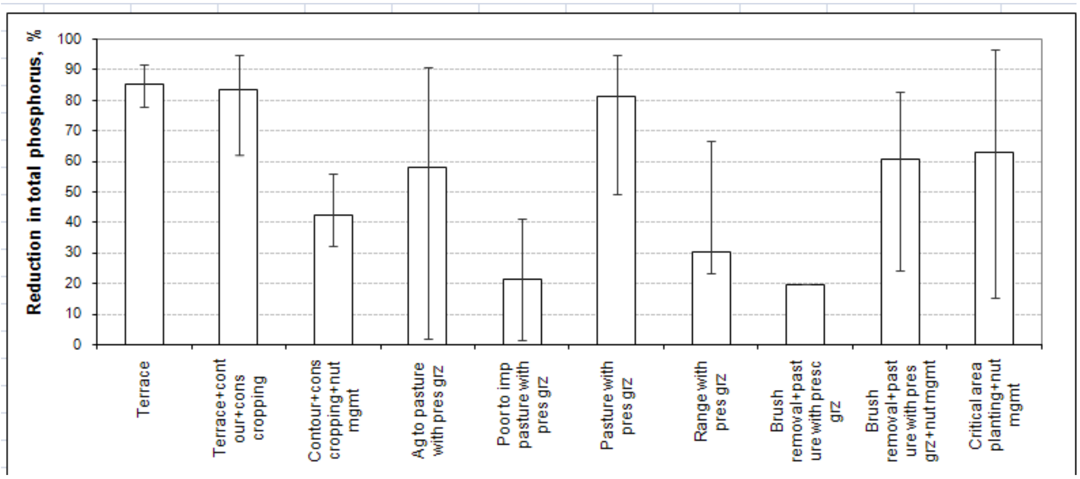

Figure 2. *HRU average load (bars) and range (minimum-maximum represented by the line through the bars) in pre- and post-BMP conditions, considering only BMP HRUs: (a) sediment, (b) total nitrogen, and (c) total phosphorus*

Conclusion

The SWAT model was used to simulate and assess the hydrologic and water quality impacts of several best management practices in Richland-Chambers Watershed in north central Texas. The BMPs simulated included terraces, conservation cropping, pasture planting, nutrient management, prescribed grazing, brush management, and critical area planting. In general, the BMPs achieved significant reductions at the HRU level. Average annual reduction in sediment ranged from 32% to 99.8%, TN ranged from 33% to 97% and TP ranged from 20% to 85%. At the watershed outlet, the reductions in sediment, total nitrogen, and total phosphorus achieved by the BMPs were 1%, 2% and 3%, respectively. The lower reductions at the watershed level are expected and reasonable due to the fact that the area of BMP implementation is only about 6% of the watershed area.

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Migration of SWAT 2005 into Open Modeling Interface (OpenMI) and its verification on the simulation of sediment transport in the Blue Nile

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Abstract

This paper describes software development of the SWAT model code into an OpenMI compliant version for improving SWAT flow and sediment routing through model integration. SWAT routing modules for flow and sediment use simplistic equations, and the model cannot simulate the sediment deposition process caused by flow velocity reduction due to the backwater effect. To improve the flow and sediment routing modules, SWAT was migrated into OpenMI for integration with a hydrodynamic model. The migration of SWAT into the OpenMI compliant version involved some modification to the source code. First, the initialization procedure was structured into one function rather than several modules. Secondly, SWAT was modified to run one time step from the beginning of simulation to the end. The last modification made to the SWAT code was to split the sediment into clay, silt and sand fractions to consider their role in the sediment transport formula of the hydrodynamic model. We undertook a case study in the Blue Nile by linking OpenMI-SWAT with SOBEK, a one-dimensional, hydrodynamic river model. The integrated model simulated the backwater effect and sediment deposition that might not have been possible using a single model. The developed OpenMI-SWAT compliant version can be further linked to groundwater, climate change and socioeconomic models to address integrated water resource management problems.

Keywords: SWAT, SOBEK, OpenMI, model integration

1. Introduction

Integrated modeling helps us to understand basin-level environmental problems such as soil erosion, reservoir sedimentation and the interactions between the two in order to make decisions based on a system-wide view. However, most of the existing models simulate individual processes, either erosion or deposition, at the catchment and channel level. Despite the fact that SWAT simulates sediment erosion and deposition processes at both the catchment and river reach scale, flow and sediment routing modules have relatively simplistic equations that do not capture the processes in long river reaches. SWAT uses Variable Storage (Williams, 1969) or Muskingum (Cunge, 1969) routing methods for flow. Both methods are approximations of the Kinematic wave model that do not consider the propagation of the upstream wave. Subsequently, these methods do not simulate the backwater effect that reduces flow velocity where there are hydraulic structures, mainly dams. The sediment routing module uses peak channel velocity to transport maximum sediment. This module is a simplification of the Bagnold's (1977) river power concept, modified by Williams (1980). Thus, the routing equations do not consider sediment transport characteristics, such as bottom shear stress, or take into account channel morphology, which determines whether erosion or deposition will occur given flow velocities (Benaman et al., 2005). Moreover, the routing methods do not simulate the effect of backwater on sediment deposition caused by hydraulic structures. Therefore, there was a need to improve SWAT routing modules either by introducing new equations or by linking SWAT with another model that has better routing of flow and sediment in long river reaches, such as a one-dimensional, hydrodynamic model. In this study, the latter option was chosen to make the best use of existing state- of-the-art models. Although there are various ways of linking models, we used the open modeling interface (OpenMI).

In this paper, we discuss the steps required to develop SWAT 2005 into an OpenMI compliant version, integrating the OpenMI compliant SWAT model with the SOBEK model and the verification of the integrated model in the Blue Nile river basin.

2. Open Modeling Interface (OpenMI)

The OpenMI standard is a software component interface definition for the computational core (the engine) of hydrological and hydraulic models (Gregersen et al., 2007). It relies entirely on a "pull-based" principle where communicating components (source and target components) exchange data in a predefined way and in a predefined format. OpenMI was developed by an EU co-financed HarmonIT project to easily link new and existing models. These linkages are quick and easy to customize. On the other hand, one limitation is that OpenMI does not account for the uncertainty introduced by each model.

3. Migrating SWAT 2005 into OpenMI

The key requirements for migrating a legacy model into the OpenMI framework is structuring the computational core to initialize, compute and finalize procedures and to allow the model to run one time-step at a time. SWAT has all the mentioned structures, except that initialization is done by several modules. Therefore, the initialization procedure was structured into one function. The other challenging task was modifying SWAT to run one time-step at a time instead of running daily loops within yearly loops. The time-step in SWAT runs in a loop from the beginning of the simulation year to the end, and loops everyday of the 365 or 366 days of the year. For example, if the SWAT simulation begins at the start of 1980 and goes to the end of 2003, it starts in 1980 and loops 1-366 days within that year. Next, it goes to 1981 and loops from 1-365 days and so on until the end of the last year, running a total of 8401 days during the simulation. Thus, SWAT was modified in such a way that the model runs only one time-step in which the day is linked to the year in order to account for the seasons. Each calendar day computed is used to simulate specific seasonal processes (such as agricultural activities). The last modification made to the SWAT code was to split the sediment into clay, silt and sand fractions to consider their role in sediment transport formula. However, the last point has nothing to do with being OpenMI compliant; it just helps to capture the transport processes.

The next step was to create a C# class that implements the ILinkableComponent interface to wrap the SWAT model engine. The process involves creating SwatDLL, SwatNativeDLL, SwatDllWrapper and SwatEngine classes (Figure 1). The former was done in Visual Fortran and the latter four classes were done using .Net framework.

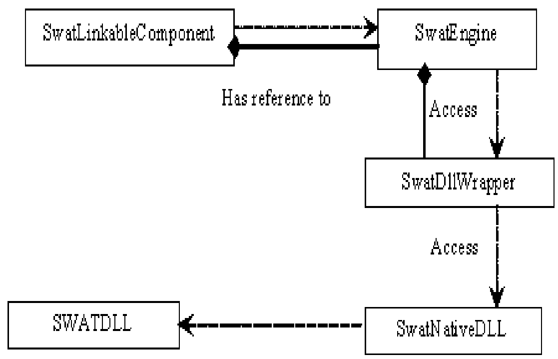

Figure 1. *Wrapping SWAT model engine*

The SWATDLL is the SWAT engine core that is compiled into a DLL. The engine core was reorganized to perform the following functions:

- initialize
- get_subbasin_count
- get_time_horizon
- compute_timestep
- get_values
- finalize

The SwatNativeDLL class is responsible for translating the Win32API from SwatDLL to .Net. It translates each function exported in FORTRAN into a method .Net (C#) format. The SwatDllWrapper class plays a role in converting FORTRAN conventions such as Array index into C# and error messages into .Net exception. In the SwatDllWrapper class, all methods from the SwatNativeDLL class are called by referencing the class. The SwatEngine class implements the IEngine interface and can be accessed through the SwatLinkableComponent class. It implements the following methods:

- Execution control methods (Initialize, PerformTimeStep and Finish)
- Time methods (GetCurrentTime , GetInputTime and GetEarliestNeededTime)
- Data access methods (SetValue and GetValue)
- Component description methods (GetMissingValueDefinition, GetComponentID and GetComponentDescription)
- Model description methods (GetModelID , GetModelDescription and GetTimeHorizon)

- Exchange items (GetInputExchangeItemCount and GetOutputExchangeItemCount)

The SwatLinkableComponent class is responsible for the creation of the SwatEngine class and for assigning this class a reference to a protected field variable in the LinkableEngine class, thus enabling this class to access the SwatEngine class.

4. Blue Nile verification

The SWAT model was used to simulate flow and soil erosion from the Upper Blue Nile. Its output (flow and sediment) was used as a boundary condition for the SOBEK model at the Upper Blue Nile outlet, El Deim. Then the SOBEK model simulated the morphological changes of river and reservoirs (Roseires and Sinnar) up till the outlet, Khartoum (Figure 2).

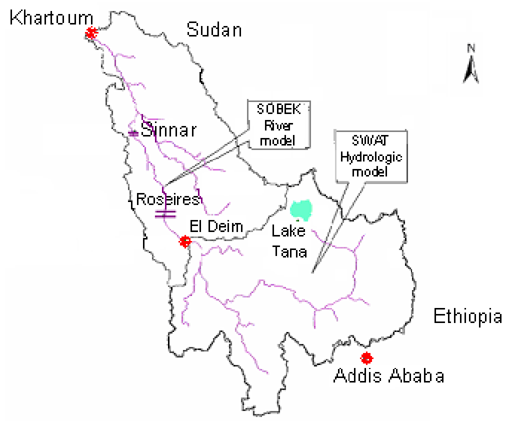

Figure 2. *Application of SWAT in the Upper Blue Nile and SOBEK in the Lower Blue Nile*

5. Models description

5.1 SWAT model

The Soil and Water Assessment Tool (SWAT) is a physical, process-based model developed in Texas by the USDA to simulate hydrological processes at the catchment scale on daily time-step (Arnold et al., 1998). The objective of SWAT model development was to be able to predict the impact of land management practices on water, sediment and agricultural chemical yields in large, complex watersheds with varying soils, land use and management conditions over long periods of time. SWAT divides a catchment or basin into subbasins by hydrological response unit (HRU). These units are based on soil type, land use and management practices. Thus, dividing the basin into HRUs will simulate hydrological processes in a semi-distributed way. SWAT simulates the hydrology of a watershed in two phases, the land phase then the water or routing phase of the hydrologic cycle. The land phase of the hydrologic cycle controls the amount of water, sediment and nutrient and pesticide loadings to the main channel. The routing phase of the hydrologic cycle defines the transport of water, sediment, nutrient and pesticide through the channel to the outlet of the catchment.

5.2 SOBEK model

SOBEK is a one-dimensional, hydrodynamic numerical modeling system capable of solving equations that describe unsteady water flow, sediment transport and morphology, and water quality. The flow module is described by continuity and momentum equations, and the morphological module is described by a sediment continuity equation (WL/Delft Hydraulics and Ministry of Transport and Management, 1995).

6. SWAT- SOBEK OpenMI model integration

SWAT was linked to SOBEK, a one-dimensional, hydrodynamic model, that was made OpenMI compliant by WL | Delft Hydraulics of Deltares. However, both OpenMI compliant models were tested carefully to determine whether they were providing the same results as their respective non-OpenMI compliant models. The test basically compared the number of files printed and their content. The next step was to link the two OpenMI compliant models using the OpenMI Configuration Editor (Figure 3). The following points were followed to link the model at run-time:

1. The calibrated SWAT and SOBEK models were populated with data using their interface and saved on the working disk together with their respective OMI files in separate folders. The OMI file contains the folder path and the filename of the OpenMI compliant LinkableComponent and the calibrated model folder name.
2. The two models were added to OpenMI editor using the Add Model method from the composition menu of the OpenMI editor. To load each model, the OMI files were browsed from the file system using the Add Model method. Each time the OMI file is loaded, the LinkableComponent reads its input file. In addition, a Trigger model was also loaded to set up a direct connection to SOBEK in order to trigger data requests from SWAT.

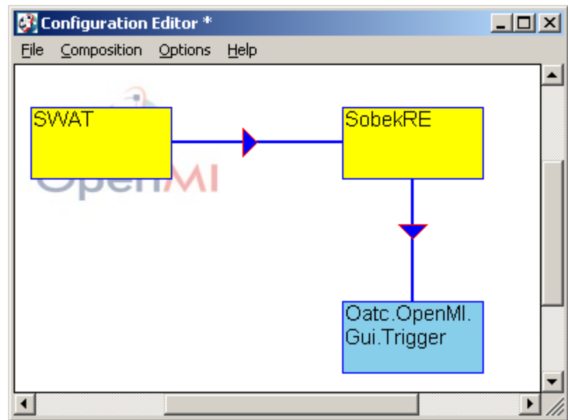

Figure 3. *OpenMI configuration editor used to configure link between the models.*

3. Connections between the models were added by clicking the Add Connection method, dragging the arrow from SWAT and dropping it on the SOBEK model. The connection link contains the output exchange items, input exchange items, quantities and elements of the models. Next, exchange items, quantities and elements were defined using the connection properties dialog box.
4. The output exchange items for SWAT define quantities such as flow, sediment (clay, silt, sand, etc.), locations (subbasin outlet and reach) and quantity properties (unit). The SOBEK model accepts these items as an input exchange items either from the node or reach where their boundary conditions were defined. However in this study, the output at reach 14 was used to define the boundary conditions for the SOBEK model.

The SWAT model ran from January 1990 to December 2003 while SOBEK ran from January 2000 to December 2003. The time-step for SWAT was one day, but for SOBEK, it was 3 hours. Computation starts when the Trigger performs Getvalues(), a call to SOBEK's linkable component at a specified timestamp. Thus, SOBEK starts the simulation, but it requires data from SWAT. Hence, it makes Getvalue() calls to the SWAT linkable component as well. Then SWAT will compute until it reaches the required time-step (2000), interpolate to three hours and return the value to SOBEK. In addition, SWAT does a data unit conversion before providing the SOBEK request. Once the models runs are completed, the results are visualized using the respective model graphic interface.

7. Integrated SWAT-SOBEK results and discussion

Before applying the coupled models to the Blue Nile case, they were tested using hypothetical flow conditions (i.e., by providing constant upstream flow boundary conditions to the calibrated SOBEK model and checking the results). Next, the input files from the OpenMI-SWAT model were provided to OpenMI-SOBEK. The runs were found to be successful, so we were assured that SWAT output was exchanged as boundary conditions for SOBEK at run time.

The integrated model was verified the observed flow at Roseires and Sinnar dams for the year 2000. During verification processes, the validated SOBEK model was used without further calibration with the SWAT output as boundary conditions. The reason we did not recalibrate the SOBEK model was to avoid double calibration since SWAT was calibrated and validated with the observed data also used as upper-boundary conditions for the SOBEK model calibration. Figure 4 shows a comparison between observed and integrated SWAT-SOBEK OpenMI model flow data. The integrated model captured the behaviors of the observed flow except the peak flow and sudden opening of the dam gate in September 2000. The reason for the peak mismatch could be attributed to ungauged inflow from the catchment between El Deim and Roseires. Flow verification of the integrated model simulation with observed data at Sinnar dam depicted good model fit (Figure 5). Unlike Roseires, peak flow at Sinnar was simulated accurately. However, the model could not simulate a sudden lowering of the gate used to flush sediment on the last week of September 2000. In addition, the model overestimated the falling limb, which could be due to water abstraction for irrigation along the Roseires-Sinnar reach.

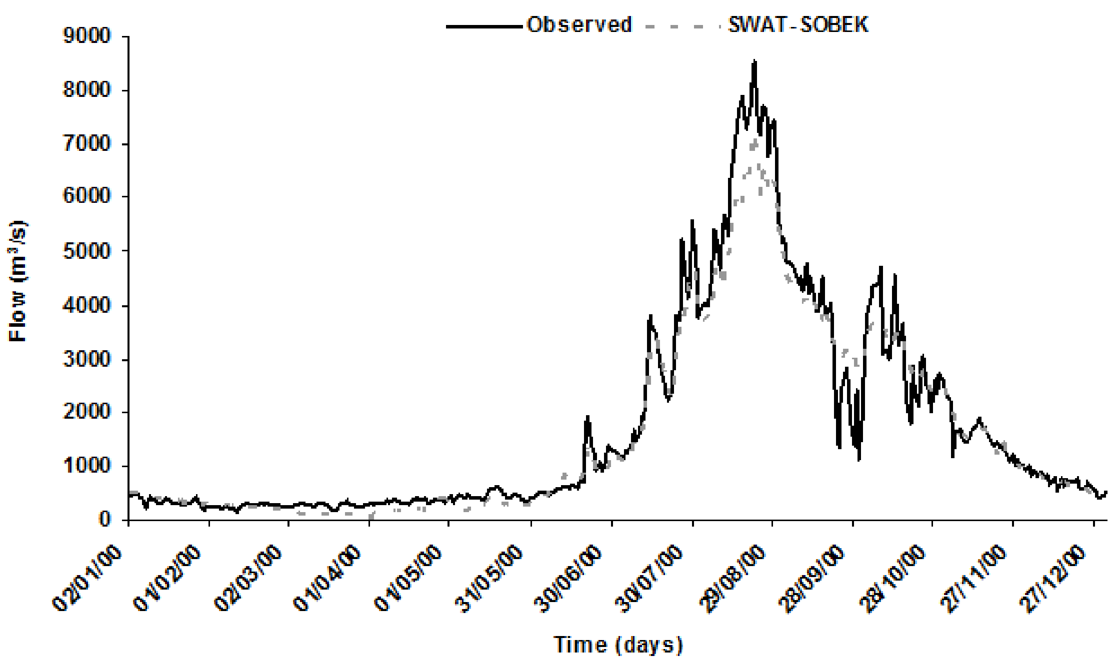

Figure 4. *Comparison of observed and integrated (SWAT-SOBEK) model results at Roseires dam for the year 2000*

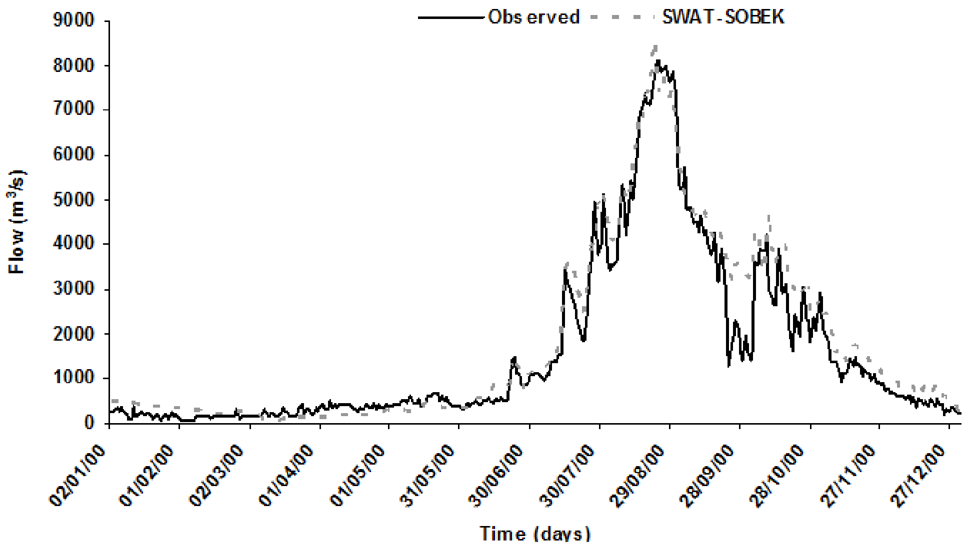

Figure 5. *Comparison of observed and integrated (SWAT-SOBEK) model results at Sinnar dam for the year 2000.*

The morphological changes feedback to the hydrodynamics and the close relationship between resistance and sediment transport, so the calibration and verification of the hydrodynamic and sediment transport modules are closely inter-linked. Thus, after a good calibration of the hydrodynamic portion, the model was run in morphological mode to compute the bed level changes. The resulting SOBEK longitudinal profile shows a deposition of suspended sediment transported from the Upper Blue Nile occurs 35 km before Roseires dam (Figure 6). This is an expected effect of the backwater curve (i.e., it is typical in the development of a reservoir delta). Close to El Deim, at the beginning of the reach, the model shows clear bed erosion. This is because the upstream sediment boundary condition consisted of only suspended sediment due to lack of measured bed load information. However, the Van Rijn sediment transport model needs this information because it computes bed load and suspended sediment transport separately. Thus, it erodes the bed to satisfy its transport need. Between Sinnar and Khartoum, there is local erosion and deposition.

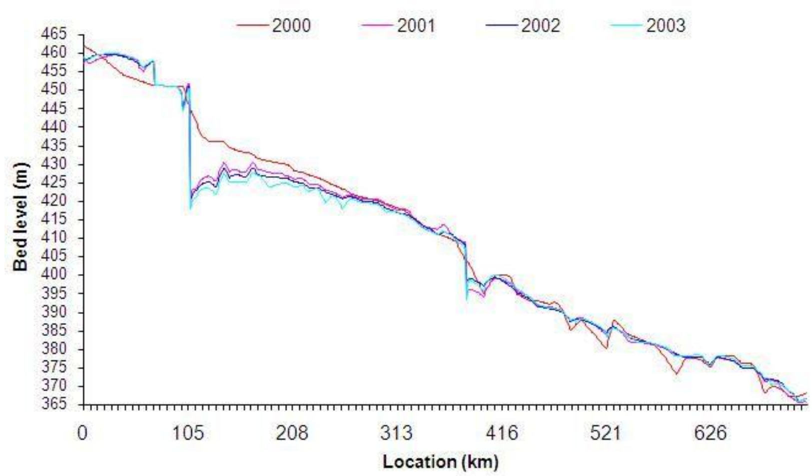

Figure 6. *The Blue Nile River morphologic change simulation during 2000 to 2003*

8. Conclusion

The model integration mainly involved software development of the SWAT code into an OpenMI compliant version. Next, the OpenMI-SWAT version was integrated with OpenMI-SOBEK to replace the flow and sediment routing modules of SWAT. The integrated model results were compared to observed flow at Roseires and Sinnar dams in the year 2000 in the Blue Nile basin. The results showed that the integrated model simulated the backwater effect and sediment deposition that might not have been possible within a single model. The developed SWAT OpenMI compliant model can be linked to other models (e.g., groundwater, climate change and socioeconomic models) to address integrated water resource management problems involving water quality and quantity. However, the uncertainty involved with linking models needs further investigation. In conclusion, OpenMI was found to be a promising tool for integrated modeling that allows users to employ the strengths of each individual model's software.

Acknowledgment

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Annual freeze/thaw temperature cycles in soils on the Canadian Boreal Plain: A comparison of SWAT predictions with measured data

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Abstract

One of the key elements in modeling the impact of changing forest cover on surface water quantity and quality is an understanding of how annual freeze/thaw cycles affect soil temperature in forested watersheds. The focus of this study is to verify the suitability of the algorithms utilized by the Soil and Water Assessment Tool (SWAT) to predict soil temperature for a range of disturbed and undisturbed forest land classification types on the Boreal Plain of Canada. As part of the Forest Watershed and Riparian Disturbance project, instrumentation was installed at five site types across the study area including burned, harvested, conifer, deciduous and wetland forest. Soil temperature and moisture were measured hourly at depths of 0.1, 0.5 and 1.0 m in the soil profile. SWAT temperature algorithms were used to predict soil temperatures and timing of the annual freeze/thaw cycle at these depths based upon average daily air temperature, soil characteristics, vegetation biomass, snow cover and solar radiation. Predicted daily soil temperatures were compared to measured values for each of the five site types. The algorithms utilized by SWAT were able to reproduce seasonal trends in soil temperatures adequately for the spring, summer and autumn seasons, with only a slight increase in the lag coefficient parameter. During winter months, the SWAT algorithms tended to predict soil temperatures that were consistently lower than measured data. Further development to the SWAT soil temperature algorithms is required to better represent the important insulating effect of snowpack.

Keywords: soil temperature, SWAT model, freeze/thaw, boreal forest, forest harvest, wildfire, wetland

1. Introduction

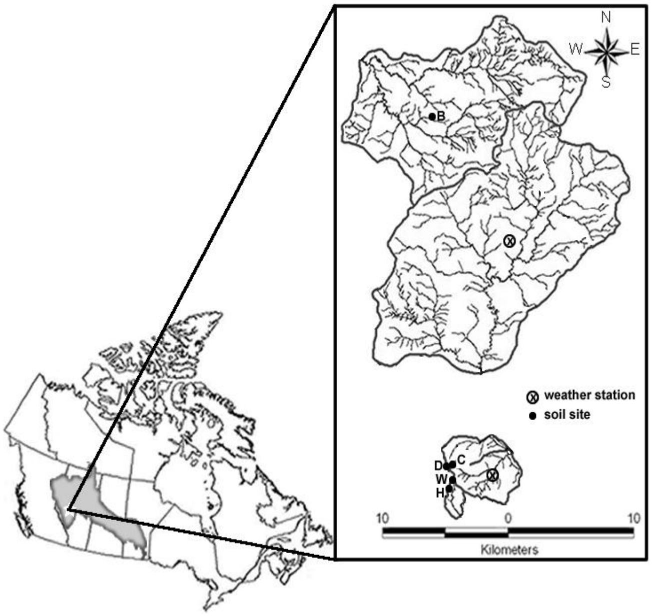
A critical element in modeling flow and water quality in streams draining both undisturbed and disturbed forested watersheds is an understanding of how annual freeze/thaw cycles affect soil temperatures. Frozen soils are important in forest hydrology because they prevent infiltration of water to deeper layers and may cause surface or saturated overland flow (Carey and Woo, 2001). Soil freezing patterns also affect solute concentrations in water moving over and through the soil because they influence the type of soil the water encounters and the contact time between water and soil. In boreal forests, soil freezing affects the relative volume of water moving over the soil surface and through shallow and deep subsurface flowpaths during autumn and following spring.

The Soil and Water Assessment Tool (SWAT) has been applied across the U.S. and around the globe to predict water movement in watersheds. However, SWAT was developed for agricultural lands in the southern U.S. (southeast Texas) where soils differ considerably from boreal forest soils. Therefore, the SWAT soil temperature submodel should require modifications for application in boreal forest conditions, as was demonstrated in other cold-region studies in which changes were made to the snowmelt and subsurface hydrology routines when frozen soils were present (Fontaine et al., 2002; Tolson and Shoemaker, 2007). The soil temperature algorithms in SWAT are similar to and based upon those in the Erosion/Productivity Impact Calculator (EPIC) (Williams et al., 1984). The lag coefficient, which controls the influence of the previous day's temperature on the current day, is set at 0.5 in EPIC, compared to 0.8 in SWAT (Potter and Williams, 1994). It is critical that the SWAT algorithms be tested stringently for cold regions because of differences in the hydrologic cycle between colder and warmer climates.

This study is part of the Forest Watershed and Riparian Disturbance project (FORWARD), a collaborative effort by researchers, forest-related industries, First Nations and the public sector in Canada. FORWARD's objectives are to adapt hydrological and water quality models to predict the effects of watershed disturbance for application in forest management planning (Smith et al., 2003; Prepas et al., 2008a). One focuses of the modeling effort in FORWARD has been to adapt the SWAT model for northern climates and forest conditions. The objective of this study was to verify the suitability of the soil temperature algorithms in SWAT for modeling soil temperatures in cold regions, specifically the Canadian Boreal Plain. We selected a representative sample of five site types: upland burned, harvested, conifer and deciduous forest and wetland forest.

2. Methods

The study area is in the Swan Hills, approximately 225 km northwest of Edmonton, Alberta (Figure 1). First to third-order watersheds constitute a subset of the watersheds monitored by FORWARD and cover an area of 178 km^2 (Figure 1; Table 1). Long-term climate norms (1971 to 2000) for precipitation and mean annual air temperature are 578 mm and 2.6^{o}C, respectively, with 24% of annual precipitation falling as snow (Environment Canada, 2008). This area is snow-covered for six to seven months beginning in October or November (Environment Canada, 2008). Upland soils are mostly fine-grained Orthic Gray Luvisols, and wetlands mainly consist of peat (ESWG, 1996). Conifer and deciduous stands are dominated by lodgepole pine (*Pinus cortorta* Dougl. ex Loud.var. latifolia Engelm) and trembling aspen (*Populus tremuloides* Michx.), respectively (ESWG, 1996) (Table 1). Wetlands are treed fens (Couling et al., 2007) dominated by black spruce (*Picea mariana* (Mill.) BSP) with some lodgepole pine and tamarack larch (*Larix laricina* (Du Roi) K. Koch) (ESWG, 1996) (Table 1).



We selected five sites. The burned site was a result of a wildfire in June 1998 (Prepas et al., 2003). Regrowth mainly consists of lodgepole pine with some trembling aspen. Tree height ranges from 1.5 to 2 m. The harvested site was the result of logging in January 2004, followed by mechanical site preparation from March to July 2004 and aerial application of glyphosate in August 2004 (Prepas et al., 2008b). Regrowth is sparse and consists of lodgepole pine and white spruce (*Picea glauca* (Moench) Voss). Tree height ranges from 0.5 to 1 m. The wetland is a peatland with a peat depth of 2.8 m. Slight differences in elevation and slope (range from 0.01 to 0.04%) exist among sites (Table 1).

Figure 6. *Location of burned (B), harvested (H), conifer (C), deciduous (D) and wetland (W) sites in the FORWARD study area*

Table 4. *Characteristics of burned (B), harvested (H), conifer (C), deciduous (D) and wetland (W) study sites*

Site ID	Watershed	Stand Tree Species* (Approx. Cover %)	Canopy Cover (%)	Elevation (m asl)	First date sampled
B	Goose	n/a	0	991	7-13-06
H	Millions	n/a	0	1016	8-10-06
C	Thistle	PL(90) AW(10)	92	1028	10-20-05
D	Thistle	AW(70) SB(20) PL(10)	84	1053	10-27-05
W	Willow	SB(80) LT(10) PL(10)	69	1026	6-28-06

*PL: lodgepole pine, AW: trembling aspen, SB: black spruce, LT: tamarack larch

Sampling sites were set up in autumn 2005 and summer 2006 (Table 1). At the conifer and deciduous sites, soil temperature was measured hourly and recorded either by water or soil temperature sensors and HOBO® dataloggers (Onset Computer Corporation, Bourne, MA, USA). At the burned, harvested, and wetland sites, YSI thermistors (YSI Incorporated, Yellow Springs, OH, USA) and Data Dolphin loggers (Optimum Instruments Inc., Edmonton, AB, Canada) were used. Measurements were taken at 0.1, 0.5 and 1 m depths for soil temperature and at the ground surface and 2 m above ground level for air temperature. Soil moisture content was measured hourly with theta probes (Delta-T Devices Ltd., Burwell, Cambridge, UK) and recorded with a DL6 soil moisture datalogger (Delta-T Devices Ltd.) or a Data Dolphin datalogger at 0.1, 0.5 and 1 m depths. Snow depth was measured a total of 44 times in 2006 and 2007. Air temperature at 2 m above ground level, precipitation and solar radiation data were collected hourly at two FORWARD weather stations (Figure 1). For each sampling site, precipitation and solar radiation data from the nearest weather station were used in the model. When air temperature data were missing, values from the nearest soil temperature site or weather station were used. Measurements of aboveground vegetation biomass and residue were obtained from an earlier study (MacDonald et al., 2007). Canopy cover was measured using a spherical densiometer (Forest Densiometers, Bartlesville, OK, USA) in August 2008. Measurements were taken at each site facing the four cardinal directions, and averages of the measurements were taken as the percent cover of each site (Table 1). Mean soil bulk density was 1.5 $Mg \cdot m^{-3}$, with the exception of wetlands at the 0.1 m depth where bulk density was 0.3 $Mg \cdot m^{-3}$ (I. Whitson, Univ. Alberta, pers. comm.).

For each site, mean, maximum and minimum daily air temperature and mean daily soil temperature and moisture were calculated at each depth. Daily snow depth (cm) was estimated using a linear regression (r^2 = 0.61; P < 0.001) between snow depth measured at the sites and snow depths recorded on the same dates at the Whitecourt A station (Environment Canada, 2008) located 50 km southeast of the FORWARD study area (Eq. 1).

*Estimated snow depth at study sites = 1.51 * snow depth at Whitecourt* (Eq. 1)

Daily snow depth estimates were modified by calculating the error between estimated and measured values on the 44 sampling dates, conducting a linear interpolation of the error between winter sampling dates and then applying the correction error to the estimated snow depth.

The soil temperature sub-model in SWAT utilizes multiple input parameters from three general categories: soils, vegetation and climate. The model calculates soil temperature at a given depth based on air temperature on the current day and soil temperature on the previous day. The SWAT algorithms for surface albedo are also relevant because SWAT varies the albedo depending on the vegetation cover. A complete description of the SWAT algorithms can be found in Sections 1:1.3.3 and 1:1.2.5.1 of Neitsch et al. (2005). The soil temperature algorithms were set up in Microsoft Excel, and all input parameters were integrated into the model. A sensitivity analysis was conducted by varying the following parameters by ± 20%: aboveground vegetation biomass and residue, depth of the soil profile, bulk density, snow equation coefficients and lag coefficient. The model was modified by changing the most sensitive parameters and other default values. Default and modified soil temperature sub-models were run for each site at various depths. Daily differences between predicted and observed data were calculated and maximum differences for summer and winter were determined. Model outputs were compared using the correlation coefficient (r^2), mean absolute error (*MAE*) and root mean square error (*RMSE*).

3. Results and Discussion

Given the broad annual range in daily air temperature conditions on the Boreal Plain (the mean daily minimum in January is -17°C and the mean daily maximum in July is 22°C (Environment Canada, 2008)), differences between predicted and observed soil temperatures were identified separately for the summer (Jun-Aug) and winter (Nov-Mar) months. For all sites and depths, the original SWAT model predicted soil temperatures that were 5.2°C (conifer) to 17.3°C (burned) warmer than observed in the summer and 4.1°C (conifer) to 7.8°C (burned) cooler than observed in the winter (Table 2; Figure 2). The latter outcome was unexpected, since air temperatures in the study area usually fall below freezing 201 days each year (Environment Canada, 2008), compared to the average 29 days in southeast Texas (National Climatic Data Center, 2009). A time-shift was identified in transition periods. Predicted soil temperatures decreased sooner in autumn and increased sooner in spring than was observed. For the original SWAT model, over the three year period for each site and depth, the *MAE* ranged from 1.8 (wetland) to 4.3 (burned) (Table 2). The time-shift increased with soil depth and was larger for treed sites than open sites (Figure 2). Cooler-than-predicted air temperatures in the spring transition period and summer could be attributed to the vertically complex, overlapping forest canopy in these boreal forest sites, which likely provided more shade than the vegetation in croplands for which the model was developed. At high latitudes, the low solar angle also reduces the solar radiation reaching the ground. Conversely, warmer than predicted air temperatures in the autumn transition period and winter could have been due to the insulation effect of aboveground vegetation biomass, particularly at conifer sites. During the winter months, differences are likely due to insulation by snow, which reaches a mean depth of 22 cm in January (Environment Canada, 2008), as compared to 2.5 cm for southeast Texas (City-Data, 2008). Snow-related equations cover a wide range of conditions, and most were probably not subjected to the same rigorous testing as the other components in the original SWAT model because below freezing days are few and deep snowpack is absent in southern latitudes. Modifications were often required when the model was applied in other cold regions, such as Pennsylvania (Peterson and Hamlett, 1998), Michigan (Wu and Johnston, 2007), Wyoming (Fontaine et al., 2002) and Finland (Francos et al., 2001).

Factors considered to address the problems in the original SWAT soil temperature sub-model included albedo, soil bulk density, depth of the soil profile, vegetation biomass and the lag coefficient. The default albedo in the original SWAT model of 0.8 for a snow-covered surface is not representative of northern disturbed or undisturbed forested sites because it does not account for vegetation in treed sites and smaller shrubs emerging from the snowpack in open sites. Reported albedo values for this region of the boreal forest are 0.43 for treed sites (conifer, deciduous and wetland) and to 0.66 for open sites (harvested and burned) (URS Corporation, 2002), much lower than the default value. As a result, the first modification to the SWAT model was to alter the albedo value for a snow-covered surface based on cover type.

