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Evaluating hydrologic responses to soil characteristics using SWAT model in a paired-watersheds in the Upper Blue Nile Basin

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ABSTRACT

Watershed responses are affected by the watershed characteristics and rainfall events. The characteristics of soil layers are among the fundamental characteristics of a watershed and they are input to hydrologic modeling similar to topography and land use/cover. Although the roles of soils have been perceived, there are limited studies that quantify the role of soil characteristics on watershed runoff responses due to the lack of field datasets. Using two adjacent watersheds (Ribb and Gumara) which have a significant different runoff response with a similar characterstics except geological settings (including soil characteristics), we studied the effects of soil characteristics on runoff and water balance. The Soil and Water Assessment Tool (SWAT) was used to simulate the surface runoff response at the outlet of the watershed and the optimal model parameters distribution was tested with a non-parametric test for similarity. Results indicated that SWAT model captured the observed flow very well with a Nash-Sutcliffe Efficiency (NSE) of greater than 0.74 and with a PBIAS of less than 10% for both calibration and validation period. The comparison of the optimal model parameter distributions of the SWAT model showed that the watershed characteristics could be uniquely defined and represented by a hydrologic model due to the differences in the soils. Using field observations and modeling experiments, this study demonstrates how sensitive watershed hydrology is to soils, emphasizing the importance of accurate soil information in hydrological modeling. We conclude that due emphasis should be given to soil information in hydrologic analysis.

1. Introduction

Soil is one of the critical hydrologic features controlling watershed responses to rainfall events, and hence detail information on soil characteristics is necessary for hydrologic analysis (Beven, 1983; Luxmoore and Sharma, 1980; Mirus, 2015). Many efforts have been made to identify and classify soils and develop soil databases. Currently, geospatial soil data are commonly used in routine of hydrologic modeling practices (Batjes, 1997; Berhanu et al., 2013; Di Luzio et al., 2004; Shangguan et al., 2014; Wahren et al., 2016). Although the importance of soil data and their accuracy has been recognized through modeling practices, the hydrologic responses of a watershed to soil characteristics has not been extensively investigated due to the lack of observations showing watershed-scale effects of soils (Bell et al., 2009; Berhanu et al., 2013; Beven, 1983; Luxmoore and Sharma, 1980; Manus et al., 2009; Mirus, 2015). Unlike land uses which are changing over time, soil characteristics that are formed by long-term geomorphological processes are relatively steady, and they are not subject to be quickly varied by human activities (Dessalegn et al., 2014; Lambin et al., 2001; Moore et al., 1993). Thus, the impacts of changes in soil features and their contributions to watershed hydrology might have fewer opportunities to be examined and quantified.

Paired watersheds have been used to evaluate the differences in watershed behaviors due to a change in management interventions such as soil water conservation, and/or water harvesting (Bishop et al., 2005; Clausen and Spooner, 1993; Genereux et al., 2005; Huang et al., 2016; King et al., 2008; Ricker et al., 2008; Veum et al., 2009). A paired watershed study have been used also “before-after-control-impact” design, where one of the watersheds serves as a control, and the other used for experimental interventions (Clausen and Spooner, 1993; King et al., 2008). The effects of the treatments can be translated by measuring differences in biophysical responses, e.g. changes in stream flow,