The sensitivity analysis showed that soil bulk density, depth of the soil profile and vegetation biomass did not significantly affect SWAT model results, as long as the parameters were varied within a representative range for this region. However, the lag coefficient (fixed at 0.8 in the original SWAT model) was identified as a sensitive parameter. The second modification to the SWAT model was to increase the lag coefficient for all land classification types and depths (Table 2; Figure 2). The lag coefficient that provided the best overall fit for each site and depth was selected. In all cases, the lag coefficient increased from the 0.1 m depth to the 0.5 and 1.0 m depths, which demonstrates that the previous day's soil temperature was more important at deeper soil depths (Table 2). Along with an increasing time-shift with increasing soil depth, this finding shows that the overlying soil layer insulates deeper layers. By increasing lag coefficients, maximum differences between predicted and observed soil temperatures were reduced by half in the summer (4.9 ± 0.9^{o}C, mean ± *SE*) and by 30% in the winter (3.7 ± 0.4^{o}C) (Table 2). The time-shift present in the spring and autumn transition periods was also reduced (Figure 2). Both changes (decreasing the albedo and increasing the lag coefficient) increased the overall efficiency of the modified SWAT model. *MAE* decreased and ranged from 0.7 (wetlands) to 3.4 (burned) (Table 2). Still, the modified soil temperature model predicted soil temperatures that were cooler than observed during the winter months when deep and persistent snow was present.

Table 5. *Maximum differences in summer and winter soil temperatures for original and modified lag coefficients.*

Site ID	SWAT model	Lag coefficient	Maximum difference in summer (°C)	Maximum difference in winter (°C)	r^2	*MAE*	*RMSE*
			0.1 m				
Burned	Original	0.80	11.6	-7.8	0.90	4.3	4.9
	Modified	0.95	6.7	-6.7	0.93	3.4	4.1
Harvested	Original	0.80	7.9	-5.0	0.89	2.3	2.8
	Modified	0.95	6.8	-5.0	0.90	1.8	2.3
Conifer	Original	0.80	13.1	-4.8	0.83	3.0	3.8
	Modified	0.96	7.3	-4.8	0.90	2.3	2.7
Deciduous	Original	0.80	17.3	-4.6	0.81	2.9	3.8
	Modified	0.96	14.9	-4.8	0.91	2.2	2.7
Wetland	Original	0.80	9.9	-4.3	0.91	1.8	2.2
	Modified	0.94	6.8	-3.8	0.94	1.4	1.7
			0.5 m				
Burned	Original	0.80	9.2	-7.2	0.77	3.7	4.1
	Modified	0.97	2.5	-4.6	0.96	1.9	2.4
Harvested	Original	0.80	7.3	-5.7	0.78	2.6	3.1
	Modified	0.96	1.8	-4.6	0.91	1.3	1.8
Conifer	Original	0.80	10.2	-4.4	0.70	2.6	3.1
	Modified	0.97	3.8	-2.9	0.92	1.1	1.4
Deciduous	Original	0.80	11.6	-4.2	0.63	2.6	3.2
	Modified	0.97	4.9	-3.4	0.90	1.2	1.5
Wetland	Original	0.80	7.9	-4.6	0.66	2.2	2.7
	Modified	0.97	1.9	-1.2	0.96	0.7	0.8
			1.0 m				
Burned	Original	0.80	7.3	-5.9	0.54	3.0	3.4
	Modified	0.97	1.7	-3.3	0.91	1.7	2.0
Harvested	Original	0.80	5.2	-6.7	0.60	2.6	3.2
	Modified	0.96	2.0	-3.9	0.88	1.8	2.1
Conifer	Original	0.80	9.3	-4.1	0.52	2.0	2.5
	Modified	0.97	5.3	-1.5	0.88	0.8	1.1
Deciduous	Original	0.80	9.1	-4.7	0.43	2.2	2.7
	Modified	0.97	4.9	-2.3	0.82	1.1	1.3
Wetland	Original	0.80	6.0	-4.8	0.26	2.1	2.6
	Modified	0.97	1.6	-2.7	0.74	1.1	1.3

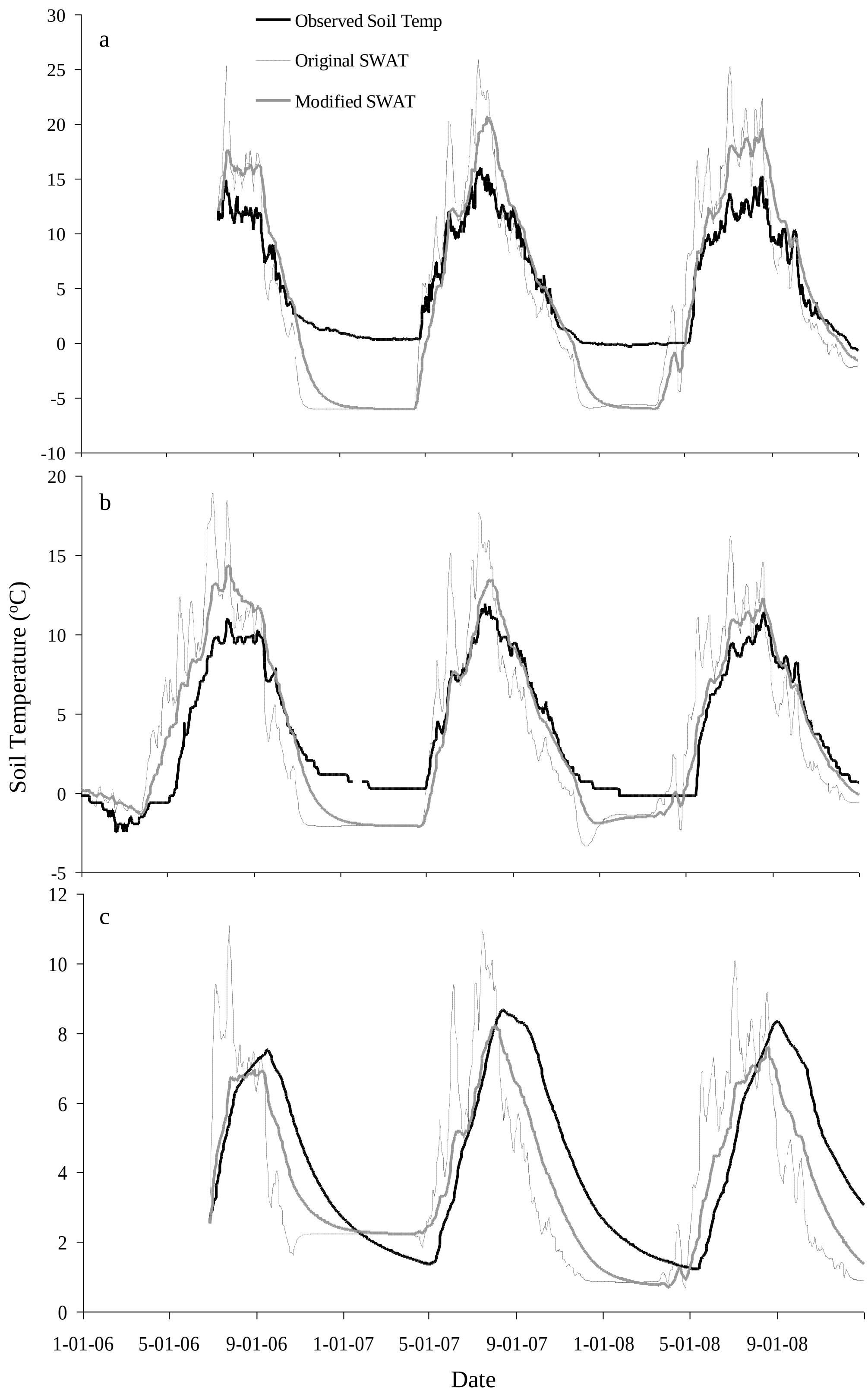


Figure 7. *Observed data and original and modified SWAT model outputs for the (a) burned site at 0.1 m, (b) conifer site at 0.5 m and (c) wetland site at 1.0 m, note differences in y-axis scales.*

Following modifications to the model, predicted soil temperatures from January to March of 2006 at the conifer site (Figure 2b) were only slightly colder than observed in comparison to the same periods in 2007 and 2008. This is because there was very little snow on the ground in the winter of 2005/2006, and the modified SWAT model was more capable of accurately modeling soil temperatures. This emphasizes the importance of considering the insulation effect of deep and persistent snowpacks. Although modifications to the albedo and lag coefficient increased the efficiency of the model throughout the spring, summer and autumn, observed soil temperatures during winter months were still generally warmer than predicted.

4. Conclusion

The comprehensive soil temperature dataset from the FORWARD study sites provided an opportunity to contribute to the reworking of SWAT for cold climates. On the Boreal Plain, the presence of snow drastically decreased the cooling effect of air temperature on soil temperatures in winter, and from the literature, one can surmise that snow also decreases the warming effect of air temperature on soil temperature in early spring. The insulation from heat transfer provided by a relatively deep snowpack is not reflected in the original SWAT model. To adequately model forested sites in northern climates with SWAT, modeling efforts need to incorporate the insulating effect of snow. By changing the lag coefficient, the modified SWAT model was able to effectively model soil temperatures in spring, summer and autumn at selected sites on the Boreal Plain where snow was absent. However, to effectively simulate soil temperatures under a snowpack, recommended modifications consist of testing the equation presently in SWAT that considers the insulating effect of snow and, if this proves insufficient, to include another parameter to account for deep and persistent snowpacks in northern climates.

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Integration of a simple process-based snowmelt model into SWAT

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Abstract

Many of the spatial hydrologic modeling systems common today use variants of a site-calibrated temperature index (TI) approach for modeling snowmelt. Justification for using the TI approach over process-based snowmelt models is that there is a high level of complexity as well as a large number of forcing variables required for running the models, as it is often hard to find reliable temperature and precipitation data from a watershed of interest. Unfortunately, TI approaches require long historical periods of meteorological and hydrologic data to calibrate, which makes the search for this data even harder. There is also the added requirement of finding representative meteorological and streamflow gauges with long and consistent temporal coverage.

For this article, we integrated a previously published process-based snowmelt model that requires only daily minimum and maximum temperature data into the Soil and Water Assessment Tool (SWAT). We compared two scenarios over four watersheds representative of four distinct regions of the U.S. In the first scenario, we examined how well each model performs in each region given a long historical period to calibrate the TI approach. Second, we considered the case of having limited historical data and compared the performance of the snowmelt models using single year histories for calibration. With the results, we developed justification for including process-based snowmelt models as an option for SWAT and other spatial hydrologic modeling systems.

Keywords: snowmelt, energy budget, distributed hydrological model, environmental energy, process-based model, temperature index, SWAT

1. Introduction

Distributed hydrologic models are used to understand fundamental processes linking water distribution from the land-atmosphere interface to the stream and river outlets. Often, these models are created by combining process-based subsystem models that require less calibration with empirically derived subsystem models that are completely dependant on local calibration. In general, it is the intent of a modeling system to move towards completely process-based subsystem models, so there are fewer requirements for location specific calibration.

One of the subsystems still frequently modeled using temperature index (TI) based empirical models is snowmelt due to a perceived complexity of obtaining additional meteorological and topographic inputs required to solve the energy budget of the snowmelt process (Zhang et al., 2008). Zhang et al. demonstrated the benefits of using the NWS River Forecast Center's (RFC) process-based snowmelt model SNOW17 in ungauged basins. The model did not require as much calibration, but the SNOW17 method did require more modification to the SWAT modeling system and required significantly more complex forcing variables (Zhang et al., 2008). The researchers concluded that calibrated, modified TI plus elevation band snowmelt algorithms incorporated into SWAT by Fontaine et al. (Fontaine et al., 2002) were as accurate as the process-based SNOW17 model.

Unfortunately, the snowmelt process is of great importance to accurate modeling since incorrect estimation on any given day not only effects that day's hydrologic transport, but also future hydrologic events when the snowmelt does or does not get added to the hydrologic system. Thus, errors in a modeled snowmelt event are noticed two or more times throughout a season. In practice, there is also a hidden benefit to cutting out several parameters required for local calibration. Auto-calibration routines for these complex modeling systems can often take many thousands of iterations, and the number of iterations required for calibration often grows exponentially with the number of parameters requiring calibration.

Walter et al. (2005) demonstrated that many meteorological inputs required for the process-based snowmelt energy balance could be estimated using only the day of the year, latitude and maximum and minimum temperatures. This study investigates the potential benefits of including an energy balance snowmelt model into the SWAT2005 hydrologic modeling system. We used the following energy balance for a snowpack:

$$\Delta SWE = (S + L_a - L_t + H + E + G + P - SWE(C\Delta T_s))/\lambda \qquad (1)$$

where ΔSWE is the change in the snowpack's water equivalent (m), S is the net incident solar radiation (kJ m^{-2}), L_a is the atmospheric long wave radiation (kJ m^{-2}), L_t is the terrestrial long wave radiation (kJ m^{-2}), H is the sensible heat exchange (kJ m^{-2}), E is the energy flux associated with the latent heats of vaporization and condensation at the surface (kJ m^{-2}), G is ground heat conduction to the bottom of the snowpack (kJ m^{-2}), P is heat added by rainfall (kJ m^{-2}), $SWE(C\Delta T_s)$ is the change in snowpack heat storage (kJ m^{-2}) and λ is the latent heat of fusion (3.35 x 10^5 kJ m^{-3}). None of these energy fluxes are input directly, as all are estimated using the methods outlined in Todd Walter et al., 2005.

2. Methods

2.1 Model Modifications

We tried to limit modifications to the distributed SWAT code base and ArcSWAT initialization system. In a subroutine written in FORTRAN, owsnowmelt.f was a direct replacement for the current SWAT snowmelt routine, snom.f, so that only one line of modification was needed for the surface.f routine. Several variables had to be tracked through the model run, so in order to account for these global variables, two lines of modification were created for the modparm.f module and four lines for the allocate.f subroutine.

There were also several modifications to SWAT and the ArcSWAT default initialization that were deemed necessary for the study areas being modeled. First, within the code base, frozen soil seepage was allowed by commenting out the logical test for frozen soil in percmicro.f. Second, in the default initialization, we encountered an initial layer less than 10 mm with very low saturated hydraulic conductivity that was required for high slope regions to counteract an overestimation of the lateral flow.

2.2 Watershed selection and descriptions

We selected several watershed basins close to the original single-point based study locations due to historical familiarity with those regions (upstate New York, northern Vermont, southern Minnesota and northwest Idaho). We also used a southwestern watershed basin in northern New Mexico to test the model's abilities outside of familiar regions for the principles of this study.

The watersheds chosen varied in size and outflow to cover the wide range of watershed sizes that have been studied successfully with SWAT. The full range, from a couple of km^2 to half a million km^2 (Spruill et al., 2000), was not achieved in this study, but we did model five watersheds ranging from tens to thousands of km^2. Results from two of these watersheds with differing modeling results, both poor and good, are discussed below.

2.3 Data Sources

Forcing data was used from the nearest ASOS meteorological station with records spanning from January 1990 through December 2008. In selecting a station to use, completeness of available data took priority over the proximity since the end goal was being able to produce real-time hydrologic modeling systems at the conclusion of the study. Temperatures were adjusted based on the lapse rate from the reporting station to the average elevation of the watershed. This adjustment is not as necessary in the Midwest and East Coast watersheds as it is in the Western watersheds.

Several steps for watershed initialization were standardized for this study. It was not the purpose of this study to produce an example of optimal modeling but rather a representation of a generic modeling project for any modeling group downloading SWAT and initializing. As such, the watersheds were initialized with the most accessible and temporally current datasets, with accessibility weighted higher in selection. For this reason, the STATSGO dataset distributed with the SWAT modeling system, METAR data from the closest ASOS stations (Wright, 1995), elevation (NED) from the EPA BASINS datasets (Luzio et al., 2002) and the 2001 Multi-Resolution Land Characteristics (MRLC) Consortium land use data (the most current as of this publication) (Homer et al., 2004) was used for each watershed's initializations and environmental forcing.

The projection used for all watersheds was that of the base STATSGO dataset distributed with the ArcSWAT modeling system (Albers, NAD 1983, central Meridian -96, Standard Parallel 1 29.5, Standard parallel 2 45.5, and Latitude of Origin of 23). Prior to initialization, DEMs were preprocessed with the Spatial Analyst extension function gp.Fill_sa. Afterward, ArcMap was closed and reopened loading the ArcSWAT distributed STATSGO database (C:\Program Files\ArcSWAT\Databases\ SWAT_US_Soils.mdb). Elevation and land use datasets were loaded, exported, and then re-projected to the spatial reference of the data frame (that of the ArcSWAT STATSGO dataset originally loaded).

Four watersheds were selected in same U.S. NWS climate regions as close to the original study areas as the Walter et al. (2005) study. However, consideration was taken to locate basins with good historical streamflow records that were also located as close as possible to an active ASOS station. To evaluate the models in a blind study, a fifth watershed was selected outside of the climatic regions evaluated in the initial Walter et al. study. Only USGS streamflow data that had non-estimated, data-value qualification code approved for publication (Code A) were used for model calibration and corroboration.

Default values were either allowed for the stream definition thresholds, networks, subbasin outlets, and subbasin parameterization, or the watershed delineation at large was defined using the default recommendations provided by the ArcSWAT interface.

2.4 Presented watersheds by state

2.4.1 Idaho

USGS gage 13345000, Palouse River NR Potlatch ID, Latah County, Potlatch quad. within Hydrologic Unit 17060108, 2.0 mi west of Potlatch, ID.

The watershed is mostly free of obstruction, although small amounts of water diverted for sprinkle irrigation systems above the gauge are reported (http://waterdata.usgs.gov/wa/nwis/uv/?site_no=13345000). The watershed ranges from about 760 to 1630 m (~2500-5350 ft) in elevation.

We captured 817 km^2 (315 mi^2) in the initialization as compared to the 821 km^2 reported by the USGS. Land use types were: 69% Forest-Evergreen (FRSE), 22% Range brush and grasses and 8% Agricultural row crops with minimal residential areas and few wetlands. Within the basin there were 12 soils types and three slope classes of 0-15%, 15-30% and 30%+, which were fairly evenly distributed. Automatic watershed delineation resulted in 31 subbasins, and using 5% HRU thresholds over defined land uses, soil classes and slope classes, resulted in 497 hydrologic response units (HRUs).

Forcing weather variables were taken from the closest real-time reporting station available in the NCDC GSOD database, Pullman Moscow Regional Airport (USAF 727857, Call KPUW), located roughly 25 km from the center of the basin. Unfortunately, 33 days of temperature and precipitation data were missing from the 1990-2008 period used for calibration and model evaluation. These days were filled in with the SWAT weather generator.

2.4.2 New York

USGS gage 01422500, Little Delaware River near Delhi, NY, Delaware County, NY, within Hydrologic Unit 02040101, 2.0 mi south of Delhi. (http://waterdata.usgs.gov/ny/nwis/uv?site_no=01422500)

The watershed ranges from approximately 410 to 1020 m (~1350-3340 ft) in elevation. We captured 129 km^2 (50.4 mi^2) in the initialization as compared to the 127km^2 reported by the USGS. Land use types were: 69% Forest-Deciduous (FRSD), 17% Hay production, 6% mixed deciduous/evergreen with minimal residential areas or water bodies. Within the basin there were three soil types and five slope classes, roughly a quarter were below 15%, half were in the 15-30% range and a quarter were above 30%. Automatic watershed delineation resulted in 29 subbasins, and using 5% HRU thresholds over the defined land uses, soil classes and slope classes, 368 HRUs were defined.

Forcing weather variables were taken from the closest real-time reporting station available in the NCDC GSOD database, the AWOS station at Monticello, New York (AWS 725145, Call KMSV), located roughly 65 km from the center of the watershed.

2.5 Calibration

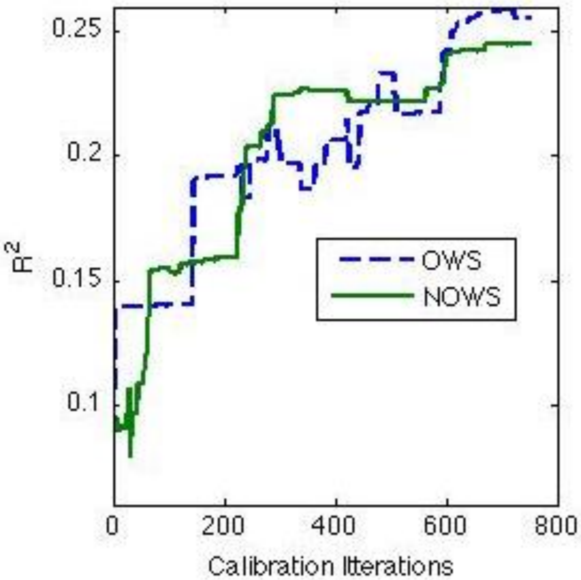
Each watershed was calibrated for both the minimally altered SWAT2005 and the version of SWAT2005 with the process-based snowmelt model using the Dynamically Dimensioned Search (DDS) Algorithm of Tolson and Shoemaker (2007) implemented in MATLAB. Progressive calibration statistics were tracked for all iterations of each calibration run to be compared and contrasted. We calibrated the 15 parameters shown to be most sensitive based on preliminary sensitivity tests (given in Table 1).

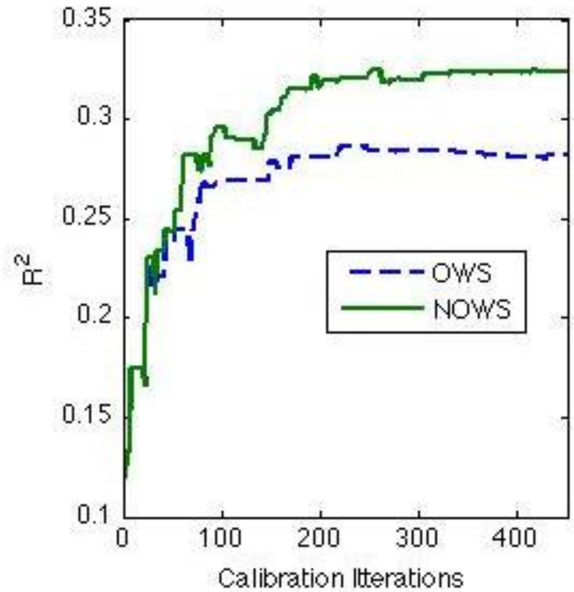
Table 1. *Parameters used for DDS auto-calibration*

Variable	Definition
SFTMP	Snowfall temperature [˚C]
SMTMP	Snow melt base temperature [˚C]
SMFMX	Melt factor for snow on June 21 [mm H2O/˚C-day]
SMFMN	Melt factor for snow on December 21 [mm H2O/˚C-day]
TIMP	Snow pack temperature lag factor
GW_DELAY	Groundwater delay [days]
ALPHA_BF	Baseflow alpha factor [days]
SURLAG	Surface runoff lag time [days]
GWQMN	Threshold depth of water in the shallow aquifer required for return flow [mm]
LAT_TTIME	Lateral flow travel time [days]
ESCO	Soil evaporation compensation factor
CN2	Initial SCS CN II value
Depth	Soil layer depths [mm]
BD	Bulk density moist [g/cc]
AWC	Ave. AW incl. rock frag
KSAT	Saturated conductivity [mm/hr]

3. Results

As mentioned in the methods section, completeness of the forcing data available took priority over proximity to the center of the watershed with the end goal of producing real-time hydrologic modeling systems at the conclusion of the study. In fact, Mehta et al. demonstrated there can be a correlation coefficient as low as .23 between precipitation gages 30 km apart (Mehta et al., 2004), and the closest operational station available meeting the criteria for our watersheds was 25 km (ID) and 80 km (NY) from the center of the watershed. With this in mind, we realize that there will be relatively poor statistical results for the calibration history when evaluated on a daily observed vs. modeled flow basis.





Figures 1 and 2. *Progressive R^2 by calibration iteration for ID watershed on left and NY watershed on right*

Figures 1 and 2 demonstrate the progressive model improvement through calibration iterations. As can be seen from the large number of iterations required for calibration any decrease in the number of iterations would be valuable to a modeling project. In fact, we did witness a decrease of several hundred calibration iterations when snowmelt parameters were removed from the parameter pool in DDS; although, this behavior is not show here.

This study compared two model performance behaviors, as summarized in Table 2. First, the performance of optimal DDS calibration is given for all parameters, representing an optimal long-term modeling study. Secondly, we used the optimized parameters for all calibrated parameters other than those of the snowmelt model. Instead, we plugged the default values assigned by the ArcSWAT initialization system into the snowmelt model. This case would represent model performance for a project in a previously ungauged (meteorologically or streamflow) watershed. While the models were optimized on SSE, we give R^2 as a simple representation of performance here.

Table 2. *Summary of model performance (R^2) for temperature index (TI) and process-based (PB) snowmelt models for ID and NY watersheds.*

	TI_ID	**PB_ID**	**TI_NY**	**PB_NY**
Full Calibration	.25	.26	.32	.28
Default SM Parms.	.12	.25	.23	.27

As shown in Table 2, the models perform equally well in Idaho with 20 years of historical data to calibrate against. Although, the TI-based model has a small advantage in the upstate New York watershed. When running with default initialization snowmelt parameters, the process-based model far outperforms the TI model.

5. Conclusion

This study demonstrates that a simple process-based snowmelt model can be incorporated into spatially distributed hydrologic models with minimal effort. For the purposes of this study, only latitude, day of year and maximum and minimum temperature were used. Although, the SWAT2005 modeling system does have the ability to use several additional variables such as solar radiation, wind and humidity, all of which could be used to refine the process-based model if locally available data exists. Several key distributed-area attributes likely to make the process-based model more accurate were slope and aspect, yet they were not available without complicating the watershed initialization process. These parameters would allow for better estimation of distributed snow depth and snowmelt throughout the subbasins, providing potentially more accurate results.

We demonstrated here that the TI model can outperform the process-based model in certain regions when there are decades of clean historical data to calibrate against. It would be of merit to investigate further to what extent this may apply across the continental U.S. For this study, it was also shown that the process-based model performed similarly to the TI-based model even when decades of data were available for calibration. More importantly, the process-based model significantly outperformed the TI-based model in cases in which there was no historical data to calibrate against, again performing similar to the optimal calibrated case.

In addition, we found that using the process-based model has the added benefit of decreasing the amount of calibration iterations. Although, there is evidence from the poorly modeled New York watershed that the additional parameters (and thus increased calibration iterations) allowed for additional error to be removed in the enhanced parameter calibration.

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AGRIRISK -SWAT: an add-on application for AVSWAT2000 to compute hydrologic and NPS pollution risk analysis in agricultural watersheds

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Abstract

We propose AGRIRISK, a decision support system (DSS), as an add-on application integrated with the GIS version of the SWAT model (AVSWAT2000). AGRIRISK computes groundwater table depth and some risk indicators of interest in agriculture using SWAT inputs and outputs. The system has been conceived to compare soil units and management scenarios based on groundwater table depth and hydrologic indicators along with cumulative frequency curves, which are the tools used to quantify and communicate risk during the decision-making process. At the watershed level, AGRIRISK performs NPS pollution risk analysis, computing the exceedance probability plots for nitrogen, phosphorus and pesticide loads in streams. In addition, AGRIRISK includes a module to compute statistical validation of SWAT output variables at subbasin level and groundwater table depth in order to save time and effort during the model calibration process. A recently available alpha version is ready to be tested, and a beta version will include cumulative frequency curves and NPS pollution risk analysis.

Keywords: hydrology, groundwater table, agriculture, risk analysis, add-on application

1. Introduction

Floods are usually considered an overflow of the basin stream network caused by large rainfall events. However, a large amount of precipitation also increases soil water content and causes the groundwater table to rise in areas not adjacent to rivers or streams.

In rural watersheds, this may produce immediate damage affecting soils and farming production. In these areas, precipitation plays a key role in the planning and execution of farm activities, both in row crop agriculture and livestock production. Water excesses can degrade soil properties for the next crop season and can also decrease the total productivity of the watershed by reducing the farming area, affecting the development of crops and delaying or stopping field-work like tillage, planting and harvest (Pivot et al., 2002). All of these factors are usually considered in farm planning, so crops and pastures are normally allocated to fields based on their soil quality and risk of flooding.

The Soil Water Assessment Tool, SWAT (Arnold et al., 1998), is a powerful tool for this kind of analysis because it is a comprehensive, continuous model that can be used in large watersheds up to the river basin-scale and allows for the evaluation of impacts involving management practices and environmental and land use changes. However, to study the state of watersheds in terms of soil moisture, groundwater table depth and suitability for farm activities throughout the year, it is necessary to include a new type of analysis in order to compute some additional variables and generate appropriate outputs. Only DRAINMOD (Skagss, 1980), which is a one-dimensional model that works only at field-scale, has proposed some risk indicators for agriculture such as working days (or trafficability), dry days and SEW-30.

In this study, the AGRIRISK (Vazquez-Amabile and Engel, 2008) system is proposed as an add-on application integrated with the GIS version of the SWAT model. An alpha version of this interface is available for download and testing at http://swatrisk.blogspot.com/. The beta version (complete version) of the application will be available this year for use as a complementary tool for AVSWAT2000. It is designed to compute groundwater table depth and evaluate both the hydrologic risk of floods and droughts on farming activities at the hydrologic response unit (HRU) scale and the NPS pollution risks of pesticides and nutrients at the subbasin scale.

The application is described as a Decision Support System (DSS) that combines the SWAT model, which integrates data sources and modeling, with AGRIRISK, which represents the analytical tool of the system. This DSS makes it possible to evaluate scenarios by performing a risk analysis focused on the year-to-year variability of the hydrologic variables.

Risk can be basically defined as the probability that an event will occur (Barnthouse and Suter, 1986), and the event of interest will depend on the variable under study. In NPS pollution, for example, the event of interest is the exceedance of a critical value, and the risk of contamination is the exceedance probability of that value, which will be different for each pollutant. In agriculture, an event of interest might be the number of consecutive days with saturated soil, and the critical value might then be different for each crop and for each stage of development. Thus, the risk of damage by water excess will be the exceedance probability of a given critical value, which will depend on the crop type and time of the year.

Cumulative frequency curves are useful in estimating probabilities without fitting the data distribution to a probability density function when two or more scenarios are compared. Furthermore, in the decision making process, some indicators can be utilized to evaluate or compare two or more alternatives in a deterministic way. The use of indicators is frequent in land evaluation when creating land quality or site indexes (Ochola and Kerkides, 2004; Hoosbeek and Bouma, 1998). In this study, some indicators are proposed in order to communicate the hydrologic risk for farming activities. These indicators are also computed along with their corresponding cumulative frequency curves in order to observe their degree of variation. Thematic and probability maps are also proposed as additional tools for risk communication in spatial analysis at the subbasin level.

2. AGRIRISK Description

AGRIRISK is intended as an add-on application program integrated with AVSWAT2000. Therefore, both components of the DSS have their own interface, and AGRIRISK is applied after the user has run SWAT for one or more scenarios. The user may run SWAT either using weather records or simulated weather data generated by the model for a period of 50 or more years if the period of record is not long enough.

AGRIRISK uses SWAT input and output files to compute some variables that the model does not calculate. These variables are groundwater table depth and some hydrologic risk indicators, such as the number of days suitable for fieldwork, planting and harvesting and the number of days with soil water content above field capacity and below 50% of field capacity. The cumulative frequency curves of these variables are computed in order to inform not only the average value, but also its probability of occurrence.

As for NPS pollution risk analysis, AGRIRISK computes the average concentration of nutrients and pesticides in streams over daily, monthly or annual periods. Cumulative frequency curves are also computed for nutrients and pesticides, so the user can identify the exceedance probability of critical values by reading the curves. This routine is still disabled in the alpha-version. The basic structure of the system is depicted in Figure 1.

As shown in Figure 1, the user may either "Perform Risk Analysis" or "Compute Model Performance" to calibrate and validate some variables.

The second option allows the user to compute the Nash-Sutcliffe coefficient, R^2 and Person correlation between observed and predicted data as well as generate plots of observed versus predicted data and time series of both, as shown in Figure 2. In this sub-routine, the variables to be calibrated and validated are: Groundwater Table Depth (computed by the application), Surface Runoff (mm), Subsurface Runoff (mm), Water Yield (mm), Sediment Yield (Ton/ha), N Yield (kg N/ha), P Yield (kg P/ha), Streamflow (m^3/s), Sediment Transported (Tons), Sediment Concentration (mg/L), N Transported (Kg N), P Transported (Kg P), N Concentration (ppm), P Concentration (ppm), Pesticide Load (mg), Pesticide Concentration (ppm).

For any of the above variables, the user must load "Observed data" in order to compare them with "Predicted results." If groundwater table depth is selected, the application first computes Groundwater Table depth (Figure 1), then compares the results with the "observed data." If any other variable is chosen, the application makes a query using the SWAT output files BSB.DBF and RCH.DBF (Figure 1).

Figure 3 depicts how SWAT and AGRIRISK are integrated to perform groundwater table depth computation and hydrologic risk analysis. At the HRU scale, the program requires some SWAT dbf input files, such as sol.dbf, sub.dbf and HRU.dbf, located in the path : AVS2000\projectname\scenarios \default\tablesin. These files are used to compute some soil parameters for every soil layer, including wilting point (WP), field capacity (FC), soil porosity, drainage porosity and drainage volume as well as the "drainage volume-water table depth" curve (DV-WTD) for each hydrologic response unit (HRU). As shown in Figure 1, the user can also supply the DV-WTD curves to compute water table depth instead of using the curves computed by the system.

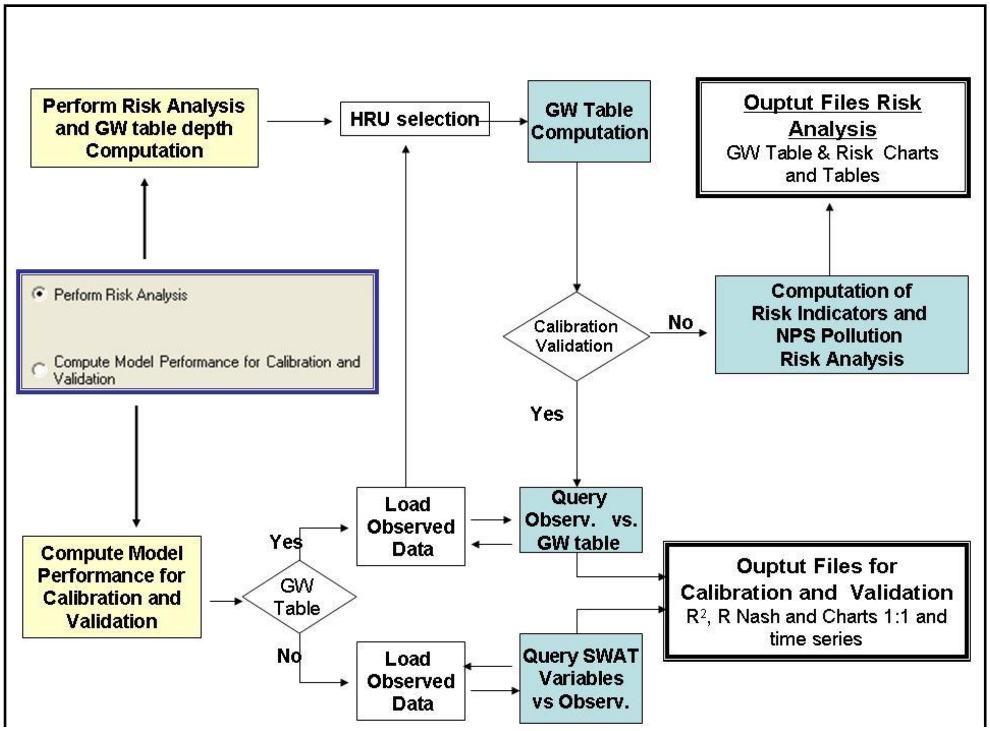

Figure 8. *Main application processes*

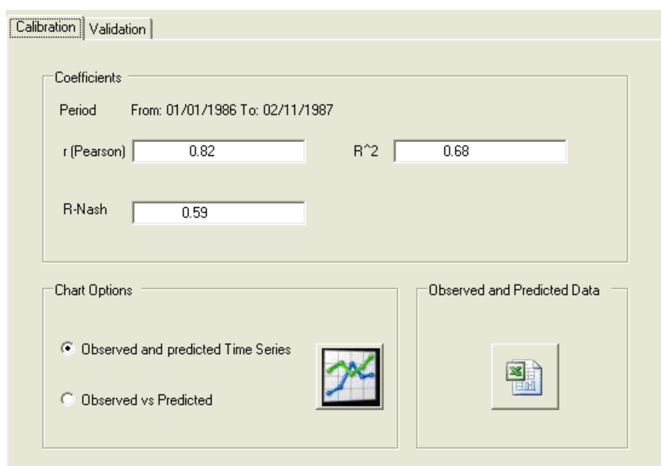

Figure 9. *Output screen for validation and calibration results*

AGRIRISK has been compiled in visual basic (VB.Net) language to run separately from SWAT as a complementary model interface. The user has to inform the program of the SWAT project file name and the scenarios of interest in order to locate the SWAT input and output files necessary for the analysis.

To compute daily perched groundwater table depth and perform hydrologic risk analysis for each scenario, the model interface uses a special SWAT output file, provided by the SWAT authors, called soilst.out. This output file provides the daily soil water content of each soil layer for each HRU, but it is not available for the current version of AVSWAT2000. Therefore, before running the model, the user must replace the SWAT executable file AVSWAT2000.exe located in the directory C:\AVS2000\AvSwatPr, with another executable file supplied along with AGRIRISK that creates the “soilst.out” output file.

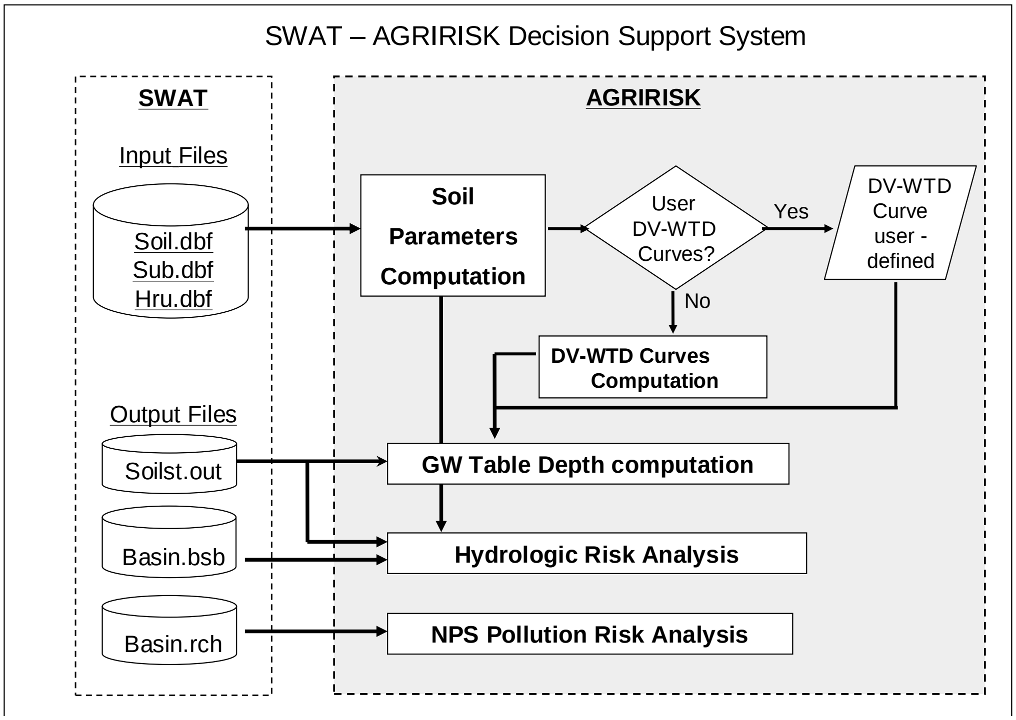

Figure 10. *Structure of the risk analysis processes*

At the subbasin scale, the program uses the information stored in the "basin.rch" output file to compute NPS pollution risk analysis and the "basin.bsb" output file to compute the average degree of saturation of the watersheds. Both files are located in either "AVS2000\projectname\scenarios\default\textinout\" for the default scenario or in "AVS2000\projectname\scenarios\scenarioname" for any other user-defined scenario.

Thus, AGRIRISK computes the following outputs: time series plots for groundwater table depth, a table with hydrologic risk analysis indicators for farming activities at HRU and subbasin level and cumulative frequency plots for NPS pollution risk analysis. The alpha version only includes groundwater table charts, the hydrologic risk indicators table at the HRU level and the calibration and validation analysis. Figure 4 shows the output screen for the hydrologic risk analysis.

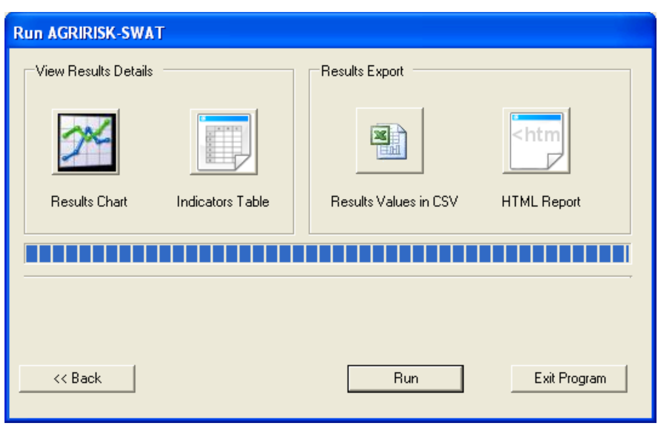

Figure 11. *Output screen for results of groundwater table depth and hydrologic risk analysis*

3. Groundwater table depth computation

Since SWAT does not compute groundwater table depth, a modification based on the drainage volume-water table depth relationship (Vazquez-Amábile and Engel, 2005) was proposed in order to incorporate the computation. AGRIRISK uses this solution to report time series plots for groundwater table depth and the average monthly water table depth.

4. Hydrologic risk analysis for agriculture

In farming activities, soil water content is a key variable. Soil water content variation throughout the year is the result of the interaction of weather, soil properties and position within the landscape and also management practices, such as no-tillage or tile drainage.

Thus, we propose a hydrologic risk analysis for farming activities, extending the capabilities of the SWAT model. Along with the computation of the groundwater table, this analysis includes time series plots for daily soil water content of first layer and of the layers within the first meter of soil, as well as some risk indicators. Soil water content charts are not yet available in the alpha version of the application.

4.1 Hydrologic risk indicators at HRU level

The use of indicators is an additional way to communicate risk. Risk indicators are useful for determining whether a situation is more or less favorable without using probabilities. In this case, some indicators are proposed for evaluating the suitability of soil units under given management practices and according to the requirements of different crops. The length of time a given condition lasts is a helpful measure to make comparisons between scenarios and soil types. The suitability of a soil for agriculture or cattle production is related to the opportunity of working it. There are key times during the growing season, like planting or harvest, that define the success of a given activity. Water excesses can delay fieldwork, increasing the chance of failure and reducing acreage. Therefore, it is important to be able to characterize soil units or landscape units in terms of their suitability for farming activities.

Thus, a simple way to determine suitability is by computing the number of days appropriate for fieldwork throughout the year. Planting, harvesting and cultivation tasks have different soil moisture requirements, so we can compute the number of days for planting, for harvest and for general fieldwork (disk, chisel or cultivator). The necessities vary among crops and regions, so the extension agents and farmers must evaluate this information according to the environmental conditions and the projected activity. AGRIRISK computes the following seven indicators for the selected HRU for every month of the year during the length of simulation:

1. *Optimum days*: An optimum day is defined as one in which the available water content (AWC) of the top soil layer is between 50% and 100%, regardless of the occurrence of precipitation.
2. *Stress days*: A stress day is defined as one in which the AWC of first soil layer is less than 50%.
3. *Excess days*: An excess day is defined as one in which the AWC of the first soil layer is higher than 100%.
4. *Fieldwork Days*: A fieldwork day is defined as one in which the AWC of the first soil layer is between 50% and 100%, and there is no recorded rain.

Table 6. *Output Table for risk indicators (Number of days of…) for Avonburg soil series*

	Optimum Days	Stress Days	Excess Days	Fieldwork Days	Planting Days	Harvest Days	GW table above 1 m (days)
Jan	3.1	0	27.9	2.3	0	2.3	26.3
Feb	2.7	0	25.6	2.5	0	2.5	25.4
Mar	3.1	0	27.9	2.6	1.8	2.6	25.4
Apr	3.7	0	26.4	3.3	2	3.3	21.7
May	9.9	0.1	20.9	8.4	1.8	8.5	16.6
Jun	18.8	4.3	6.9	14.7	1.1	18.1	5
Jul	19.7	10.5	0.8	13.6	0.6	22.2	0
Aug	13.7	13	4.3	9.7	0.7	20.5	0
Sep	19.4	7.5	3.1	14.8	0.7	21.1	0.3
Oct	20.9	4.6	5.5	17.2	5.6	20.5	2.4
Nov	7.8	2.3	19.9	6.5	4.6	8.4	5.2
Dec	3	0	27.9	2.6	2.6	2.6	22.1
Year	125.8	42.3	197.1	98.2	21.5	132.6	150.4

5. *Planting days*: A planting day is defined as one in which the AWC of the first 4 cm of soil is 100%, and there is no rain recorded. Since SWAT computes the daily average soil moisture for every layer, it is necessary to make an assumption to compute planting days. It is assumed that the soil dries downward uniformly. Thus, if the AWC is 90%, the upper 10 % of the layer is considered dry and the AWC of rest of the layer would be 100% (Eq 1).

$$\text{Planting lower AWC}\,(\%) = 100 - \left[\frac{4cm}{Top\_layer\_depth(cm)} \times 100\right] \qquad \text{(eq.1)}$$

6. *Harvest Days*: A Harvest day is defined as one in which the AWC of the first soil layer is equal to 100% or less, and there is no rain recorded.

7. *Number of Days with groundwater table depth above one meter*: These days are defined according to the groundwater table depth. The day is computed when the groundwater table is located above the first meter.

5. NPS Pollution risk analysis in streams

Unlike the NAPRA-GLEAMS system (Lim and Engel, 2003), SWAT can only model one pesticide at a time. However, SWAT has the ability to analyze large watersheds by computing the route and degradation of pollutants, which are the main limitations of NAPRA-GLEAMS when applied to large watersheds. AGRIRISK is proposed for computing the average daily or monthly sediment load and in-stream concentrations of N, P and pesticide, as calculated by SWAT at the outlet of every subbasin. Furthermore, cumulative frequency curves can also be computed to estimate the exceedance probability for nutrients and pesticides for critical values defined by the user (Vazquez-Amabile et al., 2006).

6. Conclusions: Potential Users and Future Research

The proposed system has been designed to extend the SWAT model capabilities in order to be used as a Decision Support System in agricultural watersheds by governmental authorities and technicians, extension agents and farmers. However, it might also be useful to extend the analysis of the model outputs for educational purposes and to save time in the process of model calibration and validation for researchers.

As mentioned, an alpha version of this interface is available for download and testing at http://swatrisk.blogspot.com/. The beta version of the application is currently under development and will be available this year for use as a complementary tool for AVSWAT2000.

Although AGRIRISK has been created to work along with AVSWAT2000 to analyze one or more scenarios, this procedure may be applied to any other GIS-based, continuous hydrologic model with similar characteristics in the future. It may also become part of the ArcGIS version of SWAT2005 in the future, along with a modified algorithm for groundwater table depth (Moriasi et al., 2009).

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Evaluation of different spatial discretization schemes in the hydrological response of an Andean watershed

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Abstract

A model's ability to represent a basin depends on how efficiently it represents the processes within that basin and the land features that contribute to those processes. To simulate the hydrology of a basin, it is possible to use a lumped model or a distributed model. Our work objective, as described in this paper, was to analyze the effects of changing slope definition combinations in the semi-distributed Soil and Water Assessment Tool. Changes made during the Land use/Soil/Slope definition step were evaluated based on how they influenced results obtained in a modeling exercise conducted within the Lonquimay River Basin in Chile. The watershed was delineated, taking into account eight different contributing areas. Afterward, we defined the land use, soil and slope by considering three slope classes (single, 2 classes and 3 classes). Next, HRUs were defined by considering: dominant land use and soil as well as different combinations of soil and land use. SWAT was run 128 times, and simulated monthly flows were compared with observed flows using different statistical indicators. The best results were obtained when the basin was divided into three subbasins and two slope classes were considered. As subbasin number increased incrementally, there was a need for a stronger relationship between the number of subbasins and the number of HRUs to obtain better results. This kind of analysis is relevant in countries were data availability is scarce because sometimes, during model set-up, an over discretization is done, which may not necessarily improve results.

Keywords: SWAT, hydrological response units, discretizations, Chile

1. Introduction

A model's ability to represent a basin depends on how efficiently it represents the processes within that basin and the land features that contribute to those processes. To simulate the hydrology of a basin, it is possible to use a lumped model or a distributed model. Lumped models consider the basin to be homogenous, with parameters that are representative of the entire basin. On the other side, distributed models discretize the basin in many cells in which each parameter must be defined. Between these two discretization schemas are the semi-distributed models in which different subbasins are defined. These subbasins are divided in Hydrological Response Units (HRU), which, in the case of the SWAT model, are composed of unique combinations of land use, soil and slope.

When modeling, it is important to not only obtain the best representation of basin processes possible, but also to consider data availability and computational times. Very high levels of discretization generate significant increases in computational cost without obtaining, in some cases, an increase in the efficiency of the model. Past studies regarding the best discretization (number of subbasins and HRUs) in SWAT included only soil and land use within the definition of HRUs (Bingner et al., 1997; Fitzhugh and MacKay, 2000; Jha et al., 2004; Tripathi et al., 2006). Our work objective, as described in this paper, was to analyze the effects of changing slope definition combinations in the semi-distributed SWAT model. Changes made during the Land use/Soil/Slope definition step were evaluated based on how they influenced results obtained in a modeling exercise conducted within the Lonquimay River Basin in Chile.

2. Materials and Methods

2.1 Study area

The rainfall-runoff modeling application described in this paper focuses on the Lonquimay River Basin. This basin is located in the Andes Mountain Range (38°20' – 38°41' S and 71°13' - 71°35' W; Figure 1) and has an area of 455 km^2. Elevation values range from 880 m a.m.s.l. (Lonquimay gauging station) to 2533 m a.m.s.l. Approximately 66% of the basin has elevation values lower than 1500 m, and only 2.3% of the subbasin has elevation values greater to 2000 m. The flow regime is pluvio-nival, with maximum and minimum mean monthly discharges occurring during the months of June (45.75 m^3/s) and March (8.96 m^3/s), respectively. A snowmelt peak occurs during October.

2.2 Model Setup

For application of the SWAT model (Di Luzio et al., 2002; Neitsch et al., 2005[a]; Neitsch et al., 2005[b]) to the Lonquimay Basin, a 30-m x 30-m Digital Elevation Model (DEM) (based on the final SRTM datasets) was used as a basis for the delineation of the river basin. Meteorological and fluviometric input data were obtained from the National Water Data Bank ("*Banco Nacional de Aguas*") of the Chilean General Water Directorate DGA (Figure 1). The land use description for the basin (Figure 1) was based on interpretations of aerial photographs (scale 1:70.000 and 1:115.000) from 1996-1998, which were combined with information from the "National Inventory of Vegetational Resouces of Chile" (CONAF - CONAMA – BIRF, 1995). The model was run for the period 1992 to 2002, with three years as warm-up.

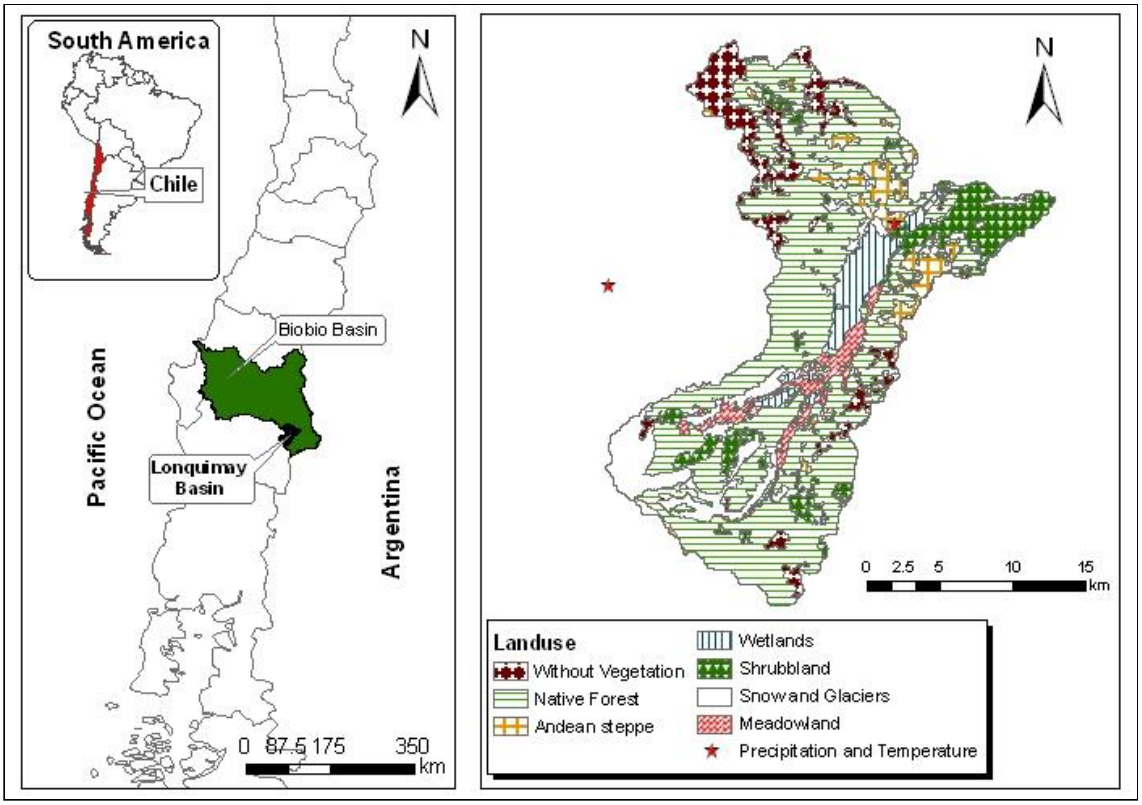

Figure 1. *Location of Lonquimay basin*

2.3 Methodology

The development of this research was carried out as follows:

1) The watershed was delineated by considering eight different contributing areas (Figure 2).
2) The land use, soil and slope were defined, with slope broken into three cases: the first case considering a single slope, the second case considering 2 slope classes (0% - 31.5 % and more than 31.5%) and the third case considering 3 slope classes (0% - 21%; 21% - 42% and more than 42%).
3) HRUs were defined by considering: dominant land use and soil and the combination of 5% of soil with 0%, 5%, 10%, 15% and 20% of land use.
4) The SWAT model was run 128 times and simulated flow was compared with observed flow

3. Results and Discussion

We obtained between 2 and 51 subbasins (Figure 2) and 3 and 439 HRUs during the delineation process. Table 1 indicates the minimum and maximum number of HRUs obtained for each subbasin. The SWAT model was run on a daily time step, but results were analyzed at a monthly level to better estimate how the performance of the model changed considering the different number of subbasins and HRUs.

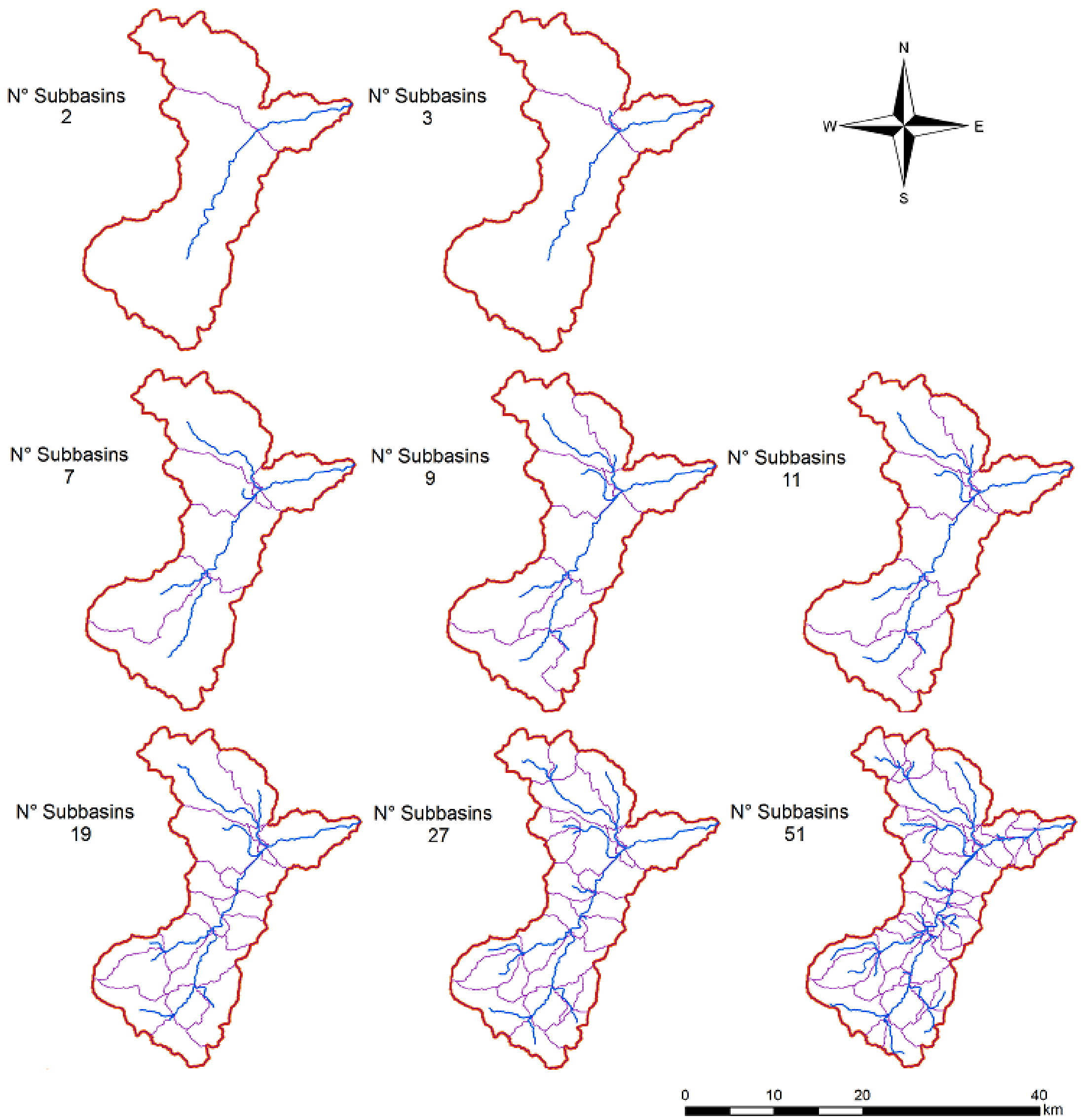

Figure 2. *Subbasin configurations used for modeling*

Table 1. *Minimum and maximum number of HRUs*

Nº of Subbasins	Minimum Nº of HRU	Maximum Nº of HRU
2	3	37
3	5	48
7	12	98
9	14	113
11	19	132
19	33	206
27	48	266
51	86	439

To estimate the monthly efficiency of the model, the following statistical indicators were used:

Nash-Sutcliffe Modeling Efficiency:

$$EF = \left[\frac{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2 - \sum_{i=1}^{n}\left(S_i - O_i\right)^2}{\sqrt{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2}} \right]$$

Goodness of fit:

$$R^2 = \left[\frac{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)\left(S_i - \overline{S}\right)}{\sqrt{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2}\sqrt{\sum_{i=1}^{n}\left(S_i - \overline{S}\right)^2}} \right]$$

where: O_i: Observed streamflow in m^3/s; S_i: Simulated streamflow in m^3/s; $\overline{O}$: Mean observed streamflow during the evaluation period in m^3/s and $\overline{S}$: Mean simulated streamflow during the evaluation period in m^3/s.

Figure 3 shows how the Nash-Sutcliffe Efficiency increases as the number of HRUs increased incrementally for the three slope cases considered. As shown, the best results were obtained when the basin was divided in three subbasins and two slope classes were considered. As subbasin number increased incrementally, there was a need for a stronger relationship between the number of subbasins and the number of HRUs to obtain better EF and R^2 (Table 2).

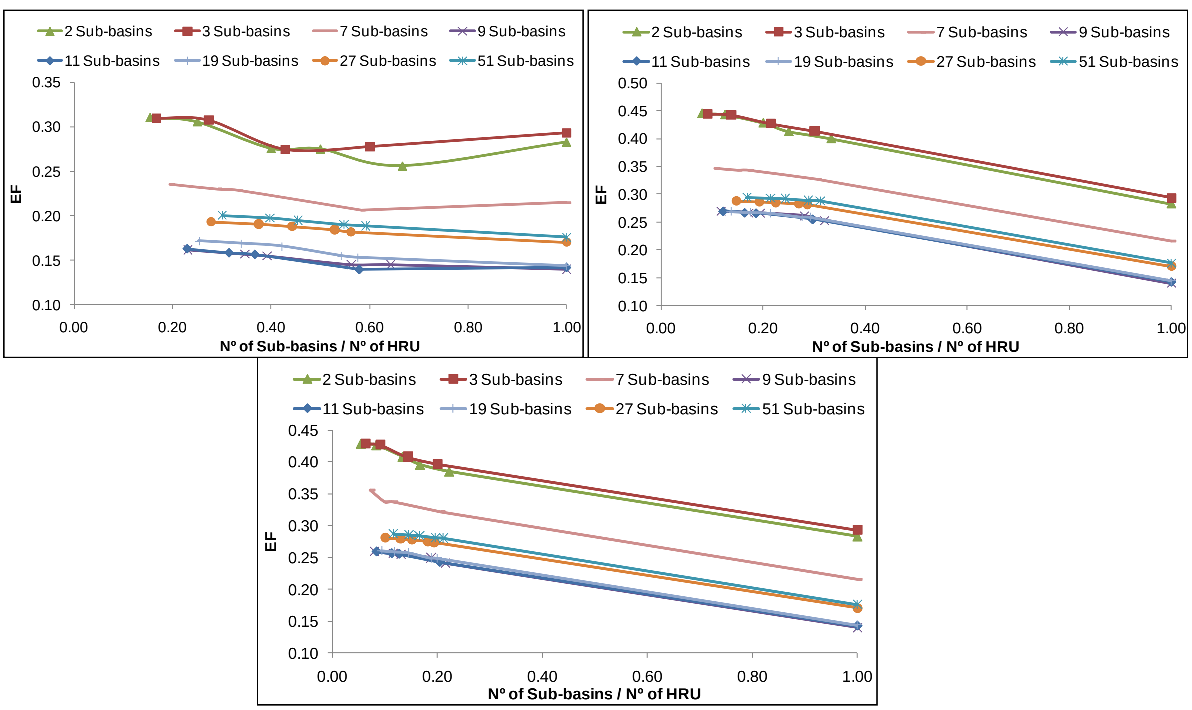

Figure 2. *Relationship between Nash-Sutcliffe Efficiency and the Nº of subbasins and HRUs a) All subbasin subdivisions in single slope case, b) All subbasin subdivisions created using two slope classes, c) All subbasin subdivisions created using three slope classes*

Table 2. *Relationship between the Nº of subbasins, the Nº of HRUs (S/H) and the Nash-Sutcliffe Modeling Efficiency (EF) and Goodness of fit (R^2) for each slope division*

Nº of Subbasins	EF 1		EF 2		EF 3		R2 1		R2 2		R2 3	
	S/H	HRU	S/H	HRU	S/H	HRU	S/H	HRU	S/H	HRU	S/H	HRU
2	0.25	8	0.08	25	0.08	24	0.25	8	0.13	16	0.08	24
3	0.27	11	0.14	22	0.09	33	0.27	11	0.14	22	0.09	33
7	0.29	24	0.15	47	0.10	70	0.33	21	0.17	41	0.07	98
9	0.35	26	0.20	46	0.12	78	1.00	1	0.32	28	0.19	48
11	0.37	30	0.19	59	0.13	87	0.23	48	0.30	37	0.13	87
19	0.42	45	0.21	89	0.14	132	0.42	45	0.29	65	0.20	96
27	0.44	61	0.23	120	0.15	178	0.28	97	0.29	94	0.18	148
51	0.40	128	0.31	164	0.12	439	0.46	112	0.31	164	0.21	241

The results obtained in this study agree in part with those obtained by Mamillapalli et al. (1996), who found that at a certain level of discretization, the model is no longer able to increase its efficiency. In the case of the Lonquimay Basin, the best results were achieved with the smallest number of subbasins, but at a certain number of subbasins and HRUs, the EF and R^2 stabilized. For example, in the case that included two slopes classes, the model no longer improves considerably in efficiency when the relationship between subbasin and HRU produces an EF of 0.35 and an R^2 value of 0.30. Jha et al. (2004) found that the ideal subbasin size is between 2 and 5% of the total area of the basin. In this study, the best results were obtained when we considered a contributing area comprising 20% of the total area of the basin in the delineation process. Outcomes of this modeling exercise disagree with the results of Muleta et al. (2007), who modeled the Big Creek Basin (133 Km^2) in Illinois. They used between 9 and 118 subbasins and 9 to 352 HRUs and concluded that the efficiency was not improved. In this study, the basin (455 km^2) was subdivided into between 2 and 51 subbasins and 3 to 439 HRUs, revealing that EF and R^2 are susceptible to subdivision.

4. Conclusions

When increasing the number of HRU´s by subbasin, stability in the model efficiency was generated without creating an increase in the associated modeling costs. We recommend using three HRUs per subbasin, generating a 52% increase in the Nash-Sutcliffe Efficiency as compared to the dominant HRU case that considered 11 subbasins. Results were greatly improved when using two slope classes to generate HRUs, but no improvement was obtained when three slope classes were used.

It is important to mention that the same analysis done at the Lonquimay Basin is being done in other Chilean basins to investigate whether results will be the same if larger subbasins are considered. This kind of analysis is relevant in countries were data availability is scarce. This is the case in Chile because sometimes, during the set up of a model, an over discretization is done. This will not necessarily improve results because the spatial variability of input data cannot represent the processes involved in the model at the same scale as that used for the discretization. For example, a basin is subdivided in 80 subbasins, but there is only one pluviometric station in the basin and three different land uses.

Acknowledgments
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SWAT Water Balance: Development and Application of a Physically Based Landscape Water Balance in the SWAT Model

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Abstract

The Soil and Water Assessment Tool (SWAT) uses the popular Curve Number (CN) method to determine the respective amounts of infiltration and surface runoff. While appropriate for engineering design in temperate climates, the CN is less than ideal in some situations (e.g., monsoonal climates, areas dominated by variable source area hydrology). The CN methodology is based on the assumption that moisture content distribution in the watershed is similar for each runoff event, a questionable assumption in many regions. To test the CN method's ability to predict runoff, the CN routine was replaced with a physically based water balance in the code base. To compare this new water-balance SWAT (SWAT-WB) to the original CN-based SWAT (SWAT-CN), several watersheds in both the headwaters of the Blue Nile in Ethiopia and in the Catskill Mountains of New York State (NYS) were initialized. Prior to any calibration of the models, daily streamflow Nash-Sutcliffe (NSE) model efficiencies improved from 0.03 with SWAT-CN to 0.33 with SWAT-WB, presumably because water deficits are better modeled. Moderate calibration (parameterization) based on soil properties in the watersheds resulted in vastly improved model performance for both models. However, SWAT-WB streamflow predictions were significantly better than those of SWAT-CN in the Ethiopian watersheds (NSE 0.74 vs 0.61) and resulted in nearly identical predictive accuracy in the NYS watershed (NSE 0.68 vs 0.67). These results suggest that replacement of the CN with a water balance routine in SWAT significantly improves model predictions in monsoonal climate regions such as Ethiopia while providing equally acceptable levels of accuracy under more typical U.S. conditions when minimal calibration is completed. Further work will investigate the implications of the model selection on the spatial distribution of processes in the watersheds.

1. Introduction

Hydrologic models are used primarily to predict water quantity, peak flows and the export of pollutant from watersheds. One common method of determining the runoff volume in these models is the USDA-NRCS Curve Number (CN) technique. This method was initially designed for determining runoff volume for engineering design purposes but has since been adapted for use as a tool in many temporal watershed models, including SWAT (Garen and Moore, 2005). Under Ethiopian conditions, runoff is mainly generated by saturation excess mechanisms, so runoff from a given amount of rain is less at the beginning of the rainfall season than at the end (Liu et al. 2008). Although the CN method can be adapted to predict this type of saturation excess (Easton et al., 2008), it assumes that similar rainfall patterns produce the same amount of runoff independent of the time of year, a problem in monsoonal climates. This is well illustrated in Figure 1 where we applied the standard CN approach to the Anjeni watershed in the Ethiopian Highlands, which has 16 years of rainfall-runoff data. It is clear that when we calibrated the CN to the storms at the end of the rainfall season, the storms at the beginning of the season with less than 500 mm of cumulative precipitation were under-predicted. Therefore, in order to apply SWAT to Ethiopian conditions, the original CN method must be replaced by a more mechanistic approach that uses soil water balances to calculate when the soil is saturated and consequently when runoff is produced.

2. Methods

To adjust the SWAT program to account for saturation excess runoff, a new subroutine was created in the code that uses a landscape water balance to calculate saturation. The new, saturation-driven SWAT model results were then compared to the original, CN-based SWAT results for two watersheds.

2.1 Original SWAT Curve Number Approach

The CN procedure lumps land use and soil characteristics into a single parameter, CN, and relates the watershed runoff response to some theoretical storage capacity obtained from tabulated values. An initial CN is assigned for each specific land use and soil combination (or Hydrologic Response Unit, HRU) in the watershed, and these values are read into the SWAT program before simulations are run. SWAT then calculates upper and lower limits for each CN following a probability function described by the NRCS to account for varying antecedent moisture conditions (CN-AMC) (USDA-NRCS, 2004). SWAT determines an appropriate CN for each simulated day by using this CN-AMC distribution in conjunction with daily soil moisture values determined by the model. This daily CN is then used to determine a theoretical storage capacity, *S*, of the watershed for each day (via eq. 1).

$$CN = 1000/(10 + \frac{S}{25.4}) \quad (1)$$

This derived storage capacity is then used to determine the runoff volume, Q, created from a precipitation event, *P* (eq. 2). By convention, the initial abstraction, I_a, is assumed to be equal to 0.2*S.

$$Q = \frac{(P - I_a)^2}{(P - I_a) + S} \quad (2)$$

While a theoretical storage capacity is assigned and adjusted for antecedent moisture for each land use/soil combination, the storage is not used to directly determine the amount of water allowed to enter the soil profile. Since this storage is a function of the land infiltration properties, as quantified by the CN-AMC, SWAT indirectly assumes only infiltration excess runoff. Prior to any water infiltrating, the exact portion of the rainfall that will runoff is calculated via these infiltration properties. This determination of runoff volume before soil water volume is an inappropriate approach for all but the most intense rain events, particularly in monsoonal climates where saturation plays an important role in runoff generation.

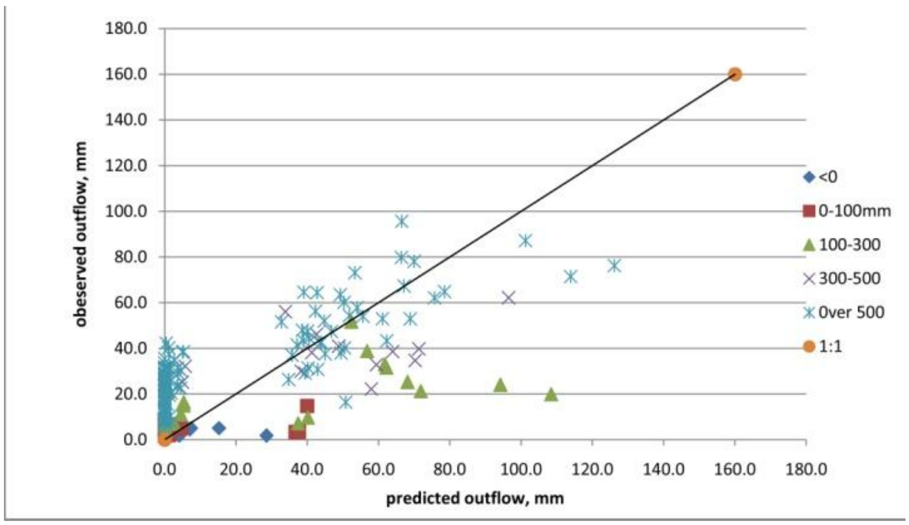

Figure 1. *Observed vs. Curve-Number predicted streamflow for the Anjeni watershed (Ethiopia) showing cumulative rainfall values for each rainy season*

2.2 SWAT-WB Saturation Excess Approach

The modified SWAT (SWAT-WB) uses a water balance for each HRU that partitions runoff, interflow and infiltration volumes. While this model simplifies the processes that govern water movement through porous media (partly-saturated regions in particular), the water balance model has been shown to be proficient for a daily model (Guswa et al., 2002). In SWAT-WB, HRUs are formed based on land use, soil information and a topographic index from Easton et al. (2008). For each HRU, a water balance is kept that is adjusted daily for plant uptake and evaporation. Therefore, rather than using the daily CN to predict runoff from a given event in SWAT-WB, runoff is equal to the amount rainfall minus the amount of water that can be stored in the soil before saturation. This volume is the available soil storage, τ:

$$\tau = D(\varepsilon - \theta) \quad (3)$$

Where D is the effective depth of the soil profile, ε is the total soil porosity, and ϑ is the volumetric soil moisture of the HRU. The porosity is a constant value of $1\text{-}\rho_b/\rho_s$ for each soil type, whereas ϑ varies by day depending upon plant uptake of water, evaporation and precipitation. For any HRU, a precipitation event that has a smaller volume than the available storage will not contribute any runoff to the channel (i.e., all rain will infiltrate as soil water). For an HRU, surface runoff is generated when a rainfall event has a higher volume of rain than it will take to saturate the soil profile. The volume of this saturation excess generated runoff is simply the portion of the rainfall, *P*, that exceeds the *τ* value for the HRU:

$$Q = P - \tau \qquad (4)$$

Note, since this model generates runoff when the soil is above saturation, total rainfall determines the amount of runoff. When results are presented on a daily basis, rainfall intensity is inconsequential. We recognize that under high intensity storms we might under-predict the amount of rainfall, but this is the exception rather than the rule (Liu et al, 2008).