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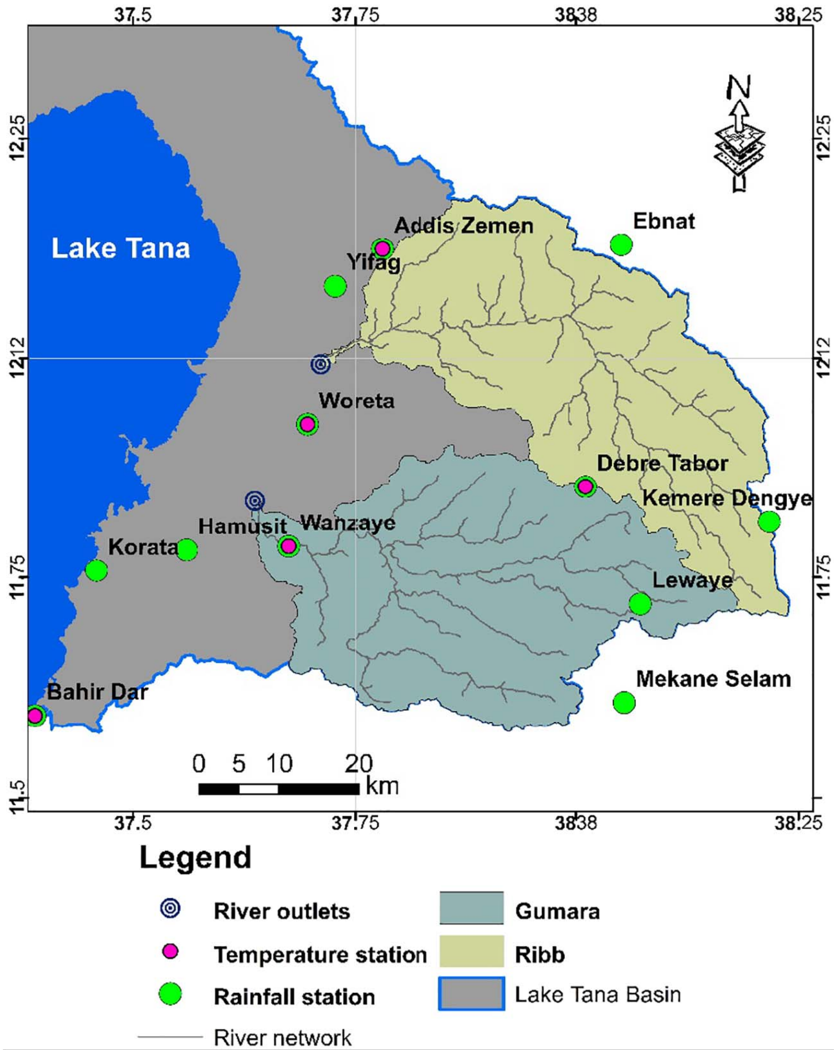

Fig. 1. Watershed boundary and stream networks of the Ribb and Gumara, and weather stations used for the hydrological modeling.

soil erosion, or nutrient loss. Obtaining sufficient data for statistical analysis in paired watershed studies is expensive and time consuming and therefore this method is not often used (Clausen et al., 1996; Clausen and Spooner, 1993; King et al., 2008). Moreover, it is often difficult to find watersheds that can be effectively paired in terms of sizes, topography, land covers, and soils to detect the effects of interventions.

Lake Tana Basin is located in the upper Blue Nile River basin of Ethiopia. It is the most studied region in Ethiopia with a relatively dense network of weather stations. This study is conducted in the Ribb and Gumara watersheds which are tributaries to the Lake Tana. These watersheds cover 25% of the Lake Tana basin. The two watersheds share a boundary of 45 km in length, and they have a comparable catchment area but the annual runoff yield of Gumara watershed is more than double of that of Ribb watershed. For example, from 1994 to 2008 Gumara has an annual runoff of 9420 m^3/ha while Ribb has about 3875 m^3/ha (Wale et al., 2009). Despite an extensive literature on streamflow modeling for the two watersheds, the disparity in the long-term mean annual water yield between these two watersheds has not been explored (Kebede et al., 2006; Rientjes et al., 2011; Setegn et al., 2008; Wale et al., 2009). Preliminary investigation on the characteristics of the watersheds showed that they have a significantly different soil while other characteristics such as land use/land cover and topography were similar. This suggests a paired-watershed study to test the effects of soil characteristics on watershed responses using soils as the differentiating factor between the two watersheds.