2.3 Watershed Descriptions

SWAT-WB was tested on two watersheds, one in the Blue Nile River basin in Ethiopia and the other in the Catskill Mountains of New York State. The Gumera watershed, located northeast of Bahir Dar, Ethiopia, is a 1270-km^2, heavily cultivated (~95%) watershed in the Lake Tana Basin. Elevation of the Gumera watershed ranges from 1797 to 3708 meters above sea level, and the predominant soils are generally characterized as chromic and haplic luvisols (24% and 63%, respectively) (FAO-AGL, 2003). Daily precipitation and temperature data from 1996 to 2005 were used, while other historic climate data (relative humidity, wind speed, solar radiation) were gathered from the United States' National Climatic Data Center for the nearest station in Bahir Dar (NCDC, 2007). We then compared the output of both SWAT-WB and SWAT-CN to daily streamflow data for the Gumera basin outlet during the years 1998 and 1999.

SWAT-WB was also tested on the Townbrook watershed in New York State, a 37-km^2 sub-catchment of the Cannonsville Reservoir Basin. The region is typified by steep to moderate hillslopes of glacial origins with shallow permeable soils that are underlain by a restrictive layer. The climate is humid with an average annual temperature of 8˚C and average annual precipitation of 1123 mm. Elevation in the watershed ranges from 493 to 989 m above mean sea level. The slopes are quite steep with a maximum of 91%, a mean of 21% (with a standard deviation of 13%) and a median of 18%. Soil depth ranges from less than 50 cm to greater than 1 m and is underlain by a fragipan restrictive layer (e.g., coarse-loamy, mixed, active, mesic, to frigid Typic Fragiudepts, Lytic or Typic Dystrudepts common to glacial tills) (Schneiderman et al., 2002). The lowland portion of the watershed is predominantly agricultural, consisting of pasture and row crops (20%) or shrub land (18%) while the upper slopes are forested (60%). Water and wetland comprise (2%). Several studies in this watershed or nearby watersheds have shown that variable source areas control overland flow

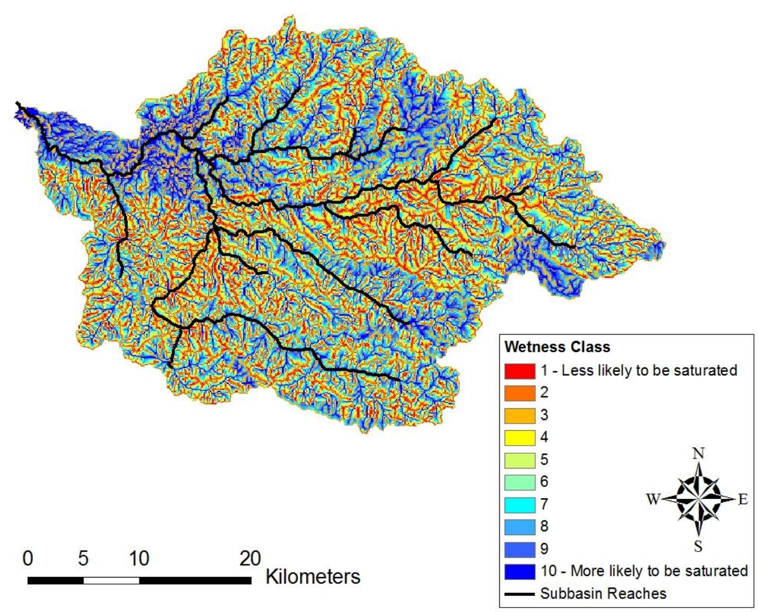

Figure 2. *Wetness class distribution in the Gumera watershed*

generation (Frankenberger et al., 1999; Mehta et al., 2004; Lyon et al., 2004; Schneiderman et al., 2007; Easton et al., 2008) and that infiltration-excess runoff is rare (Walter et al., 2003).

To better predict the spatial distribution of runoff source areas in SWAT-WB, we created a soil topographic index (*STI*)-soils hybrid map and used it in place of the standard soils input map. The associated soil properties of the map were extracted from the SSURGO (Townbrook) or FAO soil (Gumera) databases, and look-up tables were linked to the map using the ArcSWAT interface. For SWAT-WB, we lumped the watershed's *STI* into 10 equal area intervals ranging from 1 to 10, with index class one covering the 10% of the watershed area with the lowest *STI* (i.e., the lowest propensity to saturate) and index class 10 containing the 10% of the watershed with the highest *STI* (i.e., the highest propensity to saturate). These wetness index classes were intersected with the land use to create HRUs. They were also used to distribute the effective depth coefficient (*D*) in Eq. 3 across the watershed (Fig. 2). Thus, the effective depth coefficient is a calibration parameter that controls the partitioning of excess moisture in the soil profile between direct runoff and base or interflow.

3. Results and Discussion

As shown in Figure 3, results obtained with SWAT-WB indicate that a complex watershed model can produce adequate predictions of peak flows at a daily time step in both the monsoonal climate of Ethiopia and in more typical U.S. climates, like New York State, if the CN approach is replaced.

Following calibration, SWAT-WB returned more accurate results for the Gumera basin than SWAT-CN with daily NSE and R^2 values of 0.74 and 0.77, respectively. The calibrated SWAT-CN returned an NSE of 0.61 and R^2 of 0.70 (Fig. 3a). When compared to SWAT-CN, SWAT-WB returns NSE values 15% higher for the calibration period and 25% higher for the validation period. In the Townbrook watershed (Fig. 3b), both SWAT-CN and SWAT-WB returned similar results (NSE 0.67 vs 0.68).

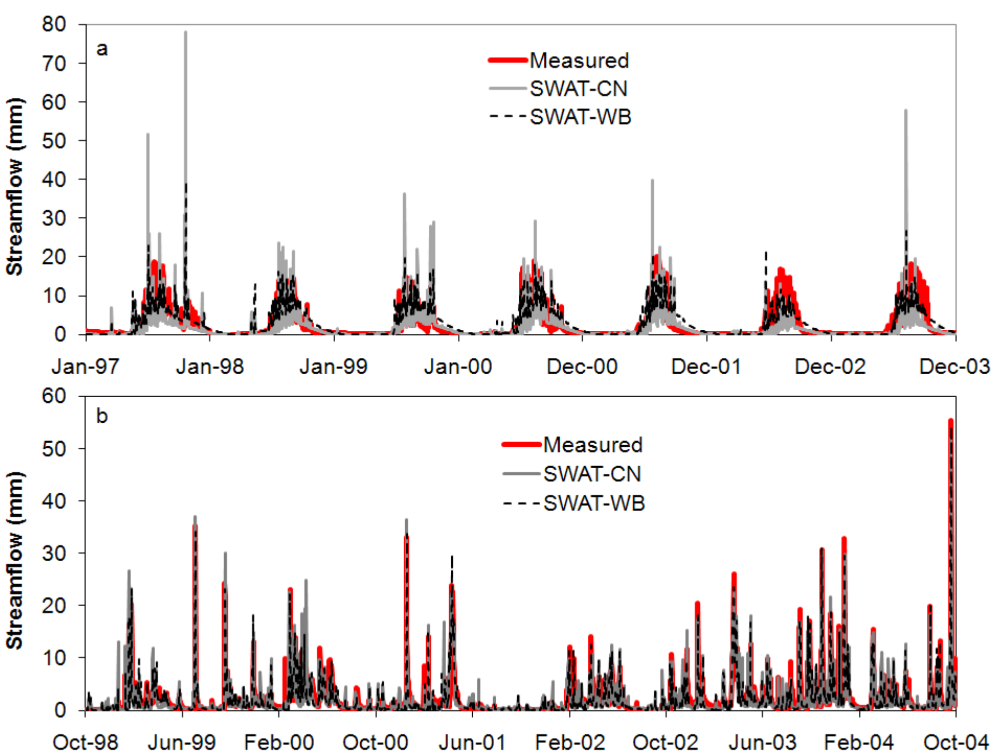

Figure 3. *Observed and modeled daily streamflow for Gumera (a) and Townbrook (b) using SWAT-WB and SWAT-CN.*

While SWAT-WB produced generally good streamflow predictions (Fig. 3), results could be enhanced by improving the soil properties data used as an input to SWAT, particularly the portion of the soil profile available for saturation (effective depth, *D,* in Eq. 1) and drainage due to gravity. This will lead to more accurate representation of the baseflow recession at the end of the rainy season and the spatial variation of runoff generating areas. Even with these preliminary simulations, several advantages that the SWAT-WB has over original SWAT-CN model were demonstrated, especially in the monsoonal Ethiopian climate.

SWAT-CN and most other watershed models were developed for temperate climates where rainfall is generally well distributed throughout the year (e.g., Townbrook in New York State). Running models developed in temperate climates in Ethiopia, which has a monsoonal climate, is problematic. Temperate models assume that there is a nearly unique relationship between each precipitation event's amount or intensity and the runoff generated. This is not the case for Ethiopia, as demonstrated by the results of Liu et al. (2008) who analyzed the applicability of the CN method in three watersheds with more than 16 years of record. The first rains after the dry season all infiltrate the soil and nearly zero runoff is generated (Fig. 3a). As the rainfall season progresses, more and more rainfall becomes runoff. For each of the watersheds analyzed, Lui et al. (2008) found that only after approximately 500 mm of effective rainfall (i.e., precipitation minus potential evaporation) a constant fraction (approximately 50%) becomes runoff. An explanation for this phenomenon is that more and more of the watershed starts generating runoff as the season progresses (Liu et al., 2008). Since the intensity of the rain did not affect the runoff amounts for a given storm, the runoff mechanism was concluded to be saturation excess from variable source areas. This is in accordance with unpublished infiltration measurements made by us in the Lenche Dima and Yeku watersheds, which indicate that the infiltration rate of most soils exceeds the rainfall intensity of most storms.

Interestingly, both SWAT-WB and SWAT-CN performed equally well in the Townbrook watershed (Fig. 3b). This is likely a result of the more evenly distributed precipitation throughout the year. As noted above, CN models were developed mainly in the US where precipitation is generally more evenly distributed. As such, an empirical relationship, such as the CN, will tend to capture those trends well. Yet, the water balance model also performs well because rainfall intensities in the Townbrook watershed are generally lower than the soil infiltration rate (Walter et al., 2003). Thus, runoff is created when the soil profile becomes saturated, a situation the water balance model was developed to capture.

Water balance models are consistent with saturation excess runoff processes because runoff is related to the available watershed storage capacity and the amount of precipitation. The implementation of a water balance approach in calculation of runoff in the Blue Nile Basin is not a novel concept, and many researchers have show that water balance models often perform better than more complicated models in monsoonal climates (Johnson and Curtis, 1994; Conway, 1997; Kebede et al., 2006; Liu et al., 2008; Ayenew and Gebreegziabher, 2006). These water balance models are typically computed with monthly or yearly values because the models are generally not capable of separating base- inter- and surface runoff flow. However, if watershed models (e.g., SWAT) are to be used to effectively model erosion and sediment transport, large events must be captured by the model, and simulations with a daily time step are needed do so. SWAT-WB not only maintains a landscape water balance, but also calculates the interflow and the base-flow component and gives a reasonable prediction of peak flows (Fig 3). SWAT-WB is more likely to realistically model sediment or pollutant transport than either SWAT-CN or water budget models with monthly time steps. Note that by choosing to run models on a daily time step, the model performance is always significantly worse than for monthly or yearly time steps.

SWAT-WB appears to capture runoff processes that occur in the Ethiopian highlands more realistically than other models that base their runoff prediction on the NRCS curve number method (Liu et al., 2008; Collick et al., 2008; Steenhuis et al., 2008). The calculations that serve as a foundation for the NRCS curve number technique assume that soil moisture conditions can be determined by taking into account the previous five days worth of rainfall events. As indicated above, the soil moisture content in the Ethiopian monsoonal climate changes after the first 500 mm of effective precipitation. SWAT-WB, on the other hand, determines runoff volume by simply calculating the available storage in each soil profile. This value is not dependent only upon the five previous days' rainfall (as the CN method is), but instead allows for progressive saturation as the rainy season continues.

Although SWAT-CN predicts streamflow, except for peak flows, reasonably well, that does not mean the spatial distribution of runoff areas is predicted correctly. This issue has been studied in the past, and numerous curve-number-based models have been adjusted to correct for the method's shortcomings. By making simple modifications to the CN approach, the percentage of a watershed that contributes runoff can be determined but not the explicit locations of these runoff-producing areas (Steenhuis et al., 1995). These modifications, among others, have been implemented into watershed models in an attempt to pinpoint the location of runoff production. This CN modification coupled with a topographic index was used by Lyon et al. (2004) and by Schneiderman et al. (2007) in the General Watershed Loading Function (GWLF) model to capture spatial variation controlled by topographic features. Easton et al. (2008) used similar modifications to create a version of SWAT that could determine the location of runoff producing areas more accurately than the traditional SWAT-CN. These modifications show that the CN method is appropriate for many regions and can be adjusted to overcome its inherent shortcomings. However, SWAT-WB goes one step further, retaining the topographic controls introduced by Easton et al. (2008) but eliminating the CN from runoff calculations completely.

4. Conclusions and Recommendations

Daily modeling of peak streamflow and surface runoff was improved in monsoonal climates by replacing the CN method with a water balance routine in the SWAT model. In addition to improving model efficiencies, the water balance method may also be a better predictor of the location of runoff-generating areas (and therefore sediment and pollutant source areas). To improve the determination runoff and pollutant source areas, a soil topographic index was incorporated into SWAT-WB, resulting in a watershed model in which surface runoff is modeled as a function of topography, soil characteristics and soil moisture. Improved soil property data should aid in more accurately determining flows during the middle of the rainy season as well as in the accurate modeling of base-flow recession after the rains end.

In general, water balance models have been found to work in nearly all climates. Therefore, incorporation of these procedures into SWAT provides a more robust model and is potentially applicable in watersheds where it has been determined that runoff generation is driven by saturation excess processes, such as in Ethiopia.

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Improving the snowmelt simulation of SWIM in the experimental basin of the Upper Danube

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Abstract

Snow is sensitive to climate changes, thus it is an important indicator in climate impact assessments. In SWIM, the snowmelt and meltwater outflow is simulated by a simple degree-day method at the subbasin scale. However, this method is not sufficient for simulating spatially distributed snowmelt or runoff generation processes, especially in snow-dominated regions. In this study, the Upper Danube (Germany) was chosen as the experimental basin. We compared both the simulated river discharge at the Hofkirchen gauge and the maximum snow water equivalent in the basin with observed values. The modifications made to the SWIM snow module were as follows: 1) snow processes were simulated at the hydrotope scale, and temperatures for each hydrotope were corrected based on elevation; 2) more snowmelt and runoff generation processes were included. As a result of these modifications, the river discharge was better simulated during the snowmelt period in the Alps, and the maximum snow water equivalent map of this basin became more precise with distinct characteristics in mountains and valleys.

Keywords: SWIM, snow melt, Upper Danube

1. Introduction

Global warming has important implications for the hydrological cycle, especially in snow-dominated regions. In Alpine regions, the snowline is expected to rise, and less snow will accumulate at low elevations (EEA, 2004). Hence, assessing the potential changes in snow patterns is significant in climate impact studies. In the SWIM model, the snowmelt water, which is treated the same as meltwater outflow, is calculated with the degree-day method at the subbasin scale. However, this method can give neither the precise spatial distribution of the snowpack within one subbasin, nor consider other snow processes that play an important role in snowmelt runoff generation. For catchments in which river discharge is strongly influenced by meltwater outflow, a more comprehensive snow module is required to improve the capability of SWIM in simulating snow processes.

The Upper Danube Basin is one part of our climate impact assessment for the whole of Germany (Huang et al., submitted). This basin receives a large amount of snow meltwater from the Alps. To test our modifications of the snow module, we chose the Upper Danube Basin as the experimental basin. As the climate data outside Germany was poor, the study focused only on the German part of the catchment, extending up to the last gauge in Germany—Achleiten (within the red contour in Figure 1). The simulated discharge was compared with measurements from the Hofkirchen gauge.

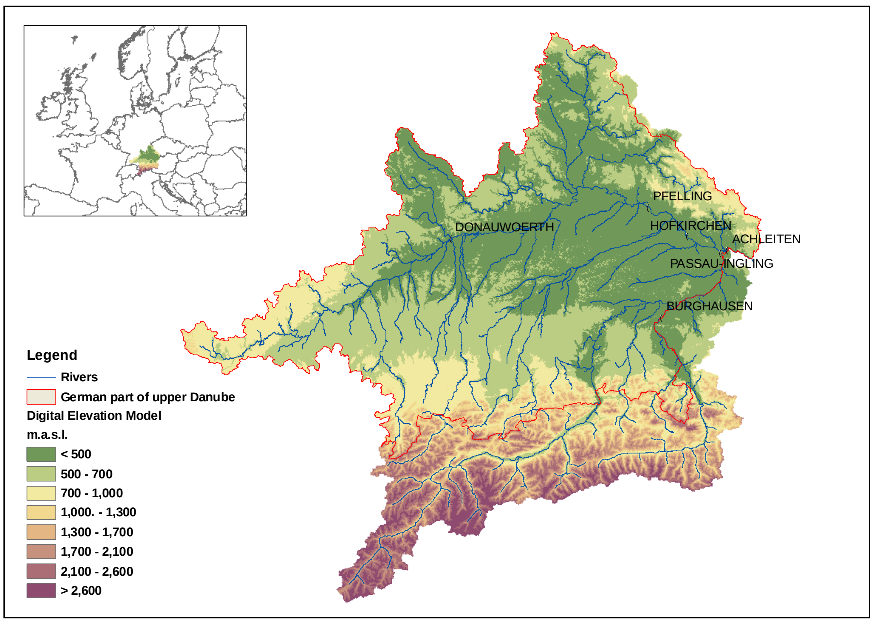

Figure 12. *Digital elevation map of the Upper Danube Basin and the locations of some other gauge stations*

2. Modifications of the snow module

To better simulate snow accumulation and snowmelt processes, two modifications were tested and evaluated in this paper.

1. The hydrotopes were reclassified by taking into account elevation, and snow processes were simulated for each hydrotope instead of each subbasin. Also, corrected temperatures for hydrotopes were included.
2. New snow processes were included in the snow module.

2.1 Hydrotope-specific snow processes

In the original SWIM model, climate information at the subbasin scale was unique in order to simulate different processes. Climate parameters were interpolated into subbasin centroids, which were treated as virtual climate stations within the basins. Hence, the climate data at the centroids (especially temperatures) do not reflect the metrological differences in the mountains and valleys of each subbasin. To solve this problem, hydrotopes, which are the basic calculation unit in SWIM, should contain elevation information, and the temperatures of each hydrotope should be corrected based on elevation conditions.

As hydrotopes are usually defined by soil and land use type within the subbasin in SWIM, it is possible for one big hydrotope to be distributed both in mountainous and plain areas. In such cases, the mean elevation of the hydrotope is not appropriate for distinguishing elevation characteristics. Hence, we used one additional map (elevation zone map) to reclassify the original hydrotopes, which were generated from subbasin soil and land use maps. For the Upper Danube region, the elevation varies from about 300 meters in the lowland to about 3800 meters in the Alps. In our case, a 100-meter threshold was used to generate the elevation zone map by reclassifying the digital elevation model. Namely, the elevations from 300 meters to 399 meters form elevation zone one, and elevations from 400 meters to 499 meters form the second zone and so on. These elevation zones help to cut the large hydrotopes into several smaller ones so that the mean elevation of each hydrotope is more reliable. After this reclassification, the number of hydrotopes was increased from 12,922 to 38,519.

The temperature of each hydrotope was calculated according to a linear correction function:

$$T_{hydrotope} = T_{subbasin} + T_{grad} * (Elev_{hydrotope} - Elev_{centroid}) \qquad (1)$$

where $T_{hydrotope}$ is the corrected temperature for hydrotopes; $T_{subbasin}$ is the temperature interpolated into the centroids; T_{grad} is the correction coefficient; $Elev_{hydrotope}$ is the mean elevation of one hydrotope and $Elev_{centroid}$ is the elevation of the centroid in the corresponding subbasin.

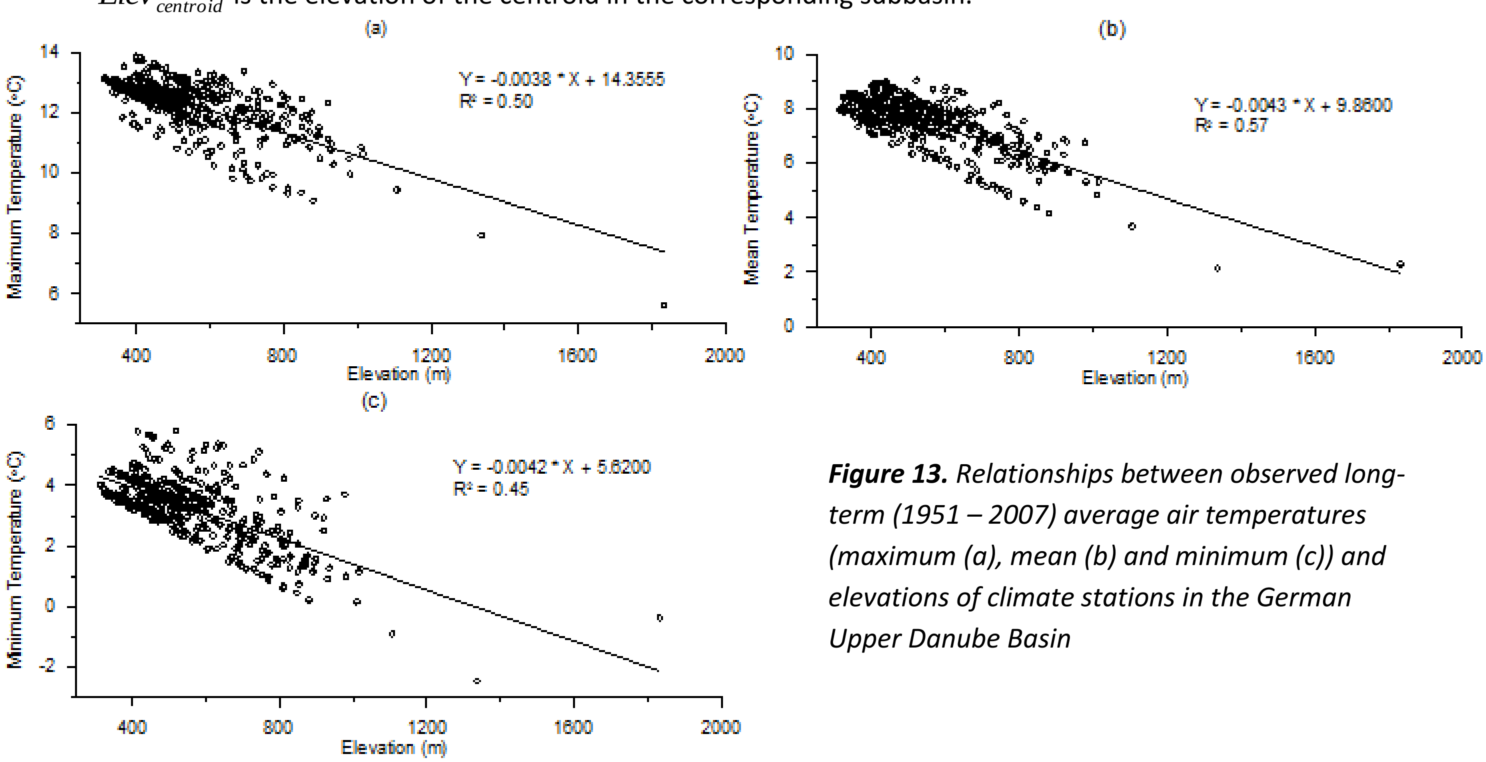

Figure 13. *Relationships between observed long-term (1951 – 2007) average air temperatures (maximum (a), mean (b) and minimum (c)) and elevations of climate stations in the German Upper Danube Basin*

The correction coefficient was obtained from the regression relationships between air temperatures and the elevations of the climate stations in the Upper Danube Basin (Figure 2). All the slopes of the regression lines are approximately -0.004 (meaning the temperature decreases 0.4°C with every elevation increase of 100 meters), so this value was used as the correction coefficient in this study.

2.2 New snow processes in the snow melt module

The second modification was to revise the snowmelt module in the SWIM code to create more detailed descriptions of the snowmelt and runoff generation processes.

During cold periods, the snowpack temperature is at or below 0°C. As it warms, some surface snow begins to melt, and the melting water percolates into the packs, hits the ice and freezes again. This recrystallization process increases the ice crystal size within the pack (namely, increasing the snowpack density and decreasing the snowpack depth) and warms the snowpack until its temperature rises to 0°C. When the water content (melting water or precipitation) in the pack is larger than the water holding capacity of the snowpack, water will be released as runoff. The temporal changes in snowpack depth are calculated as (Gelfan et al., 2004):

$$\frac{dH}{dt} = \rho_w \left[X_s \rho_0^{-1} - (S + E_s)(\rho_i i)^{-1} \right] - V \qquad (2)$$

where H is the snow depth; i is the volumetric content of ice; S is the snowmelt rate (calculated by degree-day function); E_s is the rate of snow sublimation; X_s is the snowfall rate at the snow surface; V is the snowpack compression rate; ρ_w, ρ_i and ρ_0 are the densities of water, ice and fresh-fallen snow, respectively.

The snow pack compression rate, V, is found using the equation (in cm s^{-1}):

$$V = \frac{v_1 \rho_s}{\exp(v_2 T_s + v_3 \rho_s)} \frac{H^2}{2} \qquad (3)$$

where ρ_s is the density of the snowpack (in g cm^{-3}), $\rho_s = \rho_i i + \rho_w w$ (*w* is the volumetric content of liquid water); T_s is the snowpack temperature; v_1, v_2 and v_3 are the coefficients equal to 3.4×10^{-6} cm^2 s^{-1} g^{-1}, -0.08 $^{O}C^{-1}$ and 21 cm^3 g^{-1}, respectively.

The volumetric contents of ice and liquid water (*i* and *w*, respectively) in the snowpack are calculated by the equations presented in Gelfan et al. (2004). The water is released based on the water content in the snowpack and the snow depth.

$$VSN = H * (w - ULMAX) \qquad (4)$$

where *VSN* is the water outflow from the snowpack, and *ULMAX* is the maximum water holding capacity of the snow pack.

3. Results

Using the original SWIM model, the river discharge simulated at the Hofkirchen gauge already agreed well with observed values. The Nash-Sutcliff efficiency was 0.82 and the deviation of the water balance was –3% for the period 1961–1990. However, the main problem is obvious in Figure 3: notice the underestimation of the average daily river discharge (the green line) between April and August. As this period is the main time of snowmelt in the Alps, it indicates that the simple snow module in SWIM is not capable of reproducing the meltwater outflow process in such a snow-dominated region. After the modifications of the snow module, the average daily simulated river discharge (the red line) was closer to the values observed between April and August. The Nash-Sutcliff efficiency increased to 0.84, and the deviation of the water balance was 1% for the same period. Figure 4 shows more clearly that the daily simulated river discharge is higher than the original simulated ones during the problematic period of 1962–1963.

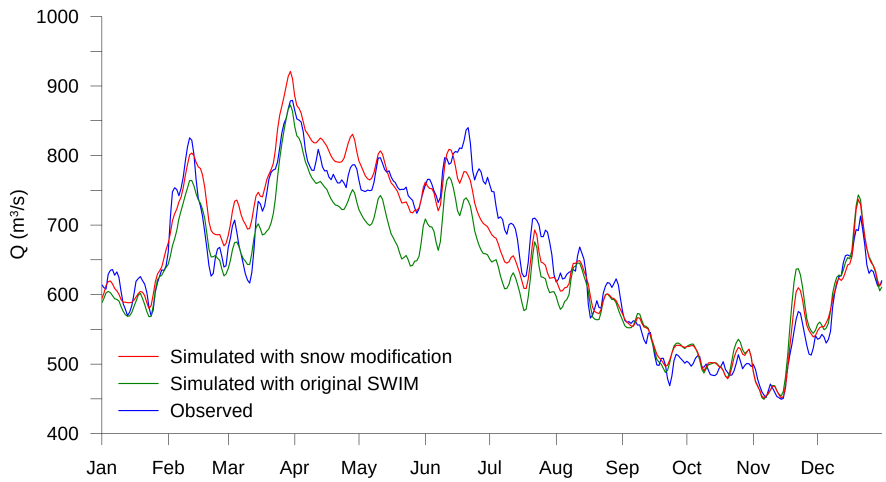

Figure 14. *Comparison of average daily simulated river discharge (with and without the snow improvement) and the observed discharge at the Hofkirchen gauge during the period 1961–1990*

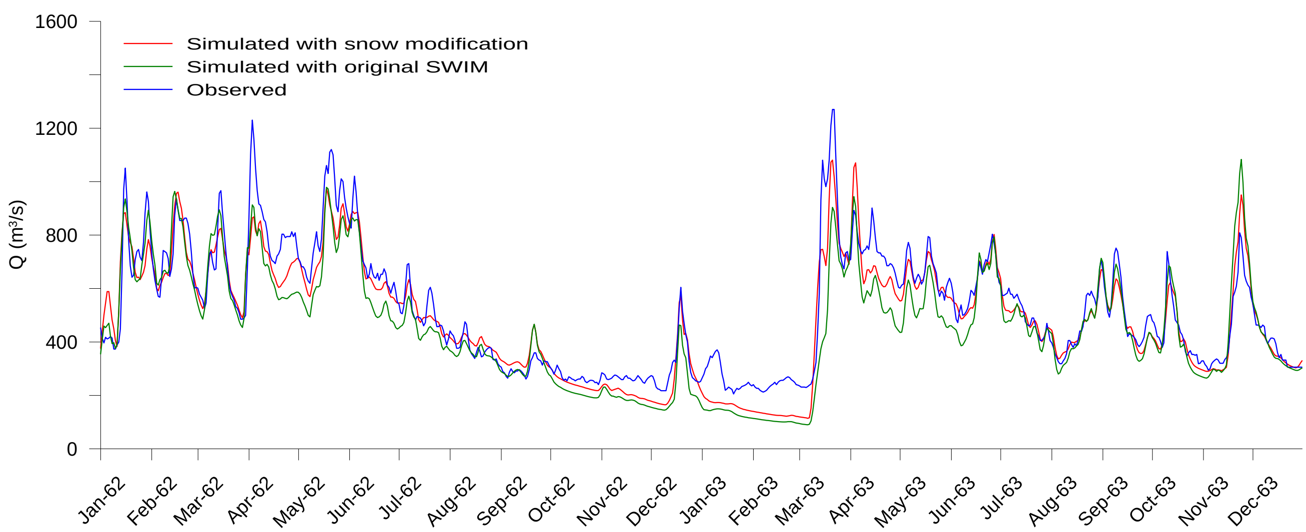

Figure 15. *Comparison of daily simulated river discharge (with and without the snow modification) and the observed discharge at the Hofkirchen gauge in the years 1962 and 1963*

In Figure 5 (a), the resolution of the mean maximum snow water equivalent (period 1961–1990) is very coarse in the Alps because snow is calculated at the subbasin unit. When snow is calculated on a hydrotope basis, the maximum snow water equivalent map (Figure 5 (b)) becomes finer and the difference in the mountains and valleys in the German Alps is more obvious. The spatial distribution in Figure 5 (b) is also more comparable with the one reported in the Hydrological Atlas of Germany (HAD, 2000).

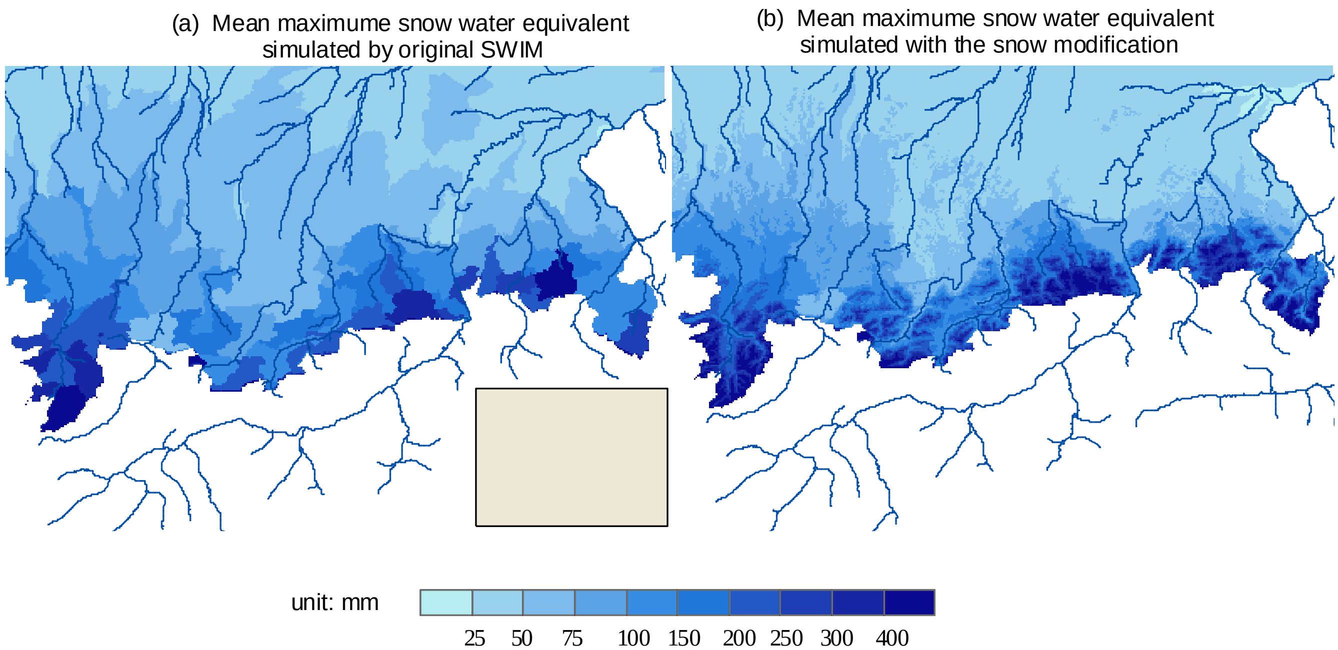

Figure 16. *Comparison of the mean maximum snow water equivalent maps during the period 1960–1990 before (a) and after (b) the modification of the snow module in SWIM*

4. Conclusion and discussion

The results reported in section 3 show that the snow module modification helped to better simulate snow processes and runoff generation in the German Alps. Generally, a better representation of the water holding processes in snowpacks can shift the time of runoff generation to a later season. Using corrected temperatures for hydrotopes leads to generation of higher snow accumulation in mountains than in valleys. The cooler temperatures in the mountains also extend the snow cover duration. As a result, the simulated discharge for the problematic period was improved, and the snow map reproduction was better than the original in terms of spatial distribution patterns.

However, finer hydrotopes also result in longer simulation times. The 100-meter intervals in the elevation zone map may not be the optimal threshold considering both computational time and results. Some other intervals will be tested in the future. As river discharge at the Hofkirchen gauge is influenced by only the German Alps, which account for a small part of the larger drainage area, the improvement in the results was not significant (the efficiency only varies from 0.82 to 0.84). Greater effects are expected in the Austrian Alps in regard to improved river discharge simulation. Further investigation of the snowmelt processes will focus on this extended region, as better climate data, including snow depth, were recently obtained from Austria.

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A Post-Processing Tool to Assess Sediment and Nutrient Source Allocations from SWAT Simulations

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Abstract

Throughout the United States, distributed-parameter hydrologic simulation models have been employed to assist state and federal agencies in the development of Total Maximum Daily Loads (TMDLs) for impaired stream systems. These models have the ability to estimate point and nonpoint source pollutant load allocations at various spatial and temporal scales within a watershed. In recent years, the Montana Department of Environmental Quality (MDEQ) has used the Soil and Water Assessment Tool (SWAT) to assess sediment, nitrogen and phosphorus load allocations for impaired stream systems throughout western Montana. Developing these assessments requires multiple SWAT simulations, retrieval of output files from the model and subsequent labor-intensive computations. A post-processing tool was recently developed by MDEQ to facilitate the computation of sediment and nutrient load allocations for 303d listed streams simulated by SWAT. To develop these pollutant load allocations, the model is run three times to generate the necessary information for computing load allocations for a particular impaired stream system within a delineated SWAT project. Output retrieved from these runs includes the output.hru (hydrologic response unit) file and the output.rch (channel reach) file, which are associated with the total load, the total load excluding bank erosion, and the total load excluding the point source load. Data retrieved from the output files are in turn input to the post-processing tool. Input data is used to compute average monthly or seasonal sediment and nutrient load allocations based on various land cover types present within the impaired stream system. The tool also computes the average monthly or seasonal sediment and nutrient load allocations associated with bank erosion, point sources and nonpoint sources present in that stream system. This newly developed post-processing tool holds considerable promise for reducing the time required to develop pollutant load allocations for specific stream systems within the large, complex watersheds typically encountered in Montana.

Keywords: SWAT, watershed modeling, sediment, nutrients, bank erosion, TMDLs

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1. Introduction

Recently, the Montana Department of Environmental Quality (MDEQ) began using the Soil and Water Assessment Tool (SWAT) to determine sediment, nitrogen and phosphorus load allocations for impaired stream systems, primarily watersheds in the western portion of Montana, USA. Developing these assessments requires multiple simulations with SWAT, retrieval of output files from the model and subsequent labor-intensive computations. The SWAT output is used to calculate average load allocations for each point source, channel source and nonpoint land cover source present in an impaired watershed over a specified timeframe. The allocation calculations assist in the development of total maximum daily loads (TMDLs). The main problem addressed in this paper is the creation of a program (or set of programs) that can extract pertinent data from SWAT output files and, through various computations, provide an averaged dataset that can easily be integrated into a TMDL. Automating the process requires an analysis of the load allocation computations necessary for programming the model. This paper explains the methodology used to create an efficient post-processor for model simulations obtained from SWAT. The motivation for this project is to reduce the daunting task of several days of manual computations to several minutes.

2. Concept and Methodology

The Soil and Water Assessment Tool (SWAT) is a comprehensive model developed by the USDA Agricultural Research Service (Arnold et al., 1998). The model divides a watershed into a number of subbasins that are further subdivided into hydrologic response units (HRUs). An HRU is a defined area containing common soil and land cover types. In the SWAT model, HRUs are not spatially explicit. Figure 1 illustrates the land cover, soil and delineated subbasin layers for a SWAT project in the Bitterroot Watershed in western Montana, USA.

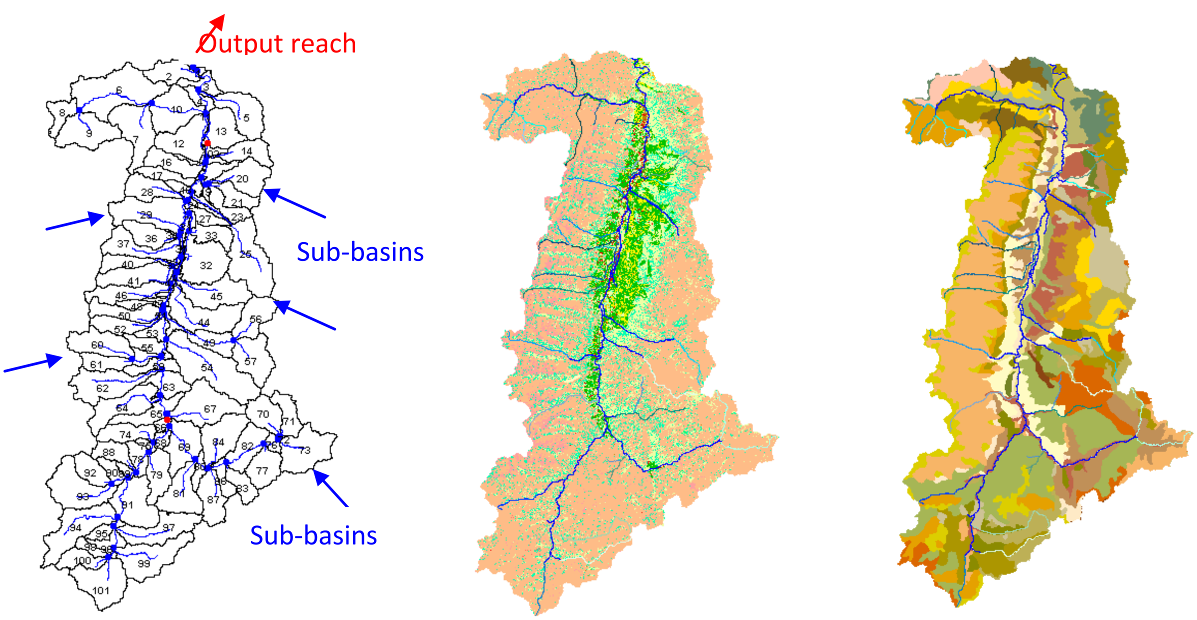

Figure 1. *Subbasin layers for the Bitterroot Watershed SWAT project in western Montana, USA*

The post-processing tool developed in this study is based on a 2005 version of SWAT. The executable version of the model was modified to consider losses of organic nitrogen and phosphorus from bank erosion in the top soil layer.

To develop the post-processing tool described in this paper, the following assumptions and methodologies were employed. Output from the SWAT reach files is not specific to particular land cover or management conditions, so it was necessary to couple the output from all HRU files with the most downstream reach file of the impaired watershed. This coupling allows for an estimation of source allocations for sediment, total nitrogen (N) and total phosphorus (P) simulated from land cover and management types present in the landscape. It was assumed that the relative proportions of these three water quality constituents were the same as those present in the most downstream reach. Constituents from bank erosion, point sources and nonpoint sources are estimated with SWAT in the following manner. First, reach and hru files are retrieved from a baseline condition used to represent existing water quality conditions in the impaired watershed for a specified simulation period. Second, SWAT is rerun without simulating the effect of channel bank erosion, and then it is rerun a third time without simulating the effect of point sources. The reach files are again retrieved for these two conditions. Thus, the first reach file contains all of the selected reach data, the second file filters out any bank erosion present in the reach and the third file filters any point source data in the reach. After completion of the three runs, the data is then used to compute the respective fractions of sediment, total N and total P from nonpoint source loads, point source loads and bank erosion. The respective estimated constituent fractions assumed to be present in the stream reach from a given land cover/management type (nonpoint source load) are computed by multiplying the particular simulated amount obtained from the landscape (hru file) times the ratio of the total constituent reach load (reach file) to the total constituent landscape load.

2.1 SWATHARD

The framework for the post-processing tool is currently divided into two parts. The first part is the SWAT Stream Reach (RCH) and Hydrologic Response Unit (HRU) dissector (SWATHARD). This program reads the three output.rch files and extracts sediment, nitrogen and phosphorus constituents for each month (Table 1). The program also reads the output.hru file from SWAT and extracts sediment, N and P constituents for each month along with the associated land use classification (Table 2). Water data is also extracted, which includes surface runoff (SURQ), lateral subsurface flow (LATQ), groundwater flow (GWQ) and overall water yield (WYLD). The program is written in such a way that it can extract data from impaired sub-watersheds within a SWAT project over a range of years simulated by the model. The program reads in the data then produces four tilde-delimited text files for each year. One file contains the hru data, while the remaining three contain the reach datasets.

It is important to note that only one stream reach, the one most downstream, is used to determine the watershed output load. Each of the three runs that are made to assess water quality load allocations must be done so on a monthly time step. After running the baseline condition (all data), the route files (*.rte) must be overwritten so that bank erosion is set to zero and then again with the point source files set to zero.

Table 1. *The columns of data extracted from the output.rch files*

Output.rch column	Description
RCH	Reach number
MON	Month (the roll-up for the year is also in this column)
SED_OUTtons	Sediment reach output in tons
ORGN_OUTkg	Organic nitrogen reach output in kilograms
NO3_OUTkg	Nitrate reach output in kilograms
NH4_OUTkg	Ammonium reach output in kilograms
NO2_OUTkg	Nitrite reach output in kilograms
ORGP_OUTkg	Organic phosphorus reach output in kilograms
MINP_OUTkg	Mineral phosphorus reach output in kilograms

Table 2. *The columns of data extracted from the output.hru files*

Output.hru column	Description
LULC	Land use / Land cover
HRU	Hydrologic response unit
SUB	Subbasin
MON	Month (year roll-up)
AREAkm2	HRU area in square kilometers
PRECIPmm	Precipitation (rain and snow) in millimeters
ETmm	Evapotranspiration in millimeters
SURQ_CNTmm	Surface runoff in millimeters
LATQmm	Lateral flow in millimeters
GW_Qmm	Groundwater flow in millimeters
WYLDmm	Water yield in millimeters
SYLDt/ha	Sediment yield in tones per hectare
ORGNkg/ha	Organic nitrogen in kilograms per hectare
ORGPkg/ha	Organic phosphorus in kilograms per hectare
SEDPkg/ha	Sediment phosphorus in kilograms per hectare
NSURQkg/ha	Nitrogen within surface runoff in kilograms per hectare
NLATQkg/ha	Nitrogen within lateral flow in kilograms per hectare
NO3GWkg/ha	Nitrate within groundwater flow in kilograms per hectare
SOLPkg/ha	Soluble phosphorus in kilograms per hectare
P_GWkg/ha	Phosphorus in groundwater flow in kilograms per hectare

The SWAT output files are fairly dynamic in that programmers may insert a column or change the width of a column. This makes data extraction from a text file more difficult, and the program that extracts the data needs to be constantly updated. One solution is to create an initialization file the program can read prior to data extraction in order to determine the column position and column width. Another solution is to automatically adjust the extraction based on column headings, but this too can cause problems if the column name changes. We decided to have an initialization file that can be modified with a simple text editor, the swatpop.ini file. The swatpop.ini file needs to have appropriate data matching the version of the SWAT model being used. However, it should be noted that the columns should align to the data and not necessarily to the column header. This is an important step that must not be overlooked if the user is to extract the correct data with no truncated or misappropriated digits.

There are two main areas that should be checked prior to running the swatpop.ini file. The first area is immediately under the heading [HRU_Columns] and lists the total number of columns, the character width of each column and the number of the column to extract from the output.hru file (where the first column is recognized as column zero (0)). The second area is [RCH_Columns] and contains the same information but for the output.rch file. These parameters much match the character positions in the output.hru and output.rch files.

Once the initialization file has been confirmed, the SWATHARD application can be run. It is important to note that the directory where the swatpop.ini file is located must not be changed. It must remain in the c:\Program Files\Swathard sub-directory; otherwise, the application will not be able to locate it.

The resulting HRU output is organized by month and subbasin, with one file for each year (e.g., HRU 1998.txt, HRU 1999.txt and so on). The RCH output contains only data for the output reach, with one file for each year and source output (e.g., BRCH 1998.txt for the baseline reach, NPSR 1998.txt for baseline reach minus point sources and NBER 1998.txt for baseline reach minus bank erosion).

2.2 SWATPOP

The second part of the post-processing tool developed in this study is referred to as the SWAT POst Processor (SWATPOP). It uses Microsoft Excel with a series of VBA macros. In order to alleviate the potential problem of exceeding the row limit for each worksheet, we decided to create a separate worksheet for each year. This also makes the data more manageable for users, especially when performing quality assurance on the data. Once each year of data is summarized, it can be rolled-up into a separate sheet that displays the averages.

Each text file created by the SWATHARD program is read into SWATPOP, and each year is assigned a separate sheet. The user must select the files to be loaded by the post-processor (see figure 2).

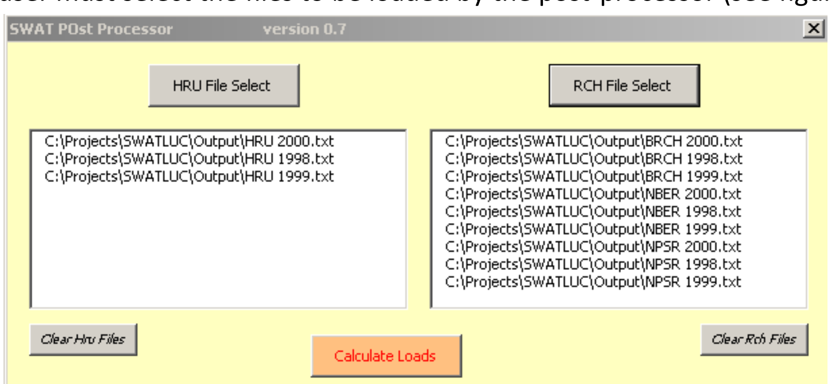

Figure 2. *Initial SWATPOP form for users to load entire files created by SWATHARD*

Once the files are read into the post-processor, the rows are sorted, first by land use/cover (LULC), second by month (MON), and third by subbasin (SUB). This sorting process makes it easier to traverse the data and compute the results. The next step is to compute the sediment load and total nitrogen and phosphorus constituent loads. Runoff components for each land use/cover type are also tabulated. These totals are performed on each HRU for each month and are added to each HRU year worksheet. Summary sheets are then created that sum the respective loads for various land use/cover types for each month of the year. Finally, all the years selected by the user are averaged, populating a new sheet that calculates averages for all years and breaks down each month by point source, bank erosion and nonpoint sources (LULC). Table 2 illustrates a summary sheet of modeled average monthly total phosphorus loads from point, bank and nonpoint sources.

Table 2. *Summary sheet of modeled sources of average monthly total phosphorus loads*

COMPUTED AVERAGE PHOSPHORUS FOR THE YEARS 1998 - 2000

MONTH	TP PS (Kg)	TP BE (Kg)	TP FPS	TP FBE	TP LSF	TP TLLE	ALFA	BARN	FRHY
1	485.1267	14.85667	0.469498	0.014932	0.51557	583.6067	2.610357	34.15803	1.2E-05
2	410.4333	42.08	0.465461	0.021848	0.512691	947.5433	10.60084	73.72797	0.014444
3	306.8667	51.33333	0.19573	0.029606	0.774664	1283.533	8.558482	33.73047	0.926174
4	293.7333	916.6667	0.078108	0.206491	0.715401	2971.267	50.08963	25.13317	2.864291
5	394	6219	0.036076	0.552882	0.411042	4478.333	11.6604	60.62599	1.366963
6	392	7961.367	0.039289	0.551894	0.408817	5803.967	21.63634	185.0201	1.583521
7	411	1655.8	0.109422	0.37746	0.513118	2076.533	14.82985	86.25142	0.306277
8	451.4733	727.4167	0.253369	0.267137	0.479494	1202.21	7.041814	74.89243	0
9	493.0667	768.0333	0.354201	0.163855	0.481944	2128.4	13.57392	80.43322	4.841176
10	496.6667	323.4333	0.356911	0.139796	0.503293	1008.2	6.565992	47.3671	3.82E-05
11	490	304.3667	0.301425	0.069694	0.628881	2401.867	9.853808	79.02757	6.050762
12	561.4667	202.3	0.355814	0.053662	0.590525	1553.6	14.28409	77.49018	0.301557

MONTH	FRSD	FRSE	FRST	HAY	ICED	LAWN	RNGB	RNGE	SEPT	SWHT	UI
1	0.002606	125	0	20.70619	0	0.275187	95.4847	190.8193	2.942178	39.81023	[illegible]
2	0.013902	122.9597	0.000169	42.12374	0	0.155791	310.5262	276.5577	3.605971	52.45372	
3	0.004426	138.5613	0	49.41708	0	0.446118	507.4543	421.3935	1.005208	66.50591	
4	0.00364	546.6786	0	113.4543	0	2.633901	1052.853	1021.89	0.299246	69.9405	[illegible]
5	0.010352	1122.651	0	196.5774	0	0.221884	1281.963	1475.173	0.583735	104.7928	
6	0.040008	389.2438	0	577.8515	0	0.719098	1866.871	1955.015	1.598888	208.6914	
7	0.004434	18.4447	0	224.2496	0	0.395046	762.8572	596.5694	1.023009	95.4924	
8	0.00031	0.590632	0	55.22569	0	0.247198	311.1188	283.0624	0.881736	122.2631	
9	0.003043	69.42377	0	99.94938	0	0.319728	708.5664	644.5481	1.125279	151.6979	[illegible]
10	0.000193	7.255759	0	51.26962	0	0.108925	402.6139	269.2869	1.004869	124.2583	[illegible]
11	0.008301	341.9265	0	98.23101	0	0.194916	727.801	870.4667	1.658394	154.1695	[illegible]
12	0.007953	183.0652	0.000332	87.83124	0	0.144195	524.6335	391.6259	3.158846	159.7491	[illegible]

3. Results

We used the newly developed post-processing tool in the 7300-km^2 Bitterroot Watershed of western Montana. First, delineation of the watershed in SWAT consisted of 85 subbasins, accounting for climatic, soil, topographic and land cover variations across the landscape. A total of 15 land cover and 38 soil types were used in the project, resulting in a delineation of 1808 HRUs within the project.

An eleven-year period of record from 1993 to 2003 was selected as the baseline period for performing model simulations representing current water quantity and quality conditions in Bitterroot. Simulations performed for this period were used to provide not only annual and monthly load estimates of sediment, total N and total P for each of the impaired stream systems within the watershed, but also estimates of the source allocation by point, bank, and nonpoint land cover/management type.

Following model simulations, the post-processing tool was used to estimate runoff characteristics and water quality load allocations for the entire Bitterroot Watershed. For brevity, only the total P allocations are illustrated in this study. For the 11 year period, SWAT simulated an average annual total P load of 76,900 Kg. Of this amount, about 30% was from bank erosion, 20% was from mixed crops, 15% was from range grass, 12% was from range brush, 10% was from forest, 7% was from point sources, and the remaining 6% was from other sources. Each of the modeled total P percentages are presented in Figure 3. Modeled total P allocations can also be displayed on a monthly basis, as shown in Figure 4. Although the post-processor provides monthly estimates of nonpoint sources by land cover type (such as those from mixed crops, range grass or forest), only the monthly totals for the combined nonpoint sources are illustrated in the figure. Modeled phosphorus allocations show that bank erosion accounts for about 14% to 56% of the total P yield during the spring runoff months from April to June. While point sources account for 21% to 25% of the total P yield during the summer months from July to September. The computations made by the post-processing tool provide valuable information that supports the development of TMDLs for impaired stream systems, as illustrated in the example above.

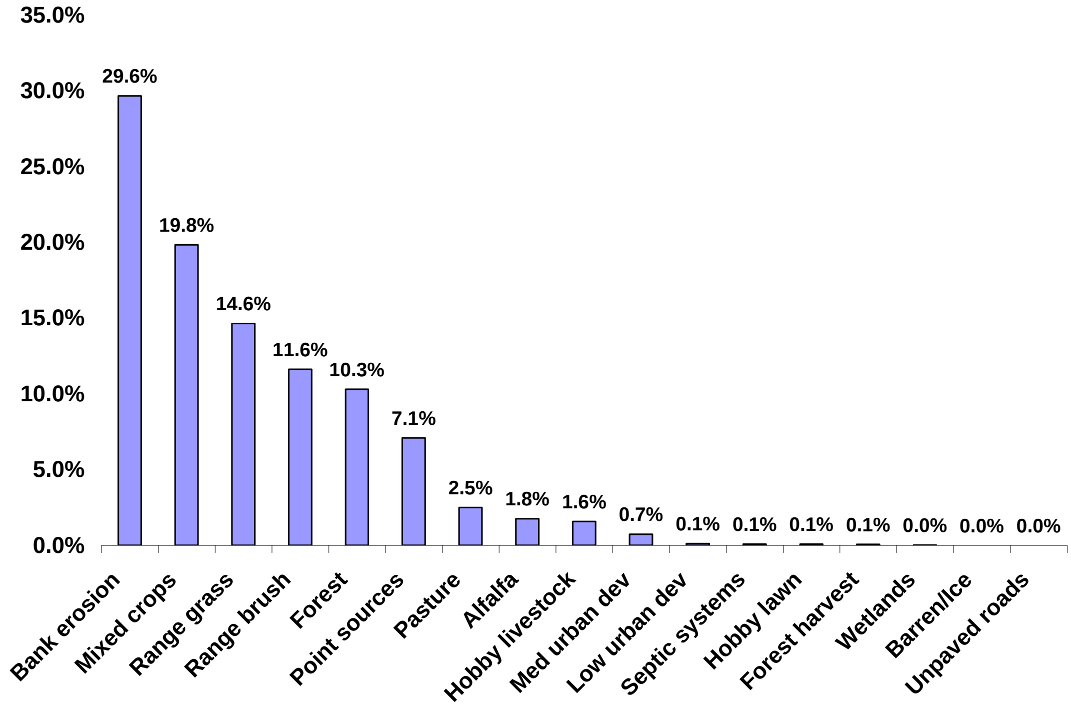

Figure 3. *Percentage of modeled sources of total phosphorus for the Bitterroot Watershed*

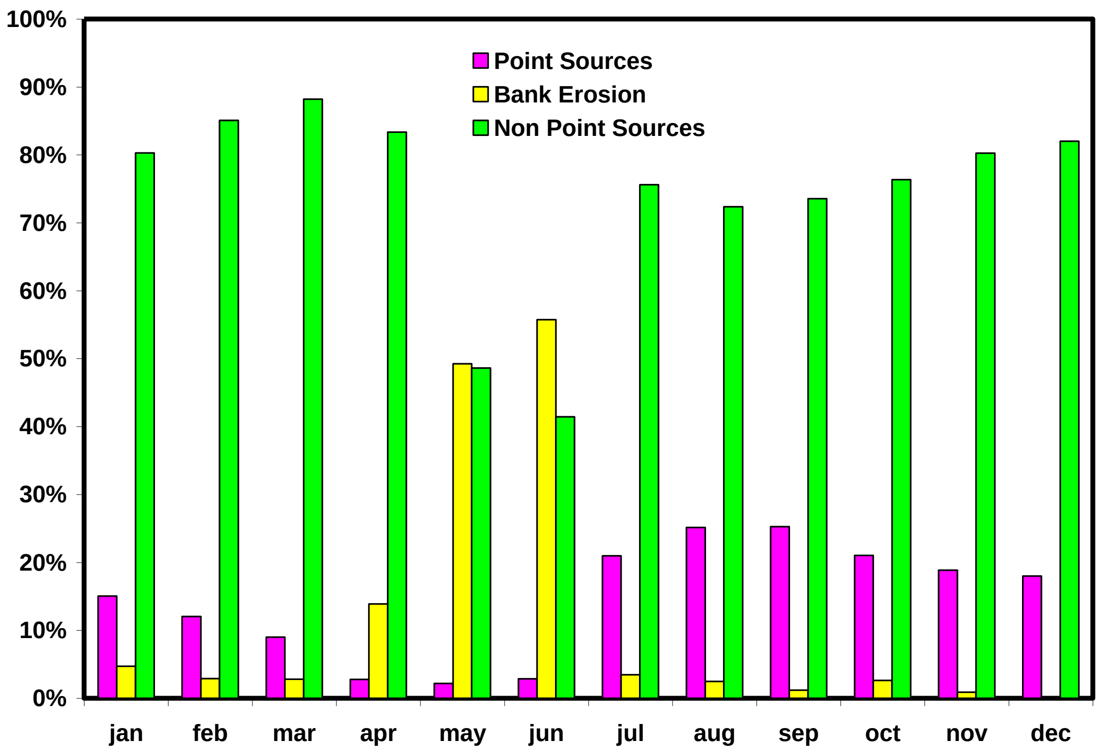

Figure 4*.* *Percentage of point, bank and nonpoint sources of total phosphorus for the Bitterroot Watershed modeled monthly*

4. Conclusions

A post-processing tool was recently developed by the Montana Department of Environmental Quality to facilitate the computation of sediment and nutrient load allocations simulated by SWAT for 303d listed streams. The post-processing tool is designed to compute average monthly or seasonal sediment and nutrient load allocations associated with the various land cover types present within an impaired stream system. The tool also computes the average monthly or seasonal sediment and nutrient load allocations associated with bank erosion, point sources and nonpoint sources present in the stream system. This newly developed post-processing tool has been shown to substantially reduce the time required to develop pollutant load allocations for specific stream systems within the large, complex watersheds typically encountered in Montana.

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Assessing the impacts of a vegetable-agroforestry system using SWAT in the Nghia Trung sub-watershed, Vietnam

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Abstract

During recent years, emerging water and soil problems have threatened the livelihood of local people and the sustainability of the whole watershed ecosystems in Vietnam. Water resources become more polluted and soil is lost due to degradation of forest or land use changes. This study is aimed at assessing factors contributing to reservoir sedimentation and land use factors associated with water quality in the Nghia Trung sub-watershed. This study is especially important in the Nghia Trung sub-watershed, where the soil is highly erodible, and forest conversion for agricultural cropping is widespread. This study also focused on how soil loss and water quality were impacted when watershed land use patterns changed. The SWAT model was applied to evaluate the effects of land use, soil and human practices on soil loss and water quality in Ong Thoai reservoir, Nghia Trung sub-watershed.

The SWAT model output indicated that land use changes and deforestation impacted surface flow and sediment yield in the Ong Thoai reservoir, Nghia Trung sub-watershed. The precipitation between 2002 and 2007 changed little, but surface flow in the year of 2007 (631.37) was about 1.36 times greater than surface flow in the year of 2002 (466.50). Also, sediment yield in the year of 2007 was about 5.78 tons/ha as compared to 3.56 tons/ha in the year of 2002. Model results also showed that 127 ha of forestland, about 12 percent of the 2002 study area, was converted to cashew and rubber production in 2007, causing both the surface flow increase and an increase in sediment yield of 1.62 times the 2002 values in the Ong Thoai reservoir. Cashew production consumes 27.52 ha, about 2.81% of the research area, but without weeding, sediment was reduced by about 0.576 tons/ha and surface flow was reduced by about 14 mm.

Keywords: SWAT, Nghia Trung sub-watershed, Vietnam

1. Introduction

One of the most important topics in watershed management is assessing the impacts of land use change, population growth and watershed development on soil loss, water quality and quantity. Rapid increases in population and the driving force of economic growth further accelerate the need for various land uses within the watershed. To contemplate the scope of such problems, as experienced in many other developing countries, pursuing integrated optimal planning to achieve sustainable use of the country's watershed resources becomes critical. Many studies have focused on multi-objective land-use planning under various conditions, such as those applied to an industrial complex, a watershed or a river basin. However, very few focus on evaluating the optimal balance between economic development and environmental quality within a watershed. Hence, this research attempts to examine the selected Nghia Trung sub-watershed in the context of water discharge and sediment yield using SWAT (Soil and Water Assessment Tool).

2. Objectives

Our primary objective is to provide decision-makers with a scientific tool for assessing the conservation of water and soil resources in order to deliver appropriate policies about land use allocation. Detailed objectives are as follows:

1. to apply SWAT in the Ong Thoai reservoir of the Nghia Trung sub-watershed to analyze the impact of land use changes on water discharge and sediment yield;
2. to make policy recommendations for decision-makers regarding the impacts of land use changes on water discharge and sediment yield.

3. Methodology

3.1 Location of the study area

Nghia Trung village is located in the Bu Dang District of Binh Phuoc Province. The village is about 130 km from Ho Chi Minh City and about 25 km from Dong Xoai town, the center of Binh Phuoc Province. Located on national road Number 14, which connects the provinces in the Central Highland with Ho Chi Minh City, the village has a favorable position for the marketing of goods and services.

3.2 A brief description of the SWAT model

The Soil and Water Assessment Tool (SWAT) has been widely applied for modeling watershed hydrology and simulating the movement of nonpoint source pollution. SWAT is a physically based, continuous-time hydrologic model with an ArcView GIS interface developed by the Blackland Research and Extension Center and the USDA-ARS (Arnold et al., 1998). It was designed to predict the impact of land management practices on water, sediment and agricultural chemical yields in large, complex basins with varying soil types, land uses and management conditions over long periods of time. The main driving force behind SWAT is its hydrological component. Hydrological processes are divided into two phases: 1) the land phase controls the amount of water as well as sediment and nutrient loads that reach receiving waters, and 2) the water routing phase simulates water and pollutant movement through the channel network. SWAT considers both natural sources (e.g., mineralization of organic matter and N-fixation) and anthropogenic contributions (fertilizers, manures and point sources) as nutrient inputs (Somura et al., 2009). SWAT is expected to provide useful information across a range of time scales (i.e., hourly, daily, monthly and yearly time steps) (Neitsch et al., 2002).

3.3 Data collection

Our team, offices of local authorities and relevant professional institutions collected available data and information related to SWAT modeling in the Nghia Trung sub-watershed. This information included maps, statistic data, forest area, forest cover, population, soil erosion parameters, precipitation, water quality and other the related data. The sources and types of data collected are shown in Table 1.

Table 7. *Sources and types of data collected for SWAT modeling*

Types of data	Sources of data
1. Physical Data	Department of Land Development, Binh Phuoc Province
Topography	
Precipitation	Binh Phuoc Meteorological Department
Soil erosion	Institute of Water Resource Research in HCMC
Parameter	Department of Land Development, Binh Phuoc Province
2. Biological Data	
2.1. Land use maps	
2.2. Forest, Agriculture	Department of Agriculture and Rural Development, Binh Phuoc Province
3. Socioeconomic Data	Binh Phuoc Statistical Department
Population	
Income	
4. Water quality (BOD, COD, DO, SS, . . .)	

The 2007 land cover categories were interpreted from field observation processing with GIS and remote sensing using satellite imagery. The definition and characteristics of each land cover type are described as follows:

(1) Young Rubber (LRUB): a rubber plantation that is less than four years old
(2) Rubber (RUBR): a rubber plantation that is four or more years old
(3) Urban medium density (settlement) (URMD): the built-up areas consisting of residential, industrial and commercial areas
(4) Forest (FRST): permanent natural forest and reforested areas (the main natural forest type is Evergreen forest [hill evergreen and dry evergreen] and deciduous forest [mixed deciduous and deciduous dipterocarp forests]).
(5) Water Body (WATR): water bodies, including both natural and man-made reservoirs
(6) Cashew (CANW): cashew production, no weeding
(7) Cashew (CASH): cashew production with weeding

3.4 The scenario planning process for the SWAT model

Figures 3 and 4 show the SWAT model approach applied to the case study area of Nghia Trung sub-watershed. The principal planning objective for this case study was to create an efficient plan for the future of the Nghia Trung sub-watershed. In order to do so, we formulated different planning scenarios determined by the socioeconomic, physical and environmental data collected. The objectives of each plan are also used later in the methodology to evaluate the efficiency of each proposed planning scenario.

The next step of the planning process was to formulate possible land-use scenarios. The following three land-use planning scenarios were formulated for the Nghia Trung sub-watershed:

Scenario A: examines 'Future Trends' based on existing socioeconomic trends

Scenario B: uses the Agroforestry Systems model to examine B1 and B2

Scenario B1: cashew production, no weeding

Scenario B2: cashew production with weeding

We analyzed the impacts of changes in land use practices and human activities on water quality and sediment contribution to the Ong Thoai reservoir from 2002–2007. For this, the SWAT model required methodological data such as daily precipitation, maximum and minimum air temperature, wind speed, relative humidity and solar radiation data. Spatial datasets including digital parameter layers such as topography (LS) and parameters R, K, C and P were digitized from the associated maps. The watershed LS factor was derived from a digital elevation model (DEM) obtained from topography data. The SWAT model was applied in Nghia Trung as shown in Figures 2 and 3.

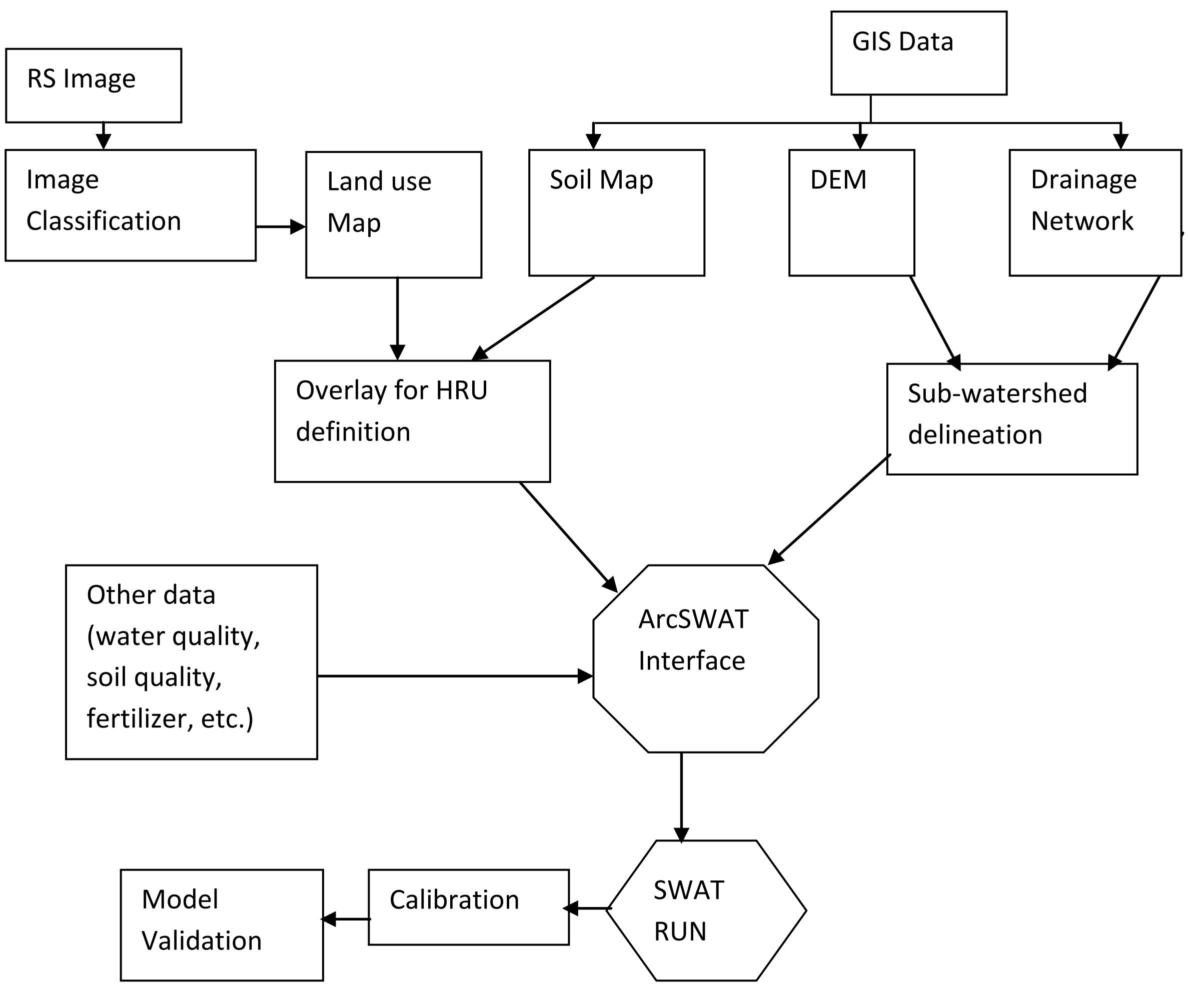

***Figure 2.** The SWAT model*

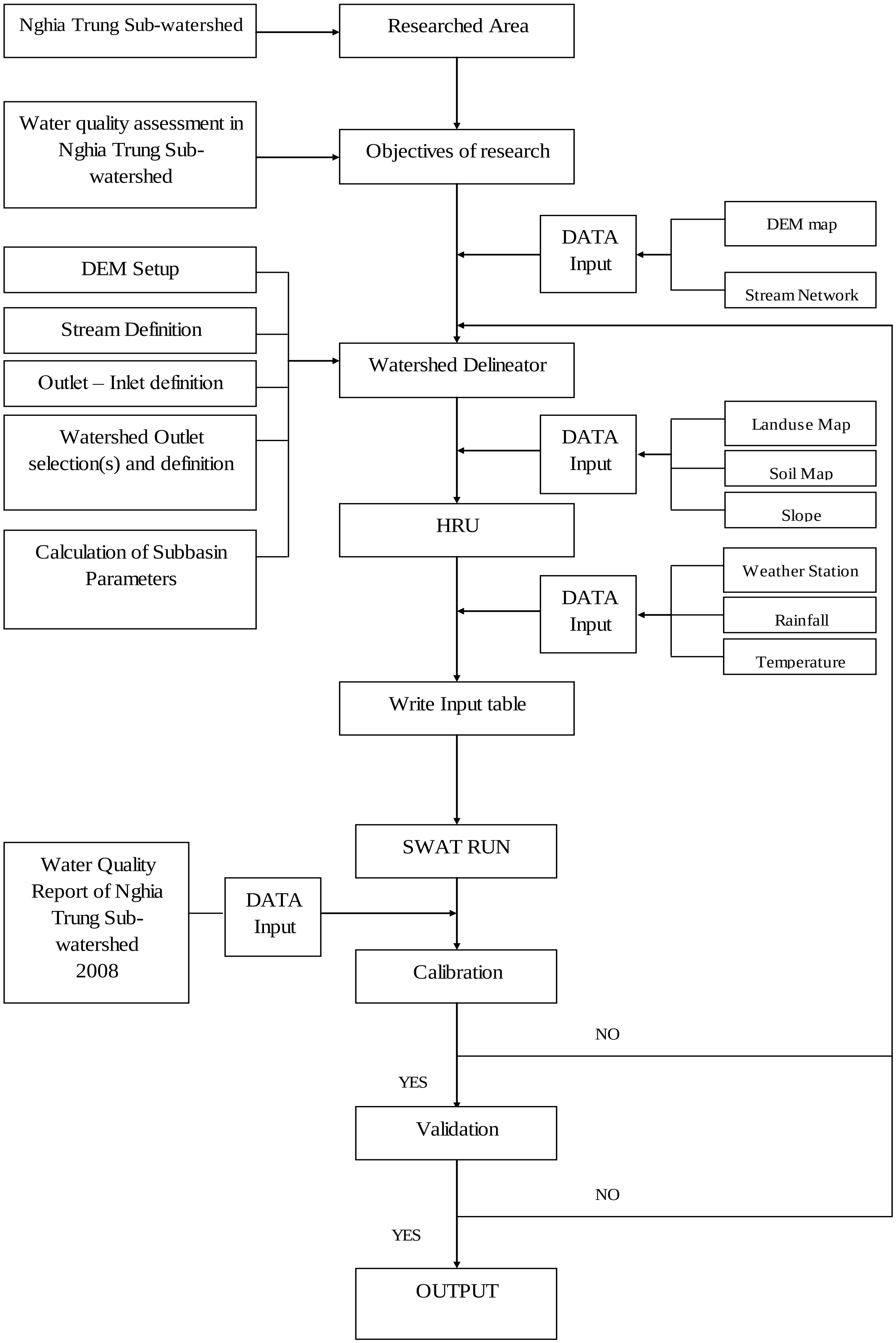

Figure 3. *Application of SWAT in the Nghia Trung sub-watershed*

4. Results and Discussion

4.1 Existing land use in the Nghia Trung sub-watershed, Binh Phuoc province

The land use types in the Nghia Trung sub-watershed for the years 2007 and 2002 were interpreted from satellite data and field observation image processing with GIS techniques. They are shown in Table 2.