Commonly implemented watershed simulation models in highlands of Ethiopia include, Parameter Efficient Distributed (PED) (Steenhuis et al., 2009; Tilahun et al., 2013; Worqlul et al., 2017), Hydrologiska Byråns Vattenbalansavdelning (HBV) (Abdo et al., 2009; Gebrehiwot et al., 2013; Uhlenbrook et al., 2010; Wale et al., 2009) for flow prediction, and Soil and Water Assessment Tool (SWAT) (Dile et al., 2013; Setegn et al., 2008) for various watershed simulations. HBV and PED models they do not incorporate some critical watershed spatial features such as soil and landscape information into simulation process, they instead represent them with single or multiple parameters, which suggest that these models could not capture the effect of soil on the watershed behavior. While SWAT model captures the spatial heterogeneity of watershed features (e.g. differences in soil) as it is spatially distributed model. Moreover, SWAT uses information about weather, topography, and land uses for modeling watershed processes in a distributed way.

The main goal of this study was to investigate the hydrologic responses of paired watersheds, Ribb and Gumara, to their unique soil characteristics to understand the contributions of soils to watershed hydrology. The two watersheds, Ribb and Gumara, possess a similar size, topography, and land uses but significantly different soils. Streamflow measurements made at the outlets of the paired watersheds were examined to quantify the impacts of soils on the overall watershed responses. Therefore, the objectives of the study are: (i) to compare watershed characteristics of both watersheds extracted from metrological, land use, soil and topographic data to identify the possible cause for significant difference in runoff, (ii) SWAT model was used to capture the observed flow of both watersheds with an automatic calibration operation. A large number of model parameter were sampled randomly (1000) and the "behavioral" parameters were used to characterize the watersheds behavior. The "behavioral" and "non-behavioral" parameters were selected with a threshold value as described in Yang et al. (2008) and Jin et al. (2010). and (iii) the distribution of the behavioral model parameters were tested with nonparametric test to study the response of watershed parameters to watershed characteristics.

2. Materials and methods

2.1. Study watersheds and data

The study watersheds, Ribb and Gumara, are located in the Lake Tana basin of upper Blue Nile of Ethiopia between 11° 30′N, 37° 30′E and 12° 13′N, 38° 25′E (Fig. 1). Lake Tana area is considered as an agricultural growth corridor by the Ethiopian government since it has considerable water and land resources with a vision of establishing a food-processing zone. If the water and land resources developed properly, it will considerably increase agricultural productivity and thereby reduce poverty (McCartney et al., 2010). Currently, extensive water resources development activities are taking place in the study watersheds.

The Ribb and Gumara has a catchment area of 1302 km^2 and 1284 km^2, respectively extracted from a 30-m resolution Shuttle Radar Tomographic Mission (SRTM) Digital Elevation Model (DEM) (Jarvis et al., 2008). The outlets for the watersheds are located 19 km far apart (Fig. 1).

Weather data was necessary to simulate biophysical processes in the watersheds. Daily rainfall data from 12 weather stations were obtained from the Ethiopian National Metrological Agency (ENMA) (Fig. 1). There is modest annual rainfall variability in the watersheds. For example, the average annual rainfall from 1994 to 2008 varies from 1000 to 1600 mm. Of the 12 weather stations, only five of the stations have recorded minimum and maximum temperature (red dots, Fig. 1). Observed streamflow, which was collected from the Ethiopian Ministry of Water, Irrigation & Electricity (EMWIE), for the period 1994 to 2008 were used to calibrate and validate the hydrological model. The long-term monthly total streamflow between Gumara and Ribb in Fig. 2 are highly correlated with a coefficient of determination of 0.98. Discharge in both rivers varies greatly with time high in July to September and low from December to May (Fig. 2). Despite correlation in the stream flow pattern, there is a large difference in average annual streamflow. The average annual streamflow of 1210 million cubic meters (MCM) for Gumara, and 505 MCM for Ribb River.