Table 2. *Land use types in Nghia Trung sub-watershed at year 2007, 2002*

Land use types	Land use code	Area (2007) (ha)	% of total area	Area (2002) (ha)	% of total area
Cashew	CASH	27.52	2.81	15.02	1.5
Forest	FRST	555.91	56.75	683.01	69.72
Young Rubber	LRUB	108.47	11.07	58.97	6.02
Rubber	RUBR	70.59	7.21	40.09	4.09
Urban medium density (settlement)	URMD	166.12	16.96	136.62	13.95
Water body	WATR	51.02	5.21	45.92	4.69
Total		979.63	100%	979.63	100%

The Nghia Trung sub-watershed has a low density of streamflow and climatic gages. Table 3 shows the SWAT simulations based on land use scenario A (land use in 2007) and land use in 2002.

Table 3. *The SWAT simulated statistics for Nghia Trung sub-watershed using land use scenario A (2007) and land use in 2002*

Year	PREC mm	SURQ mm	LATQ mm	GWQ mm	PERCOLATE mm	TILE Q mm	SW mm	ET mm
2007	1848	631.37	11.85	346.02	379.74	0.00	109.78	607.25
2002	1775	466.50	14.33	343.89	372.50	0.00	127.81	631.62

Table 3. (Continued)

Year	PET mm	WATER YIELD mm	SED YIELD Ton/ha	NO_3 SURQ Kg/ha	NO_3 CROP Kg/ha	N ORGANIC Kg/ha	P SOLUBLE Kg/ha	P ORGANIC Kg/ha
2007	1553.60	979.28	5.78	2.08	5.60	18.55	0.14	2.23
2002	1527.16	812.06	3.56	1.43	3.14	9.30	0.08	1.09

The results derived from the land uses in Table 2 imply that between 2002 and 2007 forest area decreased by about 127 ha or about 12 percent of the studied area while other land classes increased. The land-use category that increased the most was rubber because the upland areas of the Dong Nai watershed have suffered rapid increases in population, resulting in massive immigrations since the end of the war in 1975.

In Table 3, the SWAT output indicates that land use changes and deforestation impacted surface flow and sediment yield in the Ong Thoai reservoir, Nghia Trung sub-watershed. The precipitation between 2002 and 2007 changed little, but surface flow in the year of 2007 (631.37) was about 1.36 times greater than surface flow in the year of 2002 (466.50). Also, sediment yield in the year of 2007 was about 5.78 tons/ha as compared to 3.56 tons/ha in the year of 2002. Figure 3 also shows that 127 ha of forestland, about 12 percent of the 2002 study area, was converted to cashew and rubber production in 2007, causing both the surface flow increase and an increase in sediment yield of 1.62 times the 2002 values in the Ong Thoai reservoir.

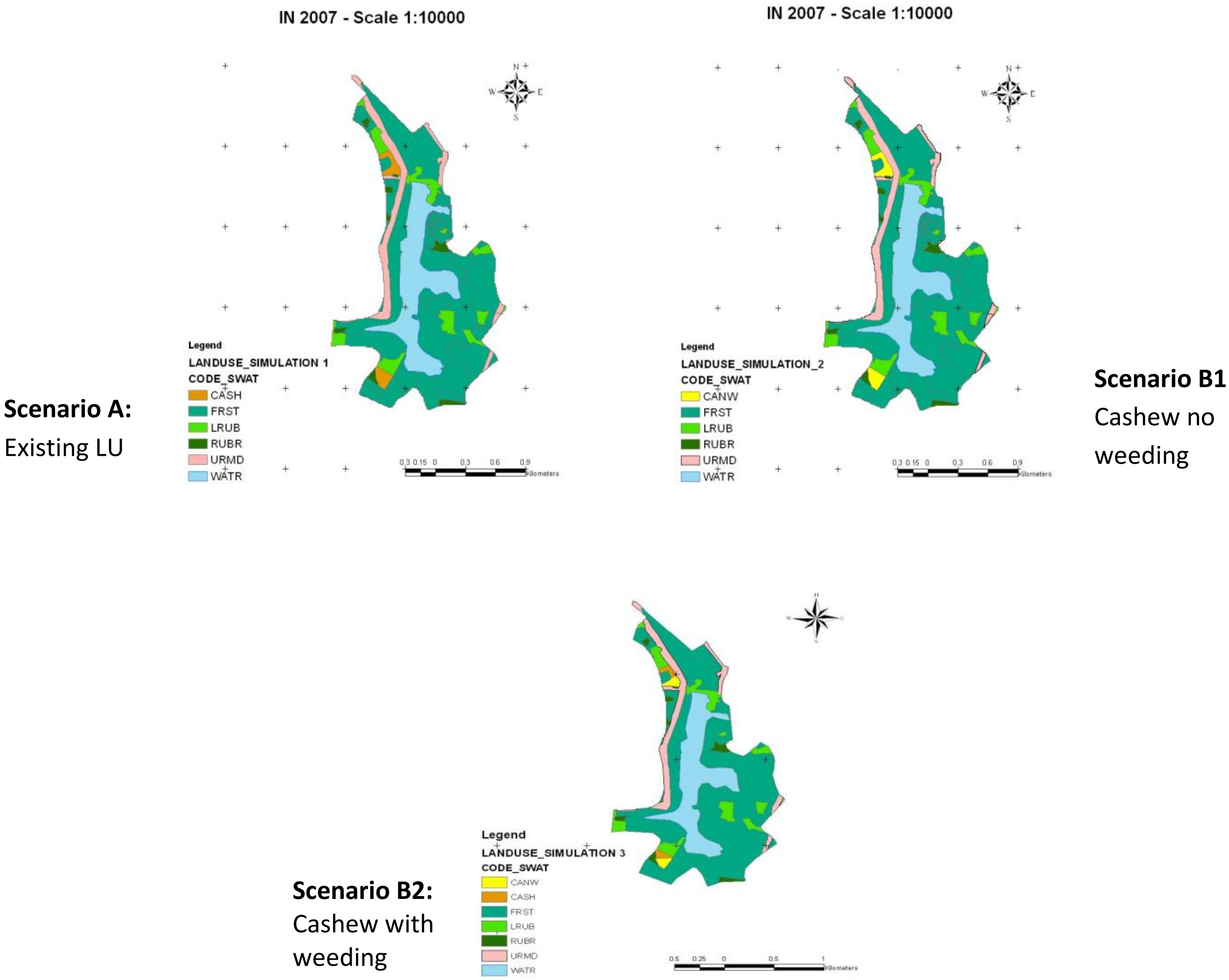

Figure 4. *Land use scenarios for the Nghia Trung sub-watershed*

The SWAT model was applied in the Nghia Trung sub-watershed using scenarios A, B1 and B2 listed in section 3.4. The three land-use scenarios are shown in Figure 4 above. The SWAT output showed that Scenario B1, “cashew no weeding”, can reduce surface flow and sediment loading on the Ong Thoai reservoir. Cashew production consumes 27.52 ha, about 2.81% of the research area, but without weeding, sediment was reduced by about 0.576 tons/ha and surface flow was reduced by about 14 mm. Figure 4 also indicates that human practices affected soil and water conservation in Nghia Trung sub-watershed.

Table 4. *Monthly SWAT output with different land use scenarios*

Month	Rain mm			Surf Q mm			Lat Q mm		
	Sce A	Sce B1	Sce B2	Sce A	Sce B1	Sce B2	Sce A	Sce B1	Sce B2
1	1.50	1.50	1.50	0.00	0.00	0.00	0.41	0.41	0.41
2	0.00	0.00	0.00	0.00	0.00	0.00	0.27	0.26	0.27
3	2.00	2.00	2.00	0.01	0.01	0.01	0.21	0.20	0.21
4	40.00	40.00	40.00	1.29	1.26	1.30	0.16	0.16	0.16
5	281.00	281.00	281.00	69.91	68.08	69.89	0.33	0.33	0.33
6	327.00	327.00	327.00	81.88	79.55	81.86	0.94	0.93	0.94
7	345.50	345.50	345.50	146.88	143.15	146.80	1.78	1.77	1.79
8	196.50	196.50	196.50	45.21	43.98	45.19	1.91	1.90	1.92
9	226.00	226.00	226.00	55.02	53.46	55.00	1.86	1.85	1.86
10	293.50	293.50	293.50	115.80	112.82	115.73	2.23	2.22	2.24
11	92.00	92.00	92.00	26.15	25.45	26.14	1.70	1.69	1.71
12	43.00	43.00	43.00	6.77	6.57	6.77	1.31	1.30	1.32

Table 4. (Continued)

WATER YIELD mm			ET mm			SED YIELD Ton/ha		
Sce A	Sce B1	Sce B2	Sce A	Sce B1	Sce B2	Sce A	Sce B1	Sce B2
3.28	3.02	3.28	19.45	19.51	19.45	0.00	0.00	0.00
1.27	1.24	1.27	10.18	10.41	10.18	0.00	0.00	0.00
0.64	0.63	0.64	76.16	75.07	76.05	0.00	0.00	0.00
1.57	1.54	1.57	30.25	30.22	30.32	0.00	0.00	0.00
70.03	68.24	70.01	87.27	86.07	87.20	0.31	0.21	0.28
90.39	88.14	90.33	60.64	59.94	60.62	0.33	0.24	0.30
196.40	191.79	196.28	57.67	56.84	57.65	0.81	0.68	0.78
108.04	105.63	107.96	63.26	62.59	63.25	0.22	0.20	0.22
115.78	113.03	115.72	63.94	63.16	63.92	0.57	0.52	0.56
186.17	181.72	186.06	58.56	57.78	58.54	1.85	1.71	1.82
82.84	80.90	82.80	49.67	49.10	49.65	0.48	0.45	0.47
39.28	38.42	39.26	42.57	42.03	42.55	0.09	0.09	0.09

Table 5. *Yearly SWAT output compared with 3 land use scenarios in the Nghia Trung sub-watershed*

No.	Parameters	Units	Results		
			Sce A	Sce B1	Sce B2
1	Precipitation	mm	1848.000	1848.000	1848.000
2	Surface runoff Q	mm	548.940	534.340	548.700
3	Groundwater	mm	344.950	336.840	344.760
4	Deep AQ recharge	mm	19.010	18.560	19.000
5	Total water YLD	mm	895.670	874.460	895.140
6	Total sediment loading	Ton/ha	4.673	4.097	4.530

5. Conclusions

This research is just the first step in applying SWAT in the Nghia Trung sub-watershed. The SWAT model performed well in simulating long-term general trends in surface flow, sediment and water quality within the sub-watershed at daily and monthly time intervals. The results showed that land use changes and human activities affected surface flow and sediment loads in the Ong Thoai reservoir. For example, cashew production consumes 27.52 ha, about 2.81% of the research area, but without weeding, sediment was reduced by about 0.576 tons/ha and surface flow was reduced by about 14 mm.

In future studies, we should observe more data (i.e., sediment yield, water quality and surface flow) in order to calibrate and validate the model.

Acknowledgements

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Streamflow, Sediment and Nutrient Simulation of the Bitterroot Watershed Using SWAT

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Abstract

The Department of Environmental Quality has employed the Soil and Water Assessment Tool (SWAT) to aid in the development of sediment and nutrient total maximum daily loads (TMDLs) for impaired stream systems within the 7300-km^2 Bitterroot watershed in western Montana, USA. To perform simulations on the watershed, the department used a revised 2005 version of SWAT consisting of a modification to consider losses of organic nitrogen and phosphorus due to bank erosion. Parameters governing streamflow, sediment, nitrogen (N) and phosphorus (P) in SWAT were calibrated in a distributed fashion for seven regions within the Bitterroot. A dryer-than-normal four-year period of record from 2000 to 2003 was used for model calibration, while a wetter-than-normal four-year period from 1995 to 1998 was used for model calibration. Based on computed values of percent bias and the coefficient of efficiency as well as graphical comparisons of streamflow, SWAT exhibited an element of robustness in that it performed at least as well under wetter-than-average conditions (validation period) as it did in dryer-than average-conditions (calibration period). Comparing measured versus simulated average monthly sediment and total N and P loads for the calibration and validation periods, it was also evident that SWAT did a reasonable job predicting sediment and nutrient constituents for the Bitterroot watershed. Model simulation results suggest that bank erosion accounts for about 45%, 25% and 36% of the total sediment, nitrogen and phosphorus yields from the watershed, respectively. These simulated nutrient yields due to bank erosion are appreciably different from previous SWAT simulations in Montana that have not considered the impact of bank erosion on nutrient transport.

Keywords: SWAT, watershed modeling, sediment, nutrients, bank erosion

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1. Introduction

In accordance with the Montana Water Quality Act (WQA), the state of Montana must monitor the extent to which its surface water bodies support legally designated beneficial uses. For those water bodies in which one or more pollutants impair legally designated beneficial uses, the State must develop TMDLs and associated restoration plans for water quality improvement. The Bitterroot watershed in western Montana represents one of a number of watersheds in the state where the development of TMDLs and associated restoration plans is currently underway. These projects are conducted under the Montana Department of Environmental Quality (DEQ). For most watersheds in western Montana, variations in climate, topography and land use add to the complexity of understanding the source and fate of water quality constituents in surface water. Montana DEQ has determined that a modeling approach is the most effective way to meet the decision-based objectives of the TMDL program. A watershed-scale simulation model referred to as the Soil and Water Assessment Tool (SWAT) has been authorized to complete the TMDL planning process in order to evaluate management and land use scenario changes within the Bitterroot drainage basin. The modeling tool will be used to complete point and nonpoint source loading analyses, allocate sediment and nutrients for TMDL development and formulate water quality restoration plans. The use of a model allows for flexibility in addressing a broad range of stakeholder interests and water quality concerns and provides for an equitable distribution of pollutant sources in the watershed regardless of origin. This paper describes the following: (1) the application of SWAT to the Bitterroot watershed, (2) details on model calibration and validation and (3) the development of area source allocations of sediment, total nitrogen and total phosphorus.

2. Description of the Bitterroot Watershed

The Bitterroot River is located in western Montana, USA, and flows north from an area near the Idaho-Montana border to Missoula, Montana, where it joins the Clark Fork River. The watershed is approximately 7300 km^2 in area and is bounded by the Sapphire Mountains to the east and the Bitterroot Mountains to the west. The Bitterroot River is approximately 135 km long and flows through a 95-km-long valley averaging 11 km in width. The main river flows from an elevation of approximately 3110 to 980 m and is surrounded by mountains that range in height from 2150 to 305 m. Annual average precipitation is estimated to be 880 mm. Snowfall averages about 3050 mm in the Bitterroot Mountains to the west and about 1525 mm in the Sapphire Mountains to the east. There are about 480 km of irrigation ditches supplying water to about 44550 ha of farm and ranch land. The hydrology of the Bitterroot River Watershed is a complex interconnection of numerous tributaries from the surrounding mountains, groundwater recharge and discharge areas, braided channels, wetlands, irrigation diversions and drains and other human withdrawals and discharges. Flow and water quality have been monitored at locations that generally represent upper, middle and lower watershed conditions. These three Bitterroot River monitoring locations are referred to herein as the: (1) Bitterroot River near Darby, (2) Bitterroot River near Florence and (3) Bitterroot River at Missoula, respectively.

3. Model Description

SWAT was originally developed by the USDA-ARS to predict the impact of land management practices on water, sediment and agricultural chemical yields in large, ungauged basins (Arnold et al., 1998). SWAT incorporates features of several ARS models and is a direct outgrowth of the SWRRB model (Simulator for

Water Resources in Rural Basins) (Williams et al., 1985). For this study, the SCS runoff curve number (CN2) was used to estimate surface runoff from daily precipitation (USDA SCS, 1986). The curve number was adjusted according to moisture conditions in the watershed (Arnold et al., 1993).

A 2005 version of SWAT was used to perform the simulations in this study. The executable version of the model was modified to consider losses of organic nitrogen and phosphorus from bank erosion in the top soil layer. Two new parameters included in the modified version of the model consisted of CH_ONCO_BSN and CH_OPCO_BSN, which were the channel organic nitrogen and organic phosphorus concentrations associated with bank erosion, respectively.

4. Watershed Delineation

Model simulations were performed using a delineation consisting of 85 subbasins to account for climatic, soil, topographic, and land cover variations within the Bitterroot watershed (Figure 1).

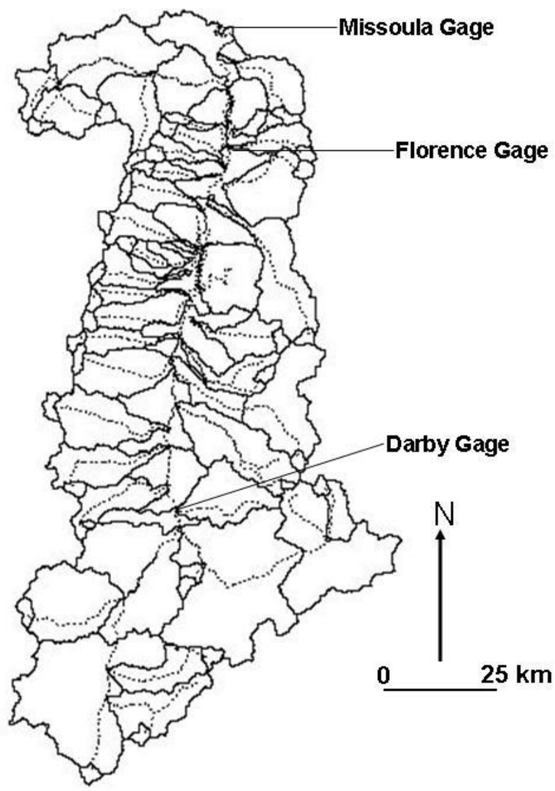


Figure 1. *Subbasin delineation of the Bitterroot watershed and location of monitoring stations on the Bitterroot River*

Considerable refinement was made to the land cover classification originally developed for the project. A total of 15 land cover and 38 soil types were employed in the project, resulting in a delineation of 1808 hydrologic response units (HRUs). Table 1 presents a listing of the respective land cover types, watershed areas, ranges in curve number values and USLE C factors for each land cover type delineated in the Bitterroot project. Sediment and nutrient loadings from waste water treatment plants within Bitterroot consisted of four sites including Darby, Hamilton, Stevensville and Lolo. Loadings from these sites were read into SWAT on a monthly basis as point sources.

Table 1. *A listing of the respective land cover types, watershed areas, ranges in curve numbers and USLE C factors delineated in the Bitterroot project*

SWAT Code	Land Cover Type	AREA (km2)	AREA (%)	Curve No. Range	USLE C Factor
ALFA	Irrigated Alfalfa	84.94	1.16%	39-74	0.04
AGRL	Irrigated Mixed Crops	109.32	1.50%	66-83	0.23
BARN	Hobby Farm Livestock	7.85	0.11%	67-87	0.95
FRHV	Forest Harvest	91.74	1.26%	30-82	0.05
FRSE	Forest	4459.65	61.10%	25-77	0.003
HAY	Irrigated Pasture	207.07	2.84%	31-79	0.012
ICED	Ice and Barren Rock	32.11	0.44%	32-58	0
LAWN	Hobby Farm Lawn	10.24	0.14%	62-84	0.012
RNGB	Range Brush	1107.96	15.18%	39-80	0.042
RNGE	Range Grass	994.83	13.63%	49-84	0.05
SEPT	On-Site Septic Systems	1.33	0.02%	62-84	0.012
ULOW	Low Density Urban	26.62	0.36%	61-87	0.008
UMED	Medium Density Urban	24.32	0.33%	77-92	0.008
UPAV	Unpaved Roads	30.04	0.41%	72-89	0.75
WETF	Wetland	110.81	1.52%	32-58	0.001
Total:		7298.83	100.00%		

5. Model Calibration and Validation

Based on available climatic, streamflow and water quality data within the watershed, model parameters in SWAT were calibrated and validated using two, four-year periods of record. A dryer-than-normal period of record from 2000 to 2003 was designated as the calibration period since it contained the largest array of measured water quality data. A wetter-than-normal period of record from 1995 to 1998 was designated as the validation period. Based on average annual precipitation of 880 mm, the calibration period was about 16% dryer than average while the validation period was about 18% wetter than average.

To account for spatial variability in topographic, soil and land use factors among Bitterroot sub-watersheds, parameters governing streamflow response in SWAT were calibrated in a distributed fashion. We used the model's automated calibration procedure in which observed and simulated outputs are compared at the same outlet points on the watershed. Following auto-calibration, a manual approach was taken to fine-tune model simulations at seven regions within the watershed.

Limited data were available to calibrate and validate sediment, total nitrogen and total phosphorus for the Bitterroot watershed. Sites selected for calibration and validation included the Bitterroot River near Darby and the Bitterroot River at Missoula. The two new model parameters, CH_ONCO_BSN and CH_OPCO_BSN, were calibrated by matching measured versus simulated average monthly nutrient concentrations during the high-runoff months of April, May and June.

6. Simulation Results

6.1 Streamflow

A comparison of measured versus simulated daily hydrographs from the three gauges on the main stem of the Bitterroot River showed very good agreement for the most part. For the calibration period from 2000 to 2003, daily Nash-Sutcliffe (1970) coefficient of efficiency (NSE) values were 0.83, 0.76 and 0.74 for the Darby, Florence and Missoula gauges, respectively (Table 2).

Table 2. *Streamflow percent bias (PBIAS) and monthly and daily coefficient of efficiency (NSE) values for the three monitoring stations on the Bitterroot River.*

Gauge Location	Drainage Area (sq km)	Period of Record	Record Type[1]	PBIAS (%)	Monthly NSE	Daily NSE
Darby	2718	1/00 to 12/03	C	0	0.9	0.83
Darby	2718	1/95 to 12/98	V	-9.8	0.92	0.88
Florence	6100	1/00 to 12/03	C	3.4	0.91	0.76
Florence	6100	1/95 to 12/98	V	-12.6	0.92	0.77
Missoula	7299	1/00 to 12/03	C	7.4	0.88	0.74
Missoula	7299	1/95 to 12/98	V	-5.5	0.92	0.78

[1]C = Calibration; V = Validation

Based on monthly NSE values, the model performance is considered very good for the three main-stem Bitterroot gauges. Monthly NSE values for the calibration and validation periods were 0.90 and 0.92 for the Darby, 0.91 and 0.92 for the Florence, and 0.88 and 0.92 for the Missoula gauge, respectively. Measured versus simulated monthly streamflow at each of the three gauges generally matched very well for most months.

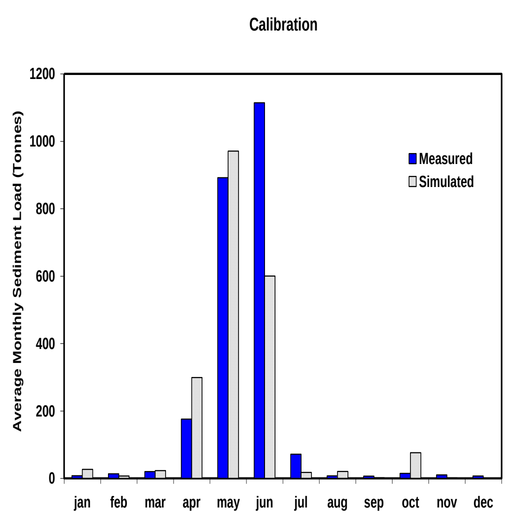
6.2 Sediment

Due to the limited amount of measured sediment data available at the monitoring stations on the Bitterroot, only the Darby and Bitterroot gauges were used to calibrate SWAT parameters governing the sediment response. In general, simulation results show that SWAT tended to overestimate sediment loads for the month of April (Figure 2). Some months, like April, had scarce sediment sampling, so measured data for that month may not be well represented. SWAT performance in simulating sediment response in the watershed was considered adequate based on respective monthly NSE values for the calibration and validation periods of 0.32 and 0.41 for the Darby and 0.64 and 0.63 for the Missoula gauge (Table 3).

Table 3. *Sediment and nutrient load percent bias (PBIAS) and monthly coefficient of efficiency (NSE) for the Bitterroot River near the Darby and Missoula gauging stations*

Constituent	Gauge Location	Drainage Area (sq km)	Period of Record	Record Type[1]	PBIAS (%)	Monthly NSE
Sediment	Darby	2718	1/00 to 12/03	C	-9.7	0.32
Sediment	Darby	2718	1/95 to 12/98	V	-18	0.41
Sediment	Missoula	7299	1/00 to 12/03	C	12.7	0.64
Sediment	Missoula	7299	1/95 to 12/98	V	-26.7	0.63
Nitrogen	Missoula	7299	1/00 to 12/03	C	18	0.82
Nitrogen	Missoula	7299	1/95 to 12/98	V	-18.8	0.79
Phosphorus	Missoula	7299	1/00 to 12/03	C	20.7	0.33
Phosphorus	Missoula	7299	1/95 to 12/98	V	-22.3	0.68

[1]C = Calibration; V = Validation



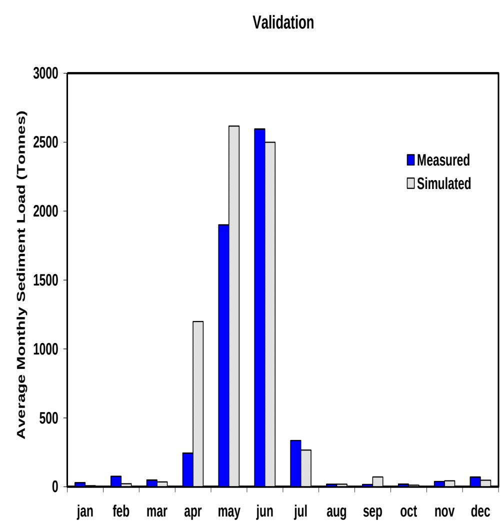


Figure 2. *Comparison of measured versus simulated average monthly sediment load during the calibration and validation periods for the Bitterroot River at Missoula*

6.3 Nutrients

Simulation results show that SWAT tended to underestimate total nitrogen (N) loads during the snowmelt runoff months of April, May and June of the calibration period but overestimated the loads during the same months of the validation period for the Bitterroot River at Missoula (Figure 3). This effect was likely attributed to the fact that the model somewhat underestimated streamflow from April to June of the calibration period and vice versa for the validation period. Based on respective monthly NSE values of 0.82 and 0.79 for the calibration and validation periods (Table 3), SWAT performance in simulating total N response in the watershed was considered good. For the most part, SWAT performed well in simulating total phosphorus (P) loads at the Missoula gauge (Figure 4). For the calibration period, monthly PBIAS and NSE values were 20.7% and 0.33, and for the validation period, these values were -22.3% and 0.68, respectively.

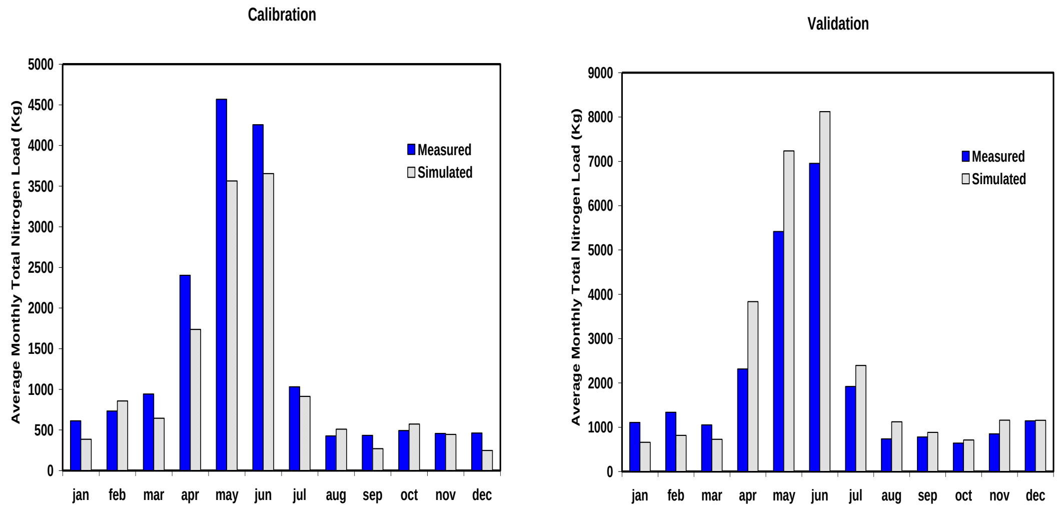


Figure 3. *Comparison of measured versus simulated average monthly total nitrogen load for the calibration (2000-2003) and validation (1995-1998) periods for the Bitterroot River at Missoula*

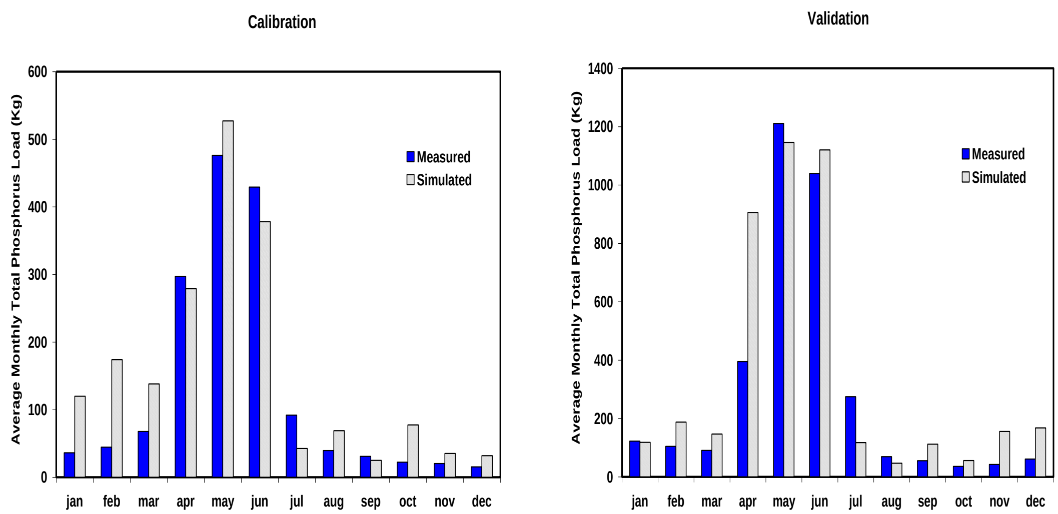


Figure 4. *Comparison of measured versus simulated average monthly total phosphorus load for the calibration (2000-2003) and validation (1995-1998) periods for the Bitterroot River at Missoula*

7. Sources of Simulated Sediment and Nutrients

Following calibration of the streamflow and water quality parameters in SWAT, a baseline period was selected to represent current water quantity and quality conditions on the Bitterroot. Simulations performed for this period not only provided estimates of sediment, total N and total P concentrations and loadings for each of the impaired stream systems within the watershed, but also provided estimates of the source allocation by land cover and management type. Using available climatic and streamflow data, an 11-year period of record from 1993 to 2003 (preceded by a five-year warm-up period) was selected as the baseline condition for the watershed.

Based on this 11-year run, the average annual sediment load simulated by SWAT at the Missoula gauge was about 120,000 metric Tonnes. Of this amount, about 53,500 Tonnes or 45% was due to the erosion of tributary and main stem banks, 23% was from range grass, 16% was from range brush, 11% was from forest and the remaining 5% was from other sources. The total N load simulated by SWAT at the Missoula gauge was about 596,000 Kg. Of this amount, approximately 25% was from bank erosion, 21% was from pasture, 17% was from mixed crops, 8% was from forest, 8% was from septic systems, and the remaining 21% was from other sources within the watershed. For the 11-year period, SWAT simulated an average annual total P load of about 84,700 Kg. Of this amount, about 36% was from bank erosion, 18% was from mixed crops, 13% was from range grass, 11% was from range brush, 9% was from forest, 7% was from point sources, and the remaining 6% was from other sources.

8. Conclusions

To perform streamflow, sediment and nutrient simulations on the Bitterroot watershed in western Montana, USA, we used a revised 2005 version of the Soil and Water Assessment Tool consisting of a modification to consider losses of organic nitrogen and phosphorus due to bank erosion. Nutrient simulations performed in this study were markedly different from those obtained using SWAT on Montana's Blackfoot watershed, a drainage area just to the northeast of the Bitterroot. In the SWAT version used in Blackfoot, no nutrient loadings associated with bank erosion could be included. In the revised version of SWAT used in the present investigation, very sizeable proportions of nitrogen and phosphorus were transported through stream reaches as a result of bank erosion. The profound differences between this study and the previous one represent a significant finding that has substantial implications regarding source allocation in the development of nutrient TMDLs. To substantiate nutrient loadings simulated in this study, field investigations need to be implemented that are designed to measure losses of nitrogen and phosphorus associated with erodible stream channels.

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SWAT modeling of critical source areas of runoff and phosphorus losses: Lake Champlain Basin, VT

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Abstract

Lake Champlain, located between Vermont, New York and Quebec, exhibits eutrophication due to continuing phosphorus (P) inputs derived mainly from upstream nonpoint source areas. To address the lake's eutrophication problem and total maximum daily load (TMDL) requirements, a state-level P reduction goal has been set by the Departments of Environmental Conservation of both Vermont and New York. Unfortunately, remedial measures undertaken to control the nonpoint P losses have thus far been based mostly on voluntary landowner participation rather than a systematic technique for implementing remedial measures where they are most needed (greater P loss risk) and where they can provide the greatest P loss reduction. Consequently, P reduction goals have not been achieved in most segments of Lake Champlain. The main objective of this study was to identify land uses with the highest P loss, referred to as critical sources areas (CSA), using a model-based approach. The Soil and Water Assessment Tool (SWAT) was used for this objective. This study focuses on the Rock River Watershed, which is one of the largest contributors of P to Lake Champlain. Spread over 71 km^2, the watershed is dominated by dairy agriculture and has fertile periglacial lacustrine and alluvial soils with an old tile drainage system. In this study, we tested SWAT's ability to simulate hydrology, sediment and P losses in the Rock River watershed. In this paper, we present outputs of model calibration, validation and CSA spatial locations for runoff, sediment and P losses. The identification of CSAs for P loss is expected to support the next phase of our project, which involves exploring cost-effective P management strategies with the highest potential for P loss reduction applicable to the study watershed and the Lake Champlain Basin.

Keywords: Critical Source Area, Lake Champlain, Phosphorus, SWAT

1. Introduction

Lake Champlain has historically exhibited eutrophication problems due to continuing phosphorus (P) inputs from upstream areas (Lake Champlain Basin Program, 1979; 2006; 2008). The 1130-km^2 Lake Champlain is located mainly between the states of Vermont and New York and partly in the providence of Quebec, Canada. Noxious algal blooms stimulated by the excessive P inputs disrupt the lake's ecology and degrade the recreational use and enjoyment of its waters. To address the excessive P loadings and the total maximum daily load (TMDL) requirements set by the United States Environmental Protection Agency (USEPA) and the Clean Water Act, the Departments of Environmental Conservation of both Vermont and New York specified state-level P reduction goals in 2002 for segments of Lake Champlain that do not meet water quality standards (Lake Champlain Basin Program, 2002). The majority of lake segments not meeting the specified targets are dominated by nonpoint source areas (> 90%), which in turn, are mostly located in Vermont. To this effect, different agencies in Vermont have made huge investments and remediation efforts to achieve P reduction goals and improve water quality in these lake segments. However, remedial measures undertaken to control the nonpoint P losses have thus far been based mostly on voluntary landowner participation rather than a systematic technique for implementing remedial measures where they are most needed (greater P loss risk) and where they can provide the greatest P loss reduction. Consequently, P reduction goals have not been achieved despite the efforts of many agencies. Due to variations in topographic, hydrologic, soil, and management factors, not all nonpoint P sources contribute equally to water impairment. Some nonpoint sources contribute disproportionally high P loads. Therefore, identification of areas with high P losses is one of the state's current and future priorities for allocating limited resources toward successfully addressing nonpoint P pollution and meeting water quality standards required by the TMDL program. Hence, there is a critical need for an improved approach to identifying and controlling land uses with high P losses referred to in this paper as critical sources areas (CSAs).

Field and model-based approaches may be useful techniques for identifying P-loss CSAs. However, the enormous resources and time required for field-based approaches, limits their applicability in identifying P-loss CSAs and evaluating management strategies. Alternatively, a model-based approach may be one of the most efficient and feasible approaches for supporting these efforts. Therefore, the main objective of this study was to identify CSAs of runoff and P losses using a model-based approach. Because of its widespread and successful applications involving TMDL analysis and conservation practice assessment, the Soil and Water Assessment Tool (SWAT; Neitsch et al., 2002) was found to be a suitable model for this objective. For this study, we used the SWAT2005 version with the ArcSWAT 2.1 interface. ArcSWAT 2.1 has been linked with a set of recently developed tools that are useful for evaluating parameter sensitivity, aiding in model calibration and assessing input parameter and model output uncertainty. Our project, funded by the Lake Champlain Basin Program, the Vermont Agency of Natural Resources and several private donors, applied SWAT on the Rock River watershed, Vermont. The Rock River watershed is dominated by agriculture and drains into the Missisquoi Bay segment of Lake Champlain, a segment that does not meet the TMDL specified P load target. The Rock River watershed has high P losses per unit area and is a high priority for watershed management activities.

In this study, we tested SWAT's ability to simulate hydrology, sediment and P losses in the Rock River watershed. In this paper, we present outputs of model calibration, validation and CSA spatial locations for runoff, sediment and P losses. The identification of CSAs for P loss is expected to support the next phase of our project, which involves exploring cost-effective P management strategies with the highest potential for P loss reduction applicable to the study watershed and the Lake Champlain Basin.

2. Materials and methods

2.1 Study Watershed Description

The Rock River is located in the northwestern corner of Vermont (Figure 1). It flows northward into the Missisquoi Bay, a northeastern arm of Lake Champlain. The river is monitored right when it crosses the USA-Canada border. The Rock River watershed modeled in this study encompasses 70.9 km^2, composed mainly of rural areas Vermont. The watershed has an average elevation of 101 meters and is relatively flat by Vermont standards. The area's climate is humid with an average annual temperature of 6˚C and average annual precipitation of 1100 mm (based on 20 years of meteorological data from a station located nearby at Enosburg, VT). Land use in the Rock River watershed consists of forest (35%), wetland and water bodies (0.6%) and build-ups (6%), which include buildings, farmsteads and roads. Agriculture claims the most land (58%) with 17% corn, 25% hay, 3% permanent pasture and 13% unidentified agricultural crops including small grain, pasture and others. Soils in the watershed are of glacial origins dominated mainly by silt loam or silty clay loam types. An old tile drainage system exists on crop fields throughout the watershed. About 90% of corn fields and 75% of the grass fields are estimated to have these systems. The fertile periglacial lacustrine and alluvial soils support an intensive and increasingly consolidated dairy farming industry.

In this watershed, there are 34 small farm operations—SFO (3165 cows), 3 medium farm operations—MFO (836 cows) and 1 large farm operation—LFO (10,000 chickens). Based on Vermont's farm size categorization, a farm with 0-199 cows is considered an SFO, a farm with 200-499 cows is an MFO and farms with cows numbering greater than 500 are categorized as LFOs.

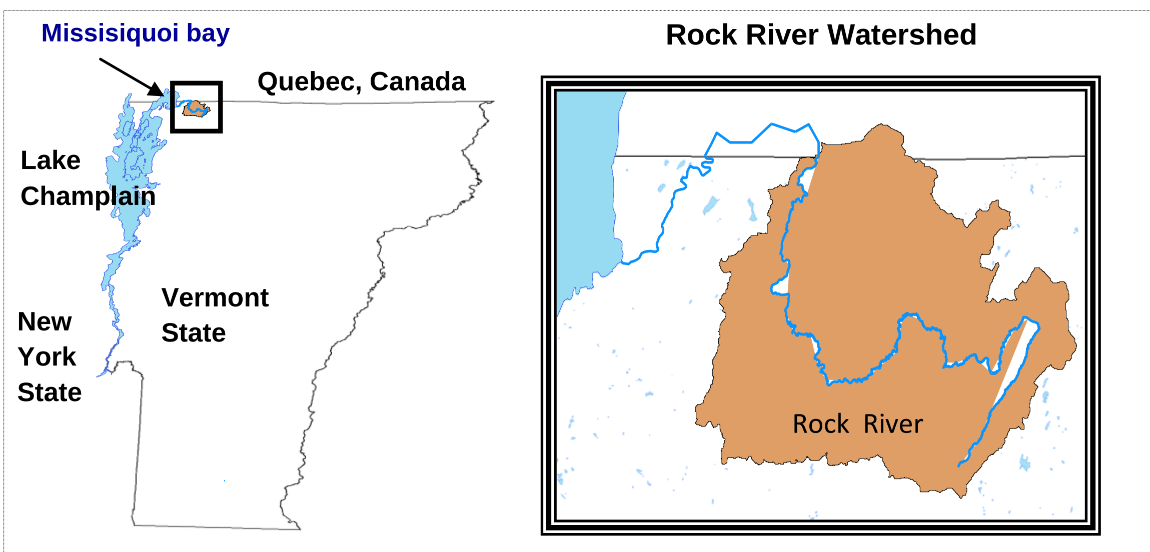

Figure 1. *Map showing the location of Rock River watershed, Missisquoi bay and Lake Champlain.*

Basic input data used for representing the Rock River watershed with SWAT included a DEM, soil map, land use maps and climatic and hydrological information. These inputs are described below with sources and resolution. Topography data (1:50,000-scale Digital Elevation Model [DEM]) was obtained from the Vermont

Center for Geographic Information, VCGI, and Canadian Digital Elevation Data, CDED. We obtained soil data from the Soil Survey Geographic Database (SSURGO) at the USDA soil data mart. Land use data was developed by combining several land use data sources: general land cover data (30-m national land cover database), Common Land Unit (CLU) of crop fields and pasture and GPS locations of active barnyards. Precipitation and temperature data were obtained from the National Weather Service (NWS) Cooperative Observer Stations in Enosburg, St. Albans, and South Hero, Vermont, and from the Canadian government at Philipsburg, Quebec. All these stations are located outside the watershed boundary, but they surround the study watershed at distances ranging from 10 km to 30 km. To generate other climate data used in the model (solar radiation, relative humidity and wind speed), we used the built-in SWAT model weather generator. Lastly, for model calibration and validation, streamflow, sediment and P data (2001-2008) measured at the outlet of the watershed were obtained from the Québec Ministère du Développement durable, de l'Environment et des Parcs (MDDEP).

The SWAT model allows a watershed to be divided into subbasins based on topographic criteria and user-defined streams. A 10-m DEM of the Rock River watershed was used to define stream networks, and a USGS digitized stream layer was also used to make sure the modeled streams closely matched this data. In the SWAT model, hydrologic response units (HRUs) within each sub-watershed are defined based on combinations of land use, soil types and slope. Land use data with defined crop-field boundaries, the SSURGO-level soils map, and four slope groups were used to define HRUs. Four slope groups (0-3%, 3-8%, 8-15% and >15%) were purposely selected to match slope categories used for a variety of farm planning purposes. During the process of HRU formation, crop fields were distinctly represented to avoid lumping similar land use, slope and soil combinations within a subbasin into one HRU. By avoiding lumping, the amount of runoff and associated sediment and P loadings for each crop field can be extracted. Most importantly, the spatial location of the crop fields can be maintained for further determination of high P loss areas.

2.3 SWAT management data inputs

Key SWAT management inputs include planting, tillage, harvesting, grazing, fertilizer and manure applications, tile drainage and plowing. It was not possible to acquire management data on a field-by-field basis for each farm in the study watershed due to either a lack of documentation and/or farmers' information privacy concerns. Therefore, the management input data were based on typical management regimes specific to crop type and were obtained from farm planners. In addition, manure production was estimated using data on the number of animals in the watershed and typical livestock manure production rates. Other management practices, such as tile drainage, were also represented as well as possible using appropriate model parameters. Barnyards in the watershed were defined in the urban land use database, and their associated parameters were set up to be consistent with barnyard characteristics. Soil-based parameters such as labile P, organic P and the phosphorus availability index were defined based on the default values specified in the SWAT model. In addition, soil P test data are being gathered from farm planners, and once acquired, they will be used to update the default soil labile P values.

2.4 Parameter sensitivity analysis

Sensitivity analysis is used to determine the sensitivity of model outputs to changes in the values of model input parameters. By identifying input parameters that are sensitive, the number of parameters included in the calibration process can be reduced, allowing for greater focus on the most sensitive input parameters. Because of the relatively large number of input parameters involved in modeling hydrology as compared to sediment and phosphorus, the sensitivity analysis done in this study was performed only on the hydrology input parameters. Hence, we included 26 hydrology-related parameters in the sensitivity analysis, using the ranges of variation provided in the SWAT default range settings. The SWAT sensitivity analysis was performed using two objective functions (OFs): 1) the first was determined by calculating the difference in the sum of squared residuals between daily simulation flows of the original run and the run after changing parameter values, and 2) the second was determined by calculating the difference in the sum of squared residuals between daily observed flows and modeled flow at the watershed outlet.

2.5 Determination of Critical Source Areas

The SWAT model simulation was run from 1997 to 2008. The first four years were used as a warm-up period to ensure proper initial model conditions, including (among others) soil moisture, aquifer water levels and crop growth. Using observed data (2001-2008) gathered at the outlet of the watershed, the model was calibrated and validated for streamflow, sediment and total phosphorus. The observed data were divided into two datasets, with the first set (10/1/2001-9/30/2004) used for calibration and the second set (10/1/2004-10/1/2007) used for validation. After completion of model calibration and validation, we analyzed the magnitude of runoff, sediment and P losses from the various land uses (HRU).

We selected HRU-level SWAT predictions to identify land uses with the highest runoff, sediment and P losses (CSAs). In this study, HRUs represented subbasin areas with unique combinations of land use, soil type and slope. Spatial locations of crop-field HRUs were also maintained in order to generate HRU-based predictions for direct transfer to a map showing the location of these CSAs for runoff, sediment and P losses within the watershed.

3. Results and Discussion

3.1 Hydrology-related parameter sensitivity analysis

Sensitivity analysis was performed using a simulation period lasting from 2001-2004, with a proceeding four-year warm-up period. Figure 2 summarizes the sensitivity rankings of the input parameters based on streamflow prediction performances, which were determined by using the two OFs previously described. In addition, calculated OF mean values used to rank the sensitivity of the input parameters are included in Figure 2.

Similar to the findings in other studies (Cryer and Havens, 1999; Eckhardt and Arnold, 2001; White and Chaubey, 2005), CN2, Sol_Awc and Esco, which affect surface runoff, were found to be among the most sensitive parameters. Of the parameters affecting groundwater flow, Gwqmn was found to be the most sensitive parameter. The importance of this groundwater parameter is not surprising due to the fact that baseflow greatly contributes to streamflow in this region. Moreover, TIMP and Smtmp, snowmelt-related parameters, were also identified among the most sensitive parameters as analyzed using the two OFs. TIMP and Smtmp are also highly relevant in this cold region where snowmelt is an important component of hydrology. *(CN2=SCS runoff curve number for moisture condition II; Sol_Awc= available water capacity (mm/mm soil); Esco= plant evaporation compensation factor; Gwqmn= threshold depth of water in the* *shallow aquifer required for return flow to occur (mm); TIMP= snowpack temperature lag factor; Smtmp= snowmelt base temperature (˚C))*

In summary, the sensitivity analysis provided the ranks of influential hydrological parameters. By using the mean values, we were able to gain insights about which parameters are more likely to affect model outputs and errors. As shown by the mean values, only a handful of parameters had a mean value greater than 0.1, indicating that changes in the value of these parameters will have a greater impact on streamflow predictions. Hence, of 26 input parameters, only 12 had a sensitivity mean value greater than 0.1 and were included in the model calibration process.

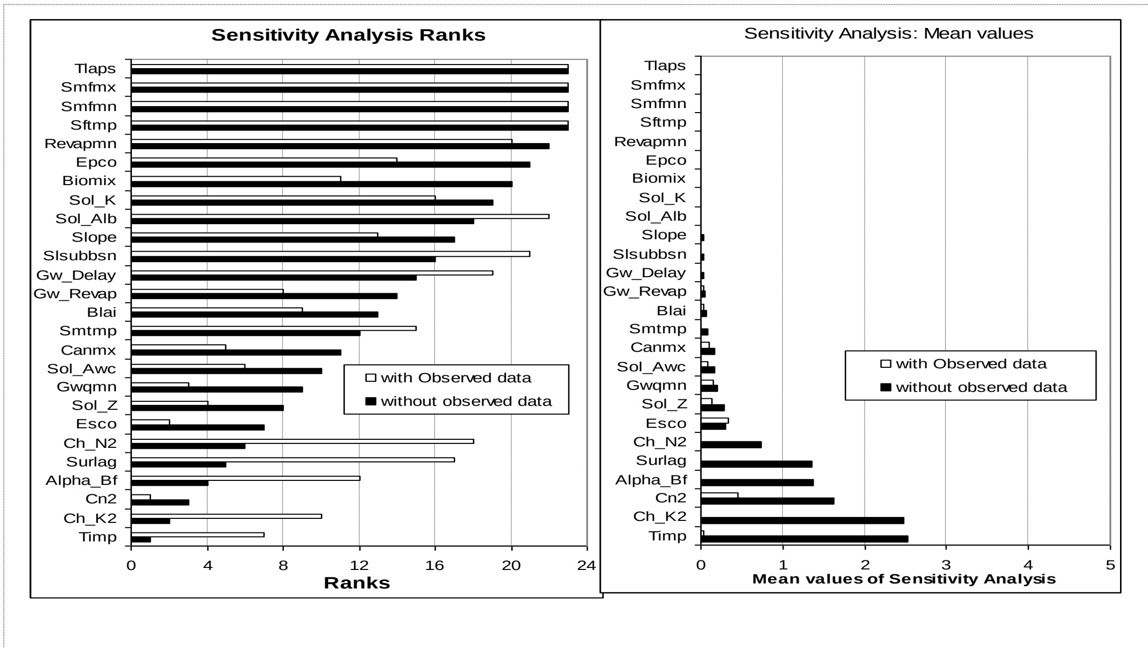

Figure 2. *Sensitivity analysis results for hydrology input parameters*

3.2 Calibration and validation of SWAT simulations

Streamflow was calibrated on a daily basis using the auto-calibration tool in SWAT for the period lasting from 2001 to 2004. Model performance was assessed using descriptive statistics for measured and simulated runs. We compared Nash-Sutcliffe coefficients, NSE, and time-series plots of simulated versus observed (measured) data (Figure 3). Model predictions were then validated for the period lasting from 2004 to 2007. Results for daily and monthly predictions gave NSE values ranging from 0.6 to 0.7 for both calibration and validation periods. Overall, daily and monthly predictions obtained for streamflow were considered acceptable for this project. Similarly, auto-calibration efforts are underway for both sediment and P. In this paper, preliminary results for sediment and total P predictions obtained by manually calibrating the model are presented (Figure 4). NSE values representing sediment concentrations for the calibration period were 0.4 and 0.7 on daily and monthly basis, respectively. The NSE values for the validation period were 0.4 and 0.5 for daily and monthly predictions, respectively. Overall, monthly sediment predictions were reasonably close to the observed data. For total P, only monthly load predictions were compared to the observed data. Based on this comparison, NSE values for monthly total P load predictions were 0.53 and 0.50 for the calibration and validation periods, respectively. Future improvements in sediment and P predictions are expected with improvements in input data (such as soil P test) and by using the auto-calibration process.

3.3 Critical source areas for runoff, sediment and P

For demonstration purposes, maps were produced from model results to show areas with the highest runoff, sediment and total P losses (Figure 5). These results are based on eight-year (2001-2008) average values. However, similar maps can be generated for specific seasons or years of interest. By using such maps and output tables obtained from the model, specific areas susceptible to runoff, sediment and P losses can be identified, and these areas can be examined more closely to obtain specific land use, slope and soil characteristics.

(a) Calibration **(b) Validation**

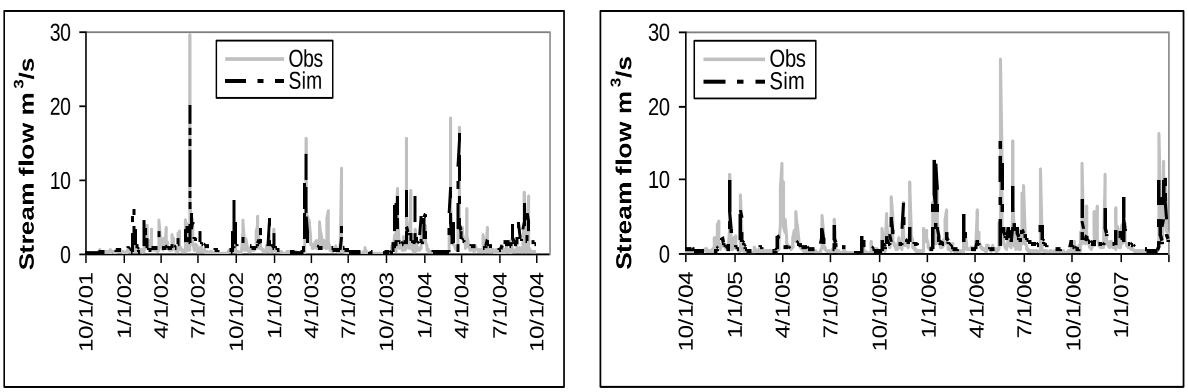

Figure 3. *Time-series plots of simulated versus observed (measured) daily streamflow during the (a) calibration and (b) validation periods*

(a) Calibration **(b) Validation**

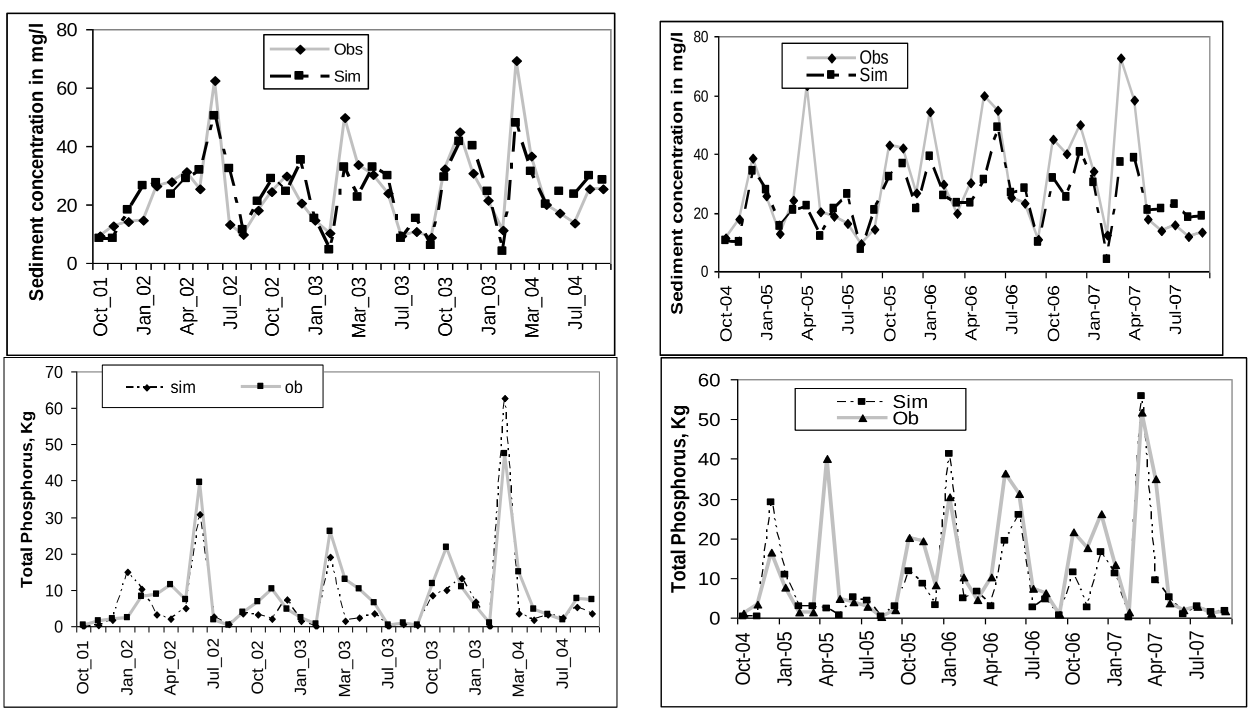

Figure 4. *Time-series plots of simulated versus observed (measured) monthly sediment concentrations and total phosphorus loads during the (a) calibration and (b) validation periods*

For sediment, for example, about 87% of the sediment yield was found to originate from only 14% of the watershed area. For soils in the study watershed, this high-loss area has sediment loss rates that are greater than the highest tolerable soil loss value, T (7 T/ha). Preliminary results from total P predictions also show that about 23% of the upland watershed area produces about 80% of the total P loads. The results of this study indicate that certain land areas produce a disproportionate amount of runoff, sediment and P losses. The study also highlights the importance of using a systematic methodology, such as the SWAT model, to identify CSAs. Such model-based identification of high-risk P loss areas is expected to help in exploring and planning cost-effective P management strategies with the highest potential for P loss reduction in the Rock River watershed.

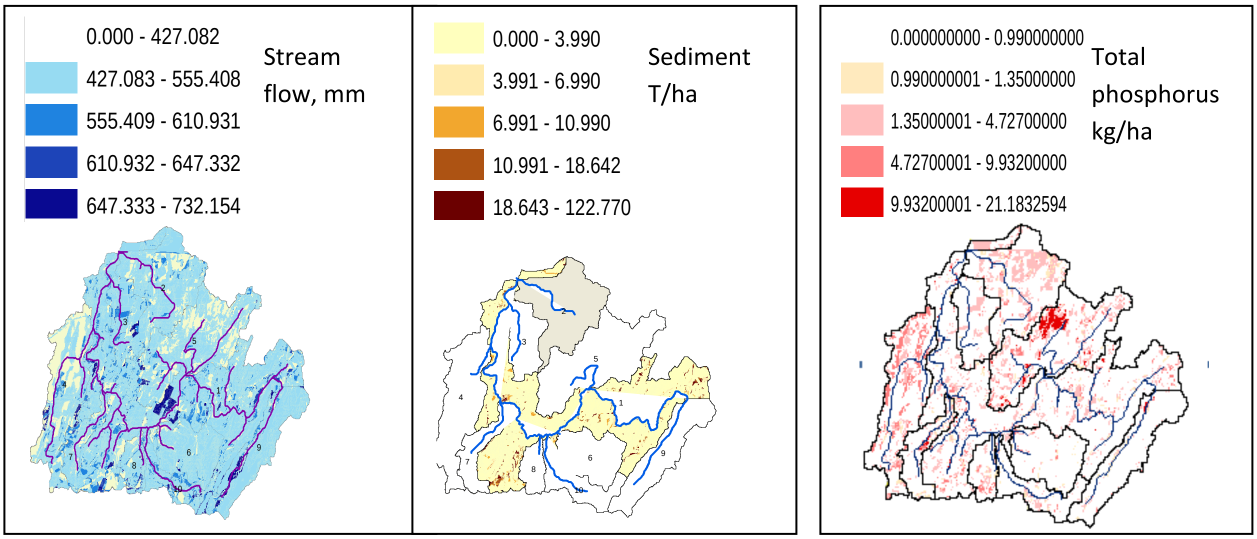

Figure 5. *Maps showing watershed source areas for runoff, sediment and total phosphorus losses.*

4. Conclusion

The SWAT model can justifiably be used in identifying critical source areas with high runoff, sediment and P losses. However, in order to generate maps representing these critical source areas that are transferable to the ground, careful HRU design during the generation process is necessary to create HRUs that depict the desired scale of representation and the objectives of a specific project. Identification of critical source areas will aid different agencies in allocating limited resources toward targeting management efforts. The next steps in this project will be to assess the effectiveness of management practices and to add uncertainties to the predictions. Knowing the degree of uncertainty associated with the model outputs will be vital in making decisions about watershed management and assessing the most effective conservation practices.

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Using SWAT as a Tool for Sustainable Land use Policy Development

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Abstract

This paper looks at sustainable development from a watershed perspective. The two facets to sustainability—environment and development, are both related and impact each other. The quality and quantity of available water affects human activities, their well-being and their livelihoods. On the other hand, anthropogenic activities and land use practices affect the quality and quantity of available water. Watershed management is a very powerful and effective tool for providing a framework and a subsequent measure of humanity's progress towards sustainability. This paper introduces a framework for measuring a "Watershed Sustainability Index" (WSI). In the study, we implemented this framework on a watershed in Millsboro Pond watershed in southern Delaware and used SWAT to measure the WSI for four land use scenarios in the watershed (created based on recharge potential and riparian widths). We found that the spatial distribution of land use impacts the sustainability of a watershed. Riparian zones, up to a certain width, improved the sustainability of the watershed. Out of the four scenarios, the current land use may be considered "sustainable" only if environmental issues are given less weight.

1. Introduction

Humans' relationships with their surroundings and among themselves are constantly changing. Once part of a "natural system," humans have created a separate system, alienated from the natural environment. The scale and intensity of environmental degradation due to human action has surpassed that of all the previous centuries. Sustainability implies maintaining natural resources for future generations and sharing them equally in the current generation (WCED, 1987). The sustainability paradigm for development recognizes the finite nature of such resources, and that the well-being of humanity depends on the healthy state of natural systems. In reality, there is no clear consensus on how to achieve sustainable development (Tortajada, 2005). One way to look at sustainability is by broadly classifying it as social, economic and environmental. Each class of sustainability focuses on maintaining its own capital. From society's perspective, natural capital can be considered a "stock of environmentally provided assets" that provide useful human services (Goodland, 1995). From the ecological perspective, natural capital includes all the living and non-living matter (like air, water and soil). Out of the three classes of sustainability, environmental sustainability should take precedence (Goodland and Daly, 1996). Social and economic sustainability depend upon the success of environmental sustainability.

To bring the debate of sustainable development out of the theoretical realm, a form of measurement is needed. Sustainability indicators can help make the sustainable development paradigm usable. These indicators are affected by the cultural, technical, economic, physical and social conditions (Tortajada, 2005). So, each region or watershed will have to come up with its own set of sustainability indicators, but the underlying principle has to be the same. Afgan (2004) suggests grouping the indicators for each subsystem then combining them into a sustainability indicator.

Barlow et al. (2004) define water sustainability as the "development and use of water resources in a manner that can be maintained for an indefinite time without causing unacceptable environmental, economic or social consequences." Gleick (1998) defines sustainable water use as "the use of water that supports the ability of human society to endure and flourish into the indefinite future without undermining the integrity of the hydrological cycle or the ecological systems that depend on it."

When talking about water sustainability, it is critical to keep in mind that it is also dependent on nature's whims. Hence, the goal of water sustainability is not necessarily to have enough water available all the time, but rather to have a system in place for adapting to changing water scenarios in a region. The system should be resilient enough to recover from occasional droughts or flooding and thus be less vulnerable to natural events. From this viewpoint, water system sustainability can be measured in terms of reliability, resilience and vulnerability. Resilience can be measured in terms of the time required by the system to return to a state of equilibrium after a disturbance. This type of resilience is called "engineering resilience" (Gunderson, 2000). Klein et al. (1998) consider vulnerability as a "degree of incapability to cope with" disturbance. While resistance is the ability of the system to avoid disturbance, the resilience (as discussed above) is the system's capacity to respond.

2. Indicators for Watershed Sustainability

Indicators for watershed sustainability can be divided into social development, environment and biodiversity. For this framework, we assumed that the economic system is constrained by the availability of natural resources (land and water to support livelihoods). As long as these resources are used to provide for livelihoods, they will lead to economic well-being. The indicators all range from 0 (worst case) to 1 (best case).

2.1 Social Development Indicators

2.1.1 Water for Domestic Use (I_{WD})

From the watershed perspective, the human residents require water, land and energy to meet their needs and to develop socially and economically. An index showing the capability of a watershed to meet the minimum requirements of a region is sufficient for this research. Since water supply is dependent upon short-term weather patterns, it is prudent to calculate the indicator on a monthly basis then convert it to an annual value.

$$I_{WD(Monthly)} = \frac{\text{Water available for domestic use}}{\text{Minimum water required for domestic use for that region}}$$

2.1.2 Water to Support Livelihood (I_{WL})

This indicator includes water required for any agricultural, industrial or commercial activities within a watershed. There is a strong relationship between sustainable livelihoods and water availability (Alan, 2000; Hope, 2003). From the watershed sustainability perspective, the indicator needs to measure the availability of water required to sustain livelihoods within the watershed. The water requirements will vary seasonally (i.e., irrigation water), so the indicator should be calculated seasonally then converted to the yearly average.

$$I_{WL(Seasonally)} = \frac{\text{Water available for livelihood use}}{\text{Minimum water required for livelihood use for that region}}$$

2.1.3 Land-Based Renewable Energy (I_{RE})

Renewable energy is an important part of the sustainable development equation. Although solar and wind are important, looking at biofuels from a watershed and land use perspective is critical. Biofuels can be very resource-intensive, as is the case for corn or soybeans. Water can become a constraining factor in regions where water is scarce. On the other hand, using native plants, which use less water, can help reduce water stress in the watershed. From the watershed sustainability perspective, some of the energy demands for the watershed should be met locally.

$$I_{RE} = \frac{\text{Biofuel source produced within the watershed}}{\text{Biofuel source required for that region}}$$

2.2 Environment

2.2.1 Water Pollution (I_{WP})

Despite having substantial water resources, many regions of the world experience water scarcity. The predominant reason for this is water pollution. Water pollution reduces the availability of water for human consumption and use. It plays an important role in increasing water poverty within a region. In this research, the water pollution indicator looked at nonpoint pollution that was above acceptable limits for our region of study.

$$I_{WP} = \frac{\text{Length of stream that is not impared * No. of months it is not impared}}{\text{Total length of stream in the watershed * No. of months considered}}$$

2.2.2 Water to Support the Ecosystem (I_{WE})

Aquatic ecosystems around the world are under stress (Gleick, 1996) due to many factors. Some of these factors include loss of habitat, changes in hydrological regimes and water pollution (including eutrophication). Habitat loss is a land use issue and can be handled under the biodiversity section. Water availability for the aquatic ecosystem can mean different criteria for different regions and ecosystems. Usually, minimum flow requirements are set to meet the needs of the ecosystem. For this research, a minimum of 90 percentile flow was used to evaluate the water requirements for ecosystem needs.

$$I_{WE(Monthly)} = \frac{\text{Water available for ecosystem(i.e., water left after domestic and livelihood use)}}{\text{Minimum water required (7Q10)}}$$

2.3 Biodiversity

2.3.1 Undeveloped Land (I_{UL})

Unaltered habitat is the most important biodiversity resource. The main cause of habitat loss is the conversion of undeveloped land for human uses such as residency, agriculture or industry. The first step to preserving the biodiversity of a region is to preserve its undeveloped land. Thus, a good biodiversity indicator is the amount of undeveloped land with respect to the total amount of land in the region. But prevention of habitat loss alone is not the only requirement for preserving biodiversity. Another important factor is habitat fragmentation (Yahner, 1996; Fahrig, 2003). A higher percentage of undeveloped land with a high area-to-edge ratio implies better conditions for biodiversity.

$$I_{UL} = \frac{\text{Land left undeveloped} * \text{parameter to area ratio}}{\text{Minimum land required as undeveloped for the region} * \text{acceptable parameter to area ratio}}$$

2.4 Watershed Sustainability Index (WSI)

As discussed earlier, watershed sustainability incorporates social, environmental and biological sustainability. Hence, a watershed sustainability index can be created by summing up the social, environmental and biodiversity indicators discussed above. Based on the region, some indicators could be more critical than others. Thus, a proper weight should be applied to these indicators based on subjective judgment regarding the issues for the region under study. This is shown in the following equation:

$I_{WS} = W_{WD}*I_{WD} + W_{WL}*I_{WL} + W_{RE}*I_{RE} + W_{WP}*I_{WP} + W_{WE}*I_{WE} + W_{UL}*I_{UL}$, where W_x is the weight of “X”

The WSI gives a measure of the watershed’s sustainability on an annual basis. A natural system cannot be sustainable all the time. During extreme events like drought or flooding, a system becomes unsustainable. Applying the analogy of sustainable livelihoods to a sustainable watershed, a good measure of watershed sustainability is the ability of the system to cope and eventually recover from the stresses of extreme (non-sustainable) events.

2.5 Measuring Sustainability by Using Reliability, Resilience and Vulnerability Concepts

To measure a watershed’s reliability, resilience and vulnerability, a methodology was developed by Loucks and Gladwell (1999).

3. Case Study

3.1 Description of the Watershed

The Inland Bays is an estuary located in Sussex County in southeastern Delaware. It is one of the four drainage basins in the state of Delaware, which empty into the Atlantic Ocean. It is approximately 51 kilometers in size and drains roughly 810 square kilometers of watershed. The Millsboro Pond sub-watershed is representative of other sub-watersheds in the Inland Bays Basin. The Millsboro Pond watershed is 8708 hectares (87 Km^2) in area. Of that area, row crop agriculture occupies 41.8 percent, followed by 30.3 percent deciduous forest cover and 11.5 percent pasture land. The water quality of the Inland Bays has been degraded over time due to anthropogenic activities. The waters of the Inland Bays are rich in nutrients (i.e., nitrates and phosphates). This nutrient enrichment has lead to the eutrophication of Inland Bays as recently as 1998, 1999 and 2000 (DNREC, 2001). The nutrients entering the Inland Bays are from various sources including agriculture as well as urban wastewater and stormwater. The watershed has also faced occasional droughts, and existing land use is highly fragmented. Current land use consists of about 45 percent agricultural land, about 40 percent forested land, roughly 9 percent pasture land and 3 percent water and wetland. The rest is low residential development and other pervious land uses. The watershed is predominantly rural and agricultural. According to the DNREC reports, 1256.7 kilograms (kg) of total nitrogen and 51.1 kg of total phosphorus are being added to the Inland Bays daily.

3.2 Applying Theoretical Framework to the Watershed

The prerequisite for applying the theoretical framework is to model a watershed as accurately as possible. The first step was to calibrate and validate the SWAT model[4]. The watershed was then simulated for the next 50 years from 2009 to 2059 (with a two-year warm-up period from 2007-2009). Thus, the model required weather data for the next fifty years. SWAT uses its own weather generator, which is based on the WXGEN weather generator model. For this study, we used 50 years of historic data from 1958 to 2007 as a basis for future predictions. A program called WXPM3020, developed and supported by the SWAT development team, was used to generate the statistical input values for the SWAT weather generator model. Before using the WXPM3020 program, the historic weather data was run through another program called WXGN3020, which simulates any missing data. The output from WXPM3020 was used as an input for the .wgn file in SWAT.

[4] In this study, we used the SWAT2000 version incorporated into the EPA's Better Assessment Science Integrating point and Nonpoint Sources (BASINS). Version 3.1 of BASINS was used. The terrain elevation data was downloaded from USGS in digital raster form as a Digital Elevation Model (DEM). The DEM used in this research was 1-degree DEMs (with 3- by 3-arc second data spacing), which provides coverage in 1- by 1-degree blocks. Surface water information in the form of 1:100,000-scale reaches data was also downloaded from the National Hydrography Dataset (NHD) developed by USGS. The NHD supersedes USGS Digital Line Graph (DLG) hydrography data and the EPA Reach File Version 3 (RF3). The soil profile was created from data downloaded from STATSGO, which was developed by the National Cooperative Soil Survey. The weather data, including precipitation, maximum and minimum temperature, solar radiation and wind speed, was obtained from the Georgetown station of the Office of Delaware State Climatologist's website. The groundwater level data was obtained from the Delaware Geological Society on the University of Delaware's website. The hydrological data was downloaded from the USGS' National Water Information System for the station 01484525 at the Millsboro Pond outlet at Millsboro, Delaware. The nutrient data (i.e., nitrogen and phosphorus) for the Millsboro Pond outlet was retrieved from the Delaware Inland Bays Water-Quality Database (DIBWQDB) distributed by the Delaware Geological Survey (DGS). This database was built as part of the "Nutrient Inputs as a Stressor and Net Nutrient Flux as an Indicator of Stress Response in Delawares' Inland Bays Ecosystem" (CISNet) and the "Inland Bays Tributary Total Maximum Daily Load" (IBTMDL) projects and has data from 1998 to 2002. For land use land cover (LULC), we used data from the National Land Cover Database (NLCD) 2001. NLCD was created through a cooperative project conducted by the Multi-Resolution Land Characteristics (MRLC) Consortium.

Two criteria considered critical in linking land use with water quantity and quality were considered in creating land use scenarios. These are:

1. *The recharge potential of the land*: Andres (2004) defines groundwater recharge as both the process and quantity of precipitation that infiltrates through the unsaturated zone to the saturated zone
2. *The riparian zone along the water body*: the vegetation in the riparian zones plays a critical role in the quality of water in the watershed.

The second scenario (the first being the business as usual land use case (Figure 1a)) was created only on the basis of the recharge potential of the watershed (Figure 1b). Areas with high recharge potential should be left undeveloped, so that maximum water infiltrates, and should not be used for agriculture because it will cause high infiltration of nutrients (from fertilizers) into the groundwater system. For this research, we used a groundwater recharge map (and GIS data) provided by the Delaware Geological Survey at the University of Delaware (Andres, 2004). The recharge potential of the watershed is classified as excellent, good, fair and poor. Thus, keeping the percentage of land use types the same, a hypothetical land use map was created with recharge classifications of excellent, good, fair and poor being assigned to forest, pasture, agriculture and development, respectively. For the first land use scenario, no particular attention was paid to the riparian zones. In the second land use scenario, two more land use options were considered—one with a 50-m riparian zone (Figure 1c) and the other with 200-m riparian zone (Figure 1d). Changing proportions of land use type within a watershed has economic implications, which are not being considered in this research.

The calibrated SWAT model was the basis for the simulation of the new land use scenarios. The GIS data of the new scenarios were used to replace the old land use data. The model had to be reconfigured for each land use scenario. Because of this, the calibrated values of the parameters were lost each time and had to be reassigned. The model was run one-at-a-time with each different land use scenario. All the data collected and analyzed is discussed in the next section.

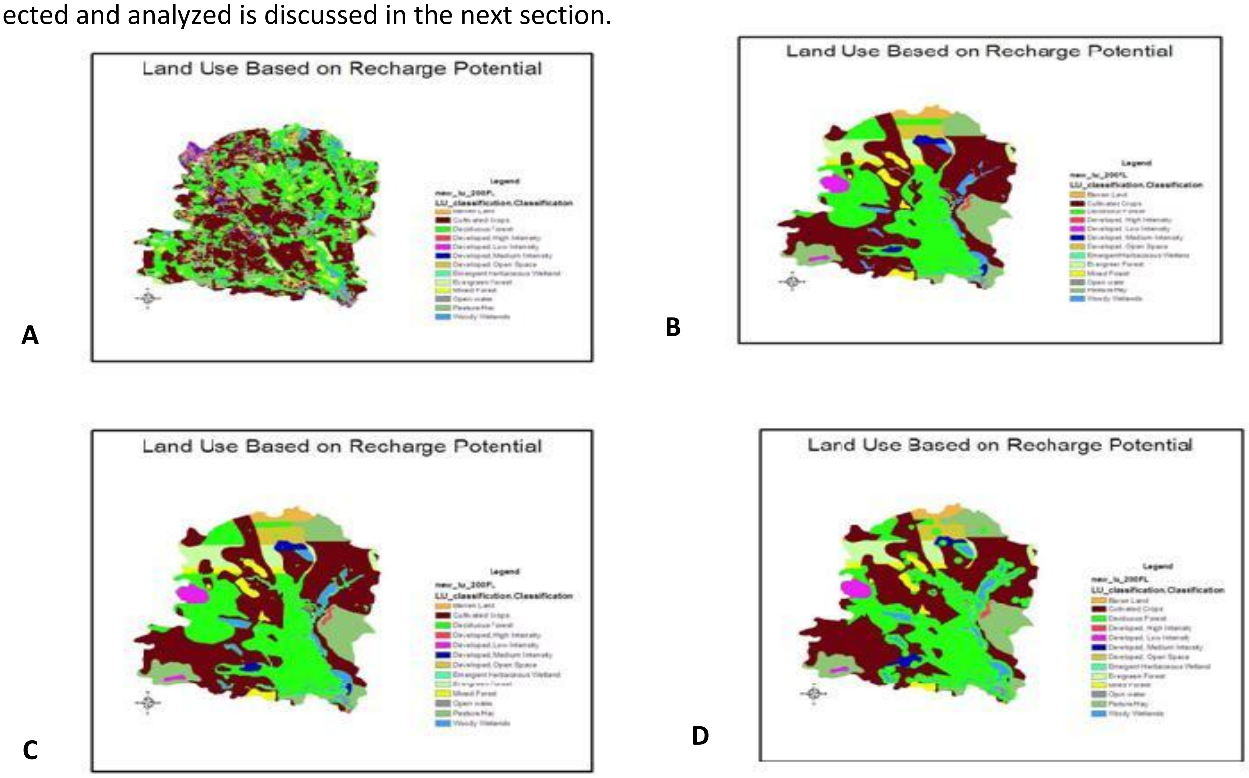

Figure 1. *(a) Current land use – Scenario 1 (b) Land Use based on Recharge Potential – Scenario 2 (c) Land Use based on Recharge Potential and 50-m riparian zone – Scenario 3 (d) Land Use based on Recharge Potential and 200-m riparian zone*

4. Results and Analysis

The social, environmental and biodiversity indicators were calculated for 50 years, as discussed in the previous section. The total water available for human use and minimum streamflow was calculated as the sum of streamflow (which is made up of surface runoff and base flow) and deep aquifer percolation. It is safe to assume that 100% of the percolation is available for human consumption because it is a renewable source and would not deplete the groundwater.

After extensive literature research, nothing substantive was found to suggest any specific combination of weight assignments for environmental, social and biodiversity issues. They tend to be region specific and are shaped by community priorities and policymaker viewpoints in a concerned region (or watershed). Since the priority of any region is water availability, the direct use of water was given more weight than other indicators. From a water use perspective, humans were considered on par with other species. Thus, the minimum flow requirements for the ecosystem were given the same importance as water required for human consumption and livelihood. The greatest threat facing biodiversity is dwindling undisturbed habitat. Pollution can be controlled through technological advances. Also, the energy demands of a watershed can be either better managed, or energy can be imported from outside the watershed. However, there is no substitute for unaltered habitat. Thus, biodiversity was given slightly more importance than pollution or energy requirements. In sum, on a scale of 100, domestic, livelihood and ecological water uses were each given a weight of 18, pollution and energy were given a weight of 15 each and biodiversity was given 16.

4.1 Indicators

For domestic indicators, we assumed that domestic water consumption in the region was 282 liters (75 gallons) per capita per day. The population of the watershed was taken as 4000 with a growth rate of 2%. Based on these parameters, the domestic indicator was calculated for each month then averaged over the year. There were three years (2013, 2046, and 2058) where the domestic water demands were not met. These years probably indicated a drought situation.

After the demand for domestic water needs was met, the remaining water was grouped together in three-month intervals to measure the seasonal demand of water for livelihood. Within the Millsboro watershed, there are two major livelihoods, agriculture and the poultry industry. About 12% of the agricultural land in the watershed is irrigated from June to August at a rate of roughly 5 cm per week. In the poultry industry, roughly 98.4 litters (26 gallons) of water are used per broiler (Northcutt and Jones, 2004). In the watershed, approximately 5.3 flocks are produced per year, and each flock contains 1,364,000 broilers. Based on this data, the livelihood water demand for the watershed was calculated on a seasonal basis. The indicator, calculated with the livelihood water demand, dips frequently in the first decade then dips again in the middle and towards the end of the simulation period. The indicator performance was similar in the most of the scenarios with the exception of 2052 and 2053 when land use scenario 2 performed the worst among all scenarios.

The minimum streamflow was based on streamflow statistics collected by the USGS gauging station at the Millsboro Pond outlet at Millsboro, Delaware (station number 01484525). A 90-percentile flow of 0.76 m^3/sec was used as the minimum streamflow required from an ecological perspective. Although none of the land use scenarios meet the ecological water demand all year, it is evident from Figure 1 that case 3 and 4 perform better than other cases most of the time.

From the perspective of nutrients in the water system, the current land use (scenario 1) fares the worst. Although scenario 2 performs better than scenario 1 most of the time, it is not much different in performance. This is understandable, as the second land use scenario lacks a good riparian zone. Numerous studies have shown that the riparian zone has a substantial affect on nutrient pollution in the water system. Land use scenarios 3 and 4 perform much better than the other two scenarios; although, the difference between them is not significant. This implies that for nutrient management there is not much difference in having a riparian zone that is 50 meters wide as compared to having a riparian zone that is 200 meters wide. Thus, it is clear that although a vegetative riparian zone is necessary for controlling nutrients in the waterway, effectiveness is reduced after a certain width. The effectiveness of riparian zones in reducing nutrients is site specific, as it depends upon soil conditions, water table, type of vegetation, etc. Thus, to define an adequate riparian buffer width, each watershed needs to be modeled separately and the appropriate riparian width defined.

For the energy indicator calculations, the per capita energy requirement of the population was taken as 306 x 10^9 joules per capita per year. The population of the watershed was estimated to be 4000 with a growth rate of 2%. It was assumed that only 3 percent of the total watershed energy demand will be met by biofuels, but 50% of biomass (i.e., corn and soybean) grown in the watershed will be used for energy. The yield (kilograms per hectare) simulated by the SWAT model was used as the biomass generated from the watershed. Also, it was assumed that through technological innovation, energy production will increase by a rate of 2% while biomass production remains constant. Since the land under agriculture was kept the same in all the scenarios, there was not much difference in the energy indicators. Land use scenario 1 and 4 come up slightly higher than the other scenarios, but as mentioned before, the difference was not significant.

For the biodiversity indicator, GIS was used to calculate the area and perimeter of the forested land in the watershed. When the area-to-perimeter ratio was calculated by considering all the land area in the watershed as forested, the resulting value was almost three times higher than the best-case land use scenario. The current land use (scenario 1) is highly fragmented and as such, had a very low area-to-perimeter ratio (roughly eight times less than the best case scenario). Among the four scenarios, scenario 2 had the highest biodiversity value. The results of the biodiversity indicator are show in Figure 2.

4.2 Watershed Index

The watershed index was calculated by adding the weighted indicators for each of the land use scenarios. The indicators were then plotted against time (in years) for the next 50 years. The results are shown in Figure 2(a). Upon visual inspection, land use scenario 1 is much worse than the other scenarios and can be outright rejected.

The major differences are due to the biodiversity indicator. As discussed in the previous section, the current land use fared poorly in regard to the biodiversity indicator because of high fragmentation. The biodiversity indicator outstrips (and hides) the significance of other indicators. Thus, the watershed index was compared in another graph plotted without the biodiversity indicator (Figure 2(b)). For this index, a different weight scheme was used (Domestic – 22, Livelihood – 22, Ecological – 22, Pollution -17, Energy -17). The new weight scheme was used to keep the ratio between the various indicators the same. This new index shows that the current-use scenario is comparable to other scenarios and in fact, sometimes performs better than scenario 2.

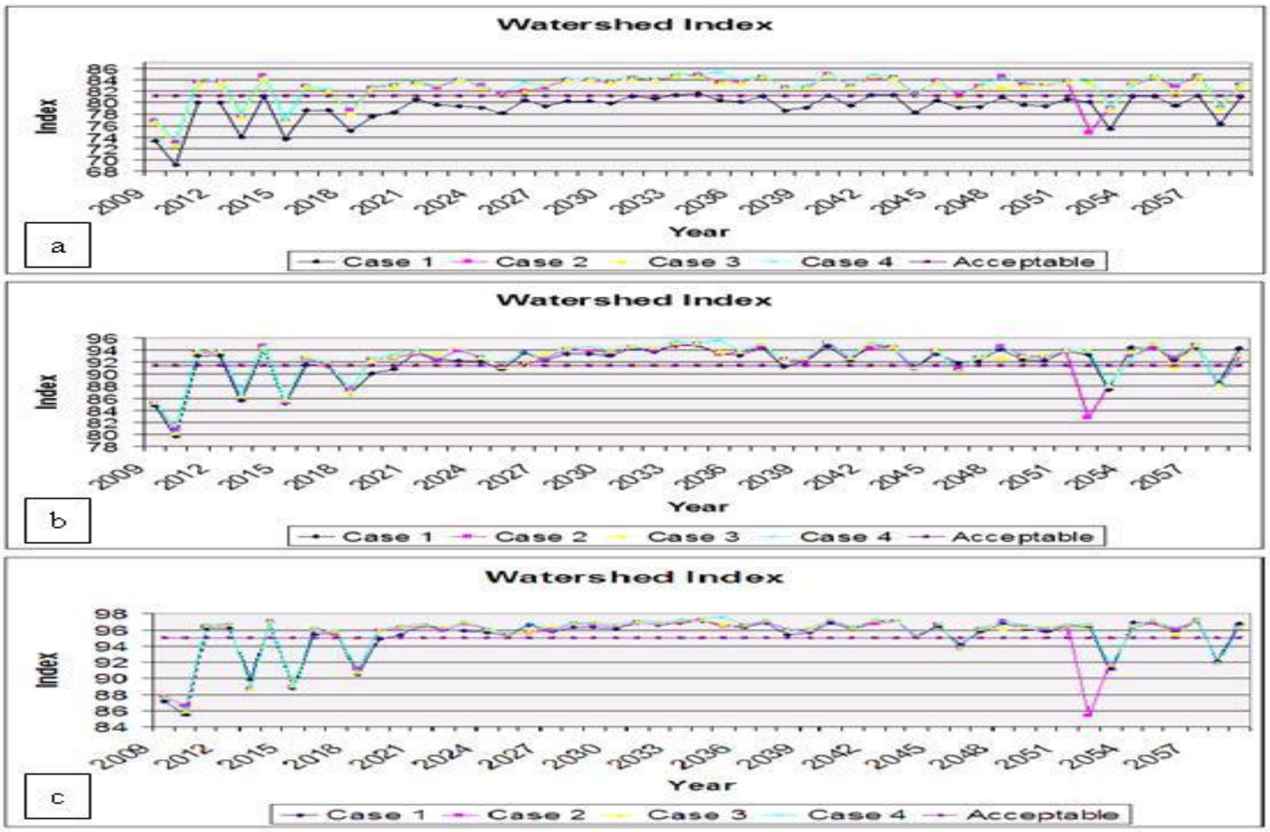

Figure 2. *Watershed Indexes for the four land use scenarios plotted over 50 years (a) all indicators (b) Without biodiversity indicator (c) without biodiversity indicator with the following weight scheme: Domestic – 22, Livelihood – 22, Ecological – 22, Pollution –17, Energy –17*

4.3 Watershed Sustainability

To calculate overall watershed sustainability, the first step was to define an acceptable value for each indicator, a subjective decision based on practicality and best judgment. Full availability of water for domestic, livelihood and ecological purposes was considered necessary. Hence, they were all assigned a value of 1. On the other hand, if pollution levels fall to 0.8 of the “no pollution” value, this could be considered acceptable. For energy, meeting 70 percent of demand would be considered acceptable. For the biodiversity indicator, 30 percent of the best-case scenario was considered acceptable because it is necessary to maintain the agricultural land-to-forest ratio (since changing that would impact the economy of the region, which is not being considered in this research). Considering that 45 percent of the watershed land use is agriculture, it would be hard to achieve a high value for this indicator. An unachievable value will make the whole system unsustainable and hide the influence of the other indicators.

Table 1 shows the results of the sustainability calculation for (a) all the indicators, (b) all indicators except the biodiversity indicator and (c) all indicators (without biodiversity) weighted more heavily toward human-use factors. In the first case with all indicators included, current land use has the least reliability and resilience and very high vulnerability. This is because the current land use's biodiversity indicator is very low. Land use scenario 3 and 4 are almost identical, with scenario 4 just outstripping scenario 3. These two scenarios are less vulnerable and a little more resilient than scenario 2.

Table 1. *Resilience, reliability, and vulnerability for (a) all indicators (b) all indicators except biodiversity (c) all indicators except biodiversity with more weight given to human requirements*

	(a) For all land use scenarios with the biodiversity indicator included				**(b) For all land use scenarios with the biodiversity indicator excluded**				**(c) For all land use scenarios with the new weight scheme (biodiversity indicator excluded)**			
	Case 1	**Case 2**	**Case 3**	**Case 4**	**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 1**	**Case 2**	**Case 3**	**Case 4**
Reliability	0.078431	0.843137	0.843137	0.843137	0.745098	0.764706	0.784314	0.803922	0.823529	0.823529	0.843137	0.843137
Resilience	0.042553	0.75	0.875	0.875	0.692308	0.75	0.909091	0.9	0.777778	0.777778	0.875	0.875
Vulnerability Extent	2.310879	4.24569	3.743589	3.420386	3.52429	4.133627	3.732527	3.997634	4.537963	5.410587	5.033877	5.0124
Vulnerability Duration	15.66667	1.333333	1.142857	1.142857	1.444444	1.333333	1.1	1.111111	1.285714	1.285714	1.142857	1.142857
Vulnerability	17.97755	5.579023	4.886446	4.563243	4.968735	5.466961	4.832527	5.108745	5.823677	6.696302	6.176734	6.155257
Relative Vulnerability	1	0.310333	0.271808	0.25383	0.908866	1	0.883951	0.934476	0.869686	1	0.92241	0.919202
Relative Watershed Sustainability	**0**	**0.436113**	**0.53722**	**0.550483**	**0.04701**	**0**	**0.082744**	**0.047408**	**0.083469**	**0**	**0.057242**	**0.059608**

When the biodiversity indicator is removed, the table shows that, in fact, land use scenario 2 is worse than the current land use scenario in terms of sustainability. The vulnerability of scenario 2 is higher. This can be explained by the lack of a good riparian buffer in scenario 2. Thus, although it has the highest biodiversity indicator value, its pollution indicator is lower than the other scenarios. Without the biodiversity indicator, land use scenario 3 is the most sustainable alternative of the four scenarios. Thus, this study shows that providing a larger riparian buffer width does not necessarily improve the sustainability of the system. If biodiversity is ignored (zero weight is given to this indicator) and ecological water needs, pollution and energy are given less importance (less weight), the outcome is much different. Domestic and livelihood water requirements were each given a weight of 35 as compared to the other relevant indicators that were given a weight of 10. Table 1(c) shows the resilience, reliability, vulnerability and watershed sustainability for this new weight scheme. In this case, the current land use scenario (scenario 1) is more sustainable than the others. Thus, if biodiversity is ignored and other environmental and ecological issues are given less significance, current land use is acceptable. In other words, the current land use was developed by keeping only anthropogenic requirements in mind and ignoring other ecological issues. Thus, although current and former planning efforts meet human needs, they did not consider a holistic approach.

5. Conclusions

This framework has many policy implications. Foremost, it provides a tool for policymakers, land use planners, zoning officials and watershed managers to look at land use in a holistic way. Currently, most planning is done using political boundaries. Thus, land use is planned on the basis of local requirements within a district or a municipality boundary without considering the impacts on the larger "ecosystem" or river basin. No consideration is given to population living outside the political boundary. In some instances, this leads to conflict between people. If the demand for the water is examined at the watershed scale, such conflicts could be avoided. Since this framework takes into account the ecosystem water requirements, it also helps in reducing conflicts between people and the environment with respect to water. Land use planning will become even more critical with the popularity of biofuels and the resulting need for more cultivated land. The greatest threat to biodiversity is the fragmentation of pristine land and interference due to human activity. Using recharge potential as a guiding principle for land use planning has two advantages: 1) leaving high recharge potential areas free of human development helps in recharging the groundwater faster. Also, infiltrating water is less polluted due to a lack of human activities in these areas. 2) Recharge potential is based on soil properties, and because soils with similar properties are grouped together, it is easier to plan with less fragmentation.

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Integration of SWAT and SWMM models

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Abstract

The Soil and Water Assessment Tool (SWAT) is a long-term, continuous watershed simulation model developed by the United States Department of Agriculture Research Service (USDA-ARS). It is widely used to evaluate the impacts of various land use and land management practices on water and sediment yield and nonpoint source loadings in the watershed. However, SWAT has difficulty assessing hydrologic impacts in urbanized areas because the model is not able to simulate urban drainage systems. In order to improve the model performance associated with urban areas, we linked the RUNOFF block of EPA's Storm Water Management Model (SWMM) to the SWAT model for this study. The procedure for integrating SWAT and SWMM was implemented with emphasis on the schematics of bridging two models. The integrated SWAT-SWMM model was applied to the Osancheon watershed in South Korea to test its applicability. The simulation results of the integrated SWAT-SWMM model were compared with those of SWAT alone for hydrological components such as surface flow, evapotranspiration and groundwater flow. Results showed that the integrated SWAT-SWMM model can be a useful tool in evaluating the effects of urbanization on planned development areas.

Keywords: SWAT, SWMM, urbanized areas

1. Introduction

Urbanization within a watershed causes land use changes due to increases in impervious areas, the addition of man-made structures and changes in the river environment. Increasing impervious surfaces alters the spatial flow pattern of water and increases runoff volume and maximum rates of runoff. Therefore, demand exists for rainfall-runoff simulation models that can quantitatively evaluate the long-term effects of urban development on hydrologic components such as surface runoff, streamflow and groundwater. Various models are available for managing urban runoff, including SWMM (Huber and Dickinson, 1988), MOUSE (Danish Hydraulic Institute, 1995), HydroWorks (HR Wallingford Ltd., 1997), etc. EPA's SWMM is a widely used, dynamic rainfall-runoff model for simulation of water quantity and quality associated with runoff from urban areas (Huber and Kickinson, 1988). SWMM is capable of both single-event and continuous simulation for almost all components of rainfall, runoff and water quality processes within a catchment. However, it cannot sufficiently account for land uses other than urban area within a watershed because this model was developed primarily for urban areas. Therefore, a more comprehensive hydrological model is required to better reflect both urban and natural watershed characteristics.

SWAT (Arnold et al., 1993) was developed to evaluate the impacts of various land use and land management conditions on water yield, sediment yield and nonpoint source loadings in the watershed. However, SWAT has a difficulty assessing hydrologic impacts in urbanized areas because the model is not able to simulate urban drainage systems. On the other hand, SWMM has the advantage of being able to consider surface and drainage characteristics in urban areas, but as mentioned above, SWMM is not well suited for other land uses. In this study, the RUNOFF block of SWMM was linked to the SWAT model in order to overcome the aforementioned shortcomings of both models and to sufficiently represent both the urban and natural aspects of the watershed. The procedure for integrating SWAT and SWMM was implemented with emphasis on the schematics of bridging two models. The integrated SWAT-SWMM model, which builds on the strengths of both models, was applied to the Osancheon watershed located in the middle of South Korea. The simulated results generated by the SWAT-SWMM model were compared to those created by SWAT alone for several hydrologic components such as surface flow, evapotranspiration and groundwater flow.

2. Model Description

2.1 SWAT

The major components of SWAT include hydrology, weather, erosion, plant growth, nutrients, pesticides, land management and stream routing. The methods for estimating hydrological components are briefly described below. The model allows for simulation of high-level spatial detail by dividing the watershed into a large number of sub-watersheds, which are then partitioned into additional areas called Hydrologic Response Units (HRUs). The water in each HRU is stored in one of four storage areas: snow, soil profile, shallow aquifer or deep aquifer. Snow melts on days when the maximum temperature exceeds a prescribed value. Melted snow is treated the same as rainfall when estimating runoff and percolation. The soil profile is subdivided into multiple layers representing soil water processes including infiltration, evaporation, plant uptake, lateral flow and percolation. Surface runoff from daily rainfall is estimated using a modified SCS curve number method, while infiltration is estimated using the Green-Ampt method. The model computes evaporation from soils and plants separately. Potential evapotranspiration can be modeled with the Penman–Monteith, Priestley–Taylor or Hargreaves methods. Potential soil water evaporation is estimated as a function of potential ET and leaf area index. Actual soil evaporation is estimated by using exponential functions of soil depth and water content. Plant water uptake is simulated as a linear function of potential ET, leaf area index and root depth, and it can be limited by soil water content. The soil percolation component is estimated by a water storage capacity technique in which downward flow occurs when field capacity of a soil layer is exceeded. Percolation at the bottom of the soil profile recharges the shallow aquifer. Percolation and lateral sub-surface flow within the soil profile are calculated simultaneously using the kinematic storage model, which is a function of saturation hydraulic conductivity, slope length and slope. Groundwater recharge and groundwater discharge are estimated based on exponential attenuation weighting functions. For each HRU, these hydrological components are summed over a sub-watershed. Calculated flow yield obtained for each subbasin is then routed through the river system. Channel routing is simulated using the variable storage or Muskingum method.

2.2 SWMM

SWMM is one of several advanced computer-assisted models designed to simulate single-event or long-term, continuous water quantity and quality aspects of stormwater events in urban watersheds. The runoff component of SWMM operates on a collection of sub-catchment areas that receive precipitation and generate runoff and pollutant loads. The routing portion of SWMM transports this runoff through a system of pipes, channels, storage/treatment devices, pumps and regulators. SWMM tracks the quantity and quality of runoff generated within each sub-catchment as well as the flow rate, flow depth and quality of water in each pipe and channel during the simulation period. SWMM consists of four functional program blocks: RUNOFF, TRANSPORT, EXTRAN and STORAGE/TREATMENT, plus a coordinating executive block. The blocks can be overlain and run sequentially, or they can be run separately with interfacing data files. In this study, the RUNOFF block was used for integration between SWAT and SWMM.

The runoff block simulates continuous runoff hydrographs and pollutographs for each sub-catchment in the drainage basin. Hydrologic computations in the RUNOFF block are based on the theory of nonlinear reservoirs in which each sub-catchment surface is treated as a non-linear reservoir with rainfall as the single inflow. However, there are several outflows including surface runoff, infiltration and evaporation. Surface runoff occurs only when the depth of water in the reservoir exceeds the maximum depression storage associated with ponding, surface wetting and interception. Surface runoff is calculated using the nonlinear storage equation made by coupling the continuity equation and Manning’s equation. The water in storage is depleted by infiltration and evaporation. Infiltration occurs only in pervious areas and is modeled by one of three methods: Horton’s equation, Green-Ampt equation or the curve number method. Evaporation occurs only where standing water exists on sub-catchment surfaces or is held in storage units. It can also occur for subsurface water held in groundwater aquifers. Evaporation rates can be stated as a single constant value, a set of monthly average values, a user-defined time series of daily values or daily values read from an external climate file. The lumped storage scheme is applied when modeling soil and groundwater with SWMM. In SWAT, soil layers are defined for modeling soil water movement. However, in SWMM, soil layers are not assigned, so the subsurface lateral flow cannot be modeled. Instead, SWMM assigns two zones for subsurface groundwater areas used to model the vertical movement of infiltrated water: an unsaturated zone and a saturated zone. If the infiltrated water exceeds the storage capacity of an unsaturated zone, then the excess infiltration is added to surface runoff. The moisture content of the unsaturated zone, groundwater level, groundwater discharge of the saturated zone and groundwater loss to deep aquifer from the saturated zone are calculated using parameters such as soil porosity, hydraulic conductivity, evapotranspiration depth, bottom elevation and the loss to deep aquifer rate. Actual evapotranspiration initially occurs in depression storage; then it occurs within the unsaturated zone, reducing the moisture content of the unsaturated zone. The infiltration of groundwater into the drainage system or exfiltration of surface water from the drainage system can be also permitted, depending on the hydraulic gradient. The same aquifer object can be shared by several sub-catchments. Both surface runoff and groundwater are discharged at the outlet of the sub-catchment, but the user can assign other target points of groundwater discharge. The calculated runoff enters the inlet of the channel/pipe system, and then, routing is simulated using the nonlinear storage equation in the RUNOFF block.

3. Procedure to Integrate SWAT and SWMM

Integration is performed by linking SWAT with the RUNOFF block of SWMM. First, both SWAT and SWMM are divided into three parts: the input, computation, and writing parts, as shown in Figure 1. In Figure 1(b), W-2 is the subroutine "HYDRO" of SWMM where the watershed and the channel/pipe routings are simulated.

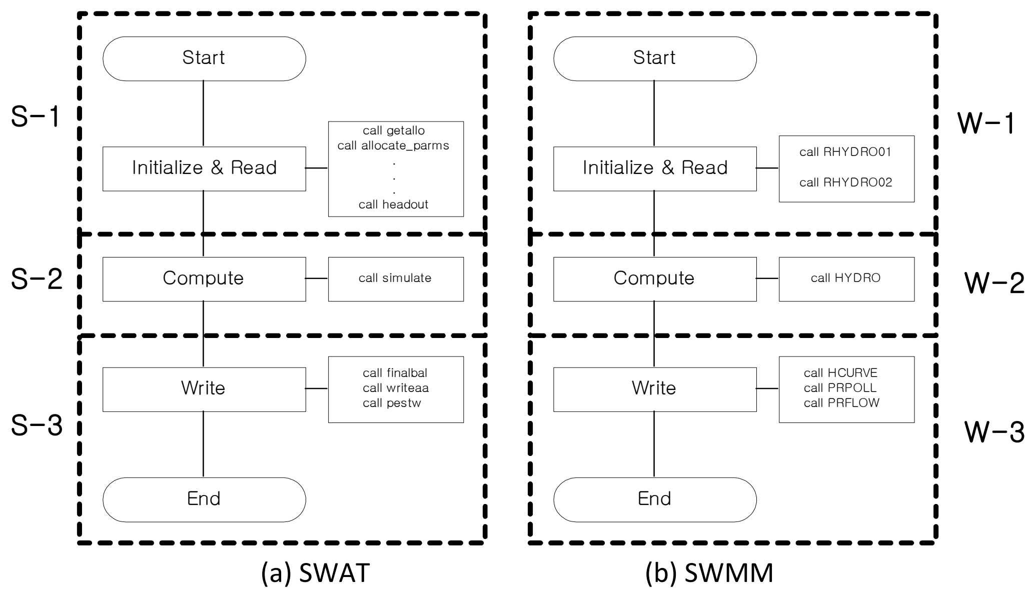


Figure 1. *Partitioning of SWAT and SWMM*

As shown in Figure 2(a), the subroutine "HYDRO" is composed of several subroutines. Thus, it was separated into a watershed routing portion and a channel/pipe routing part for consistency with the simulation time interval of SWAT, as illustrated in Figure 2(b) below.

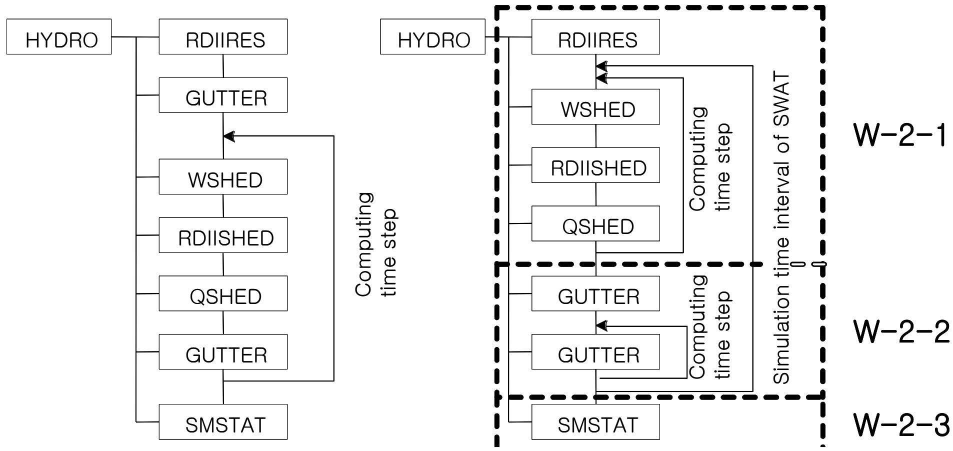


Figure 2. *Revised W-2 of SWMM*

The decomposed routines of the revised SWMM were embedded in SWAT, as presented in Figure 3. The integrated SWAT-SWMM model can simulate an urbanized subbasin using either SWAT or SWMM. If SWMM is selected for simulation of runoff from an urbanized subbasin, the SWAT subroutines 'simulate" and "route" are replaced by W-2-1 and W-2-2 of SWMM, respectively.

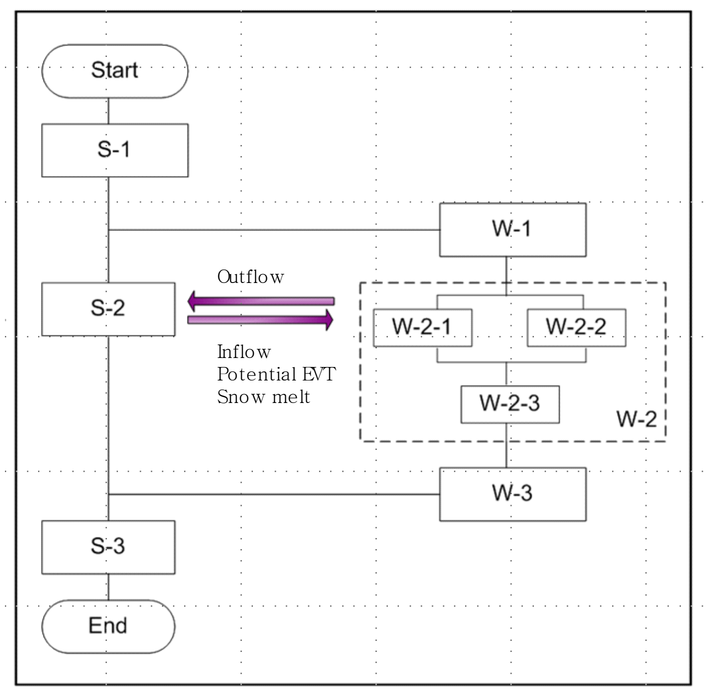


Figure 3. *Flowchart of SWAT-SWMM integration*

4. Application of SWAT-SWMM

The SWAT-SWMM model was tested in the Osancheon Basin, which has an area of 47.9 km^2. This drainage basin is divided into 3 subbasins as shown in Figure 4. Downstream subbasin3 was recently urbanized, so it was considered primarily urbanized and thus modeled by the SWMM algorithm. Therefore, subbasin3 was further divided into 17 sub-catchments (Fig. 6). Each sub-catchment matched the corresponding HRU in SWAT, created using the “Dominant Land Use and Soil” option for HRU distribution. Figure 5 shows the preprocessed land use and soil maps. Figure 7 demonstrates the schematic diagram for linked sub-catchments with channels in subbasin3. The information for channel dimension can be easily obtained with SWAT’s GIS interface, such as the AVS2000 (DiLuzio et al., 2001). For simplicity, channels were considered but not the pipe network. The current version of SWAT-SWMM is limited to modeling only one urban subbasin.

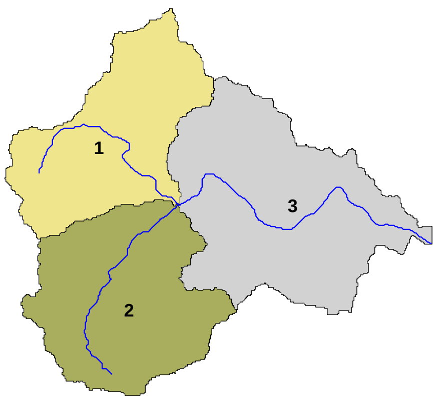


Figure 4. *Osancheon basin*

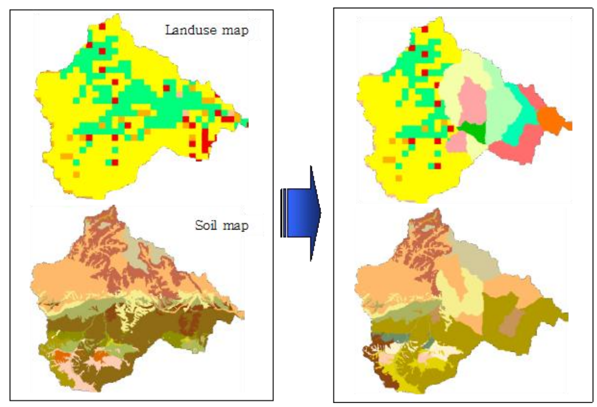


Figure 5. *Pre-processing for land use and soil maps*

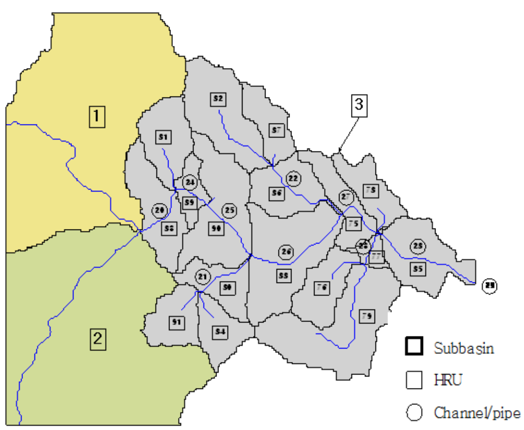


Figure 6. *Subdivision of subbasin3*

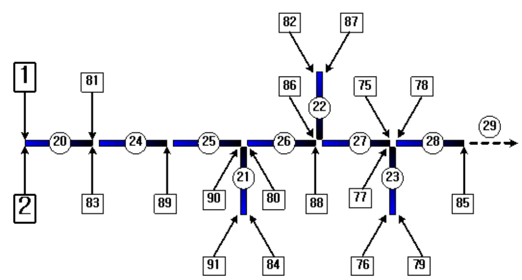
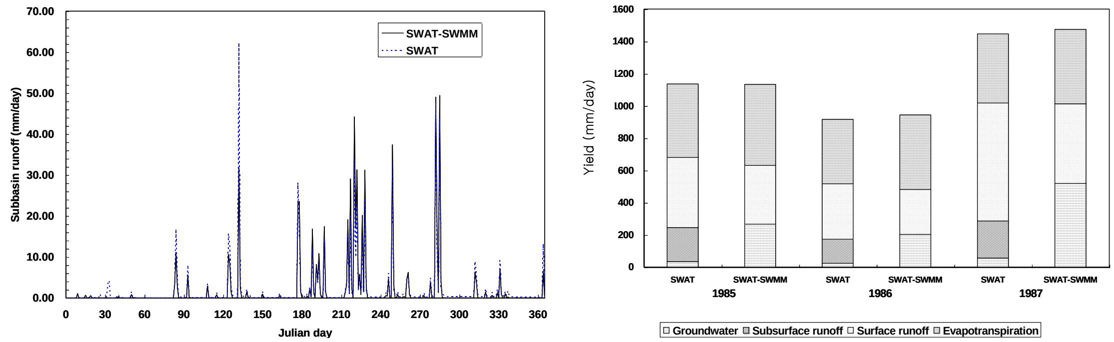


Figure 7. *Schematic diagram for SWMM simulation*

Figure 8 shows a comparison of the simulated results between the SWAT-SWIM model and SWAT alone. In the SWAT simulation, total runoff from subbasin3 shows higher peaks than SWAT-SWMM (Fig. 8(a)). The reason is that SWAT generated much higher surface runoff on rainy days, which was mainly attributed to the difference in algorithms for surface runoff estimation, including the infiltration theory used in this study. SWAT’s SCS-CN method and SWMM’s Horton’s equation were used in the joint-model surface runoff simulation. Moreover, SWMM’s lag effect resulting from the subdivision of urban areas was included. Figure 8(b) shows the hydrologic components simulated by both models. The magnitude of total runoff is similar between the two, but clear differences are shown between simulated evapotranspiration, surface and groundwater flow.



(a) total runoff from subbasin3 (b) hydrological component yield

Figure 8. *Comparison of SWAT-SWMM and SWAT results*

5. Conclusion

In this study, we made an attempt to integrate the continuous, long-term, rainfall-runoff simulation model SWAT and the RUNOFF block of SWMM, which is frequently used in runoff analyses of urban areas in order to consider both urban and natural watersheds. The characteristics of SWAT and SWMM were briefly described, and the integration of SWAT and SWMM was implemented with emphasis on the schematics of bridging two models. The integrated SWAT-SWMM model was applied to the Osancheon watershed located in the middle of South Korea, and the simulated results of the integrated SWAT-SWMM model were compared to those of SWAT alone. By comparing the simulation results, significant differences were found, reflecting the different features of SWAT and SWMM. This study focused on introducing the bridging structure of SWAT-SWMM, and therefore, further studies are required for examining the performance of this model.

Acknowledgements

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