The spatial data required for SWAT model setup includes Digital Elevation Model (DEM), soil, and land use. DEM data, which has a spatial resolution of 30 m, was used to delineate the watershed, define

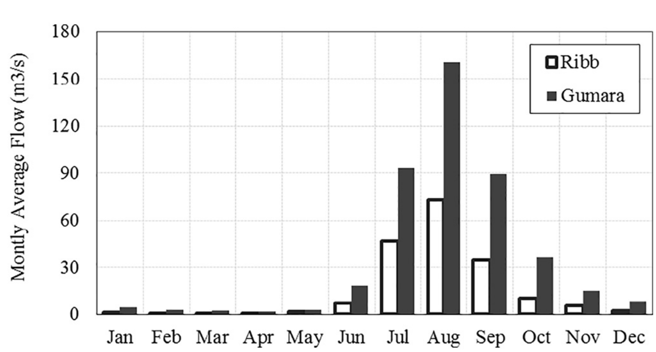

Fig. 2. Long-term monthly average streamflow of Gumara and Ribb for the period from 1994 to 2008.

the drainage patterns, and calculate slopes of the overland areas and channels. The soil and land use data were obtained from the EMWIE (BCEOM, 1999). The soil physical properties required by the SWAT model were calculated based on Saxton and Rawls (2006) pedotransfer functions using soil texture and organic carbon information at multiple soil layers.

2.2. Methods

The watershed response to soil characteristics was studied in three steps: (i) a total of twenty physical catchment characteristics consisting of observed metrological data, land use, soil and topographic information were extracted for both watersheds and compared to identify the difference characteristics which may possibly affected the difference in streamflow; (ii) the SWAT model was calibrated to capture the watershed behavior and the calibrated model parameters were evaluated if the differences in catchment characteristics were reflected in the watershed response; (iii) after applying cutoff threshold to separate the behavioral model parameters from non-behavioral parameters, the distribution of the behavioral model parameters of both watersheds were compared with non-parametric test Kolmogorov–Smirnov test (K–S test) to check the response of the watershed parameters to the watershed characteristics.

The K–S test was selected since it does not assume the distribution of the data to be normal it is a distribution free test (Massey, 1951). The K–S test measures the maximum distance between the curves of the cumulative distribution of the behavioral paramters to test the similarity of the behavioral model paramters distribution.

2.2.1. Physical watershed characteristics

A watershed comprises of unique combinations of different watershed characteristics such as climate, topography, land use/cover, and soil. Such unique physical characteristics resulted in different biophysical response to climatic conditions. Climatic conditions in hydrologic models are often represented by rainfall, temperature, wind, relative humidity and solar radiation over a long period of time. Using the nearby weather stations the potential evapotranspiration (PET) was calculated using the Penman-Monteith equation (Penman, 1948) at the stations. The areal PET was estimated by interpolating the PET at the stations using inverse distance method. The ratio of long-term annual rainfall to evapotranspiration (hereafter referred as climate index) was calculated and used as a measure to compare the climate of the two watersheds.

Topographic characteristics such as size, shape, and slopes of a watershed as well as the length of the stream network and drainage density are critical to study hydrologic responses of a watershed. The topographic features were derived from the 30 m SRTM DEM. A land use/land cover data, which was studied as part of the 1998 Abay (Upper Blue Nile) master plan (BCEOM, 1999) was obtained from the MWIEE. The land use and cover map showed that the watersheds mainly consists of cropland, forest, grassland, woody savannah, and urban (Fig. 3a). Crop and land management practices are similar in both watersheds. Despite significant amount of irrigatable land, currently irrigation is practiced minimally due to lack of water resources in the dry phase (McCartney et al., 2010; Worqlul et al., 2015). The main crops cultivated as a rainfed are maize, teff, sorghum, finger millet, wheat and barley (Teshome et al., 2009). The soil map obtained from the MWIEE indicated six soil classes, namely Eutric Fluvisols, Eutric Leptosols, Haplic Luvisols, Chromic Luvisols, Haplic Nitisols and Eutric Vertisols classification is based on FAO (Michéli et al., 2006) (Fig. 3b).

2.2.2. River discharge and base flow separation

The flow analysis showed that Gumara and Ribb exhibit a similar seasonal runoff patterns with a significant differences in the annual runoff volume (Fig. 2). For a further analysis of the streamflow, baseflow of the two watersheds were separated from the daily runoff. The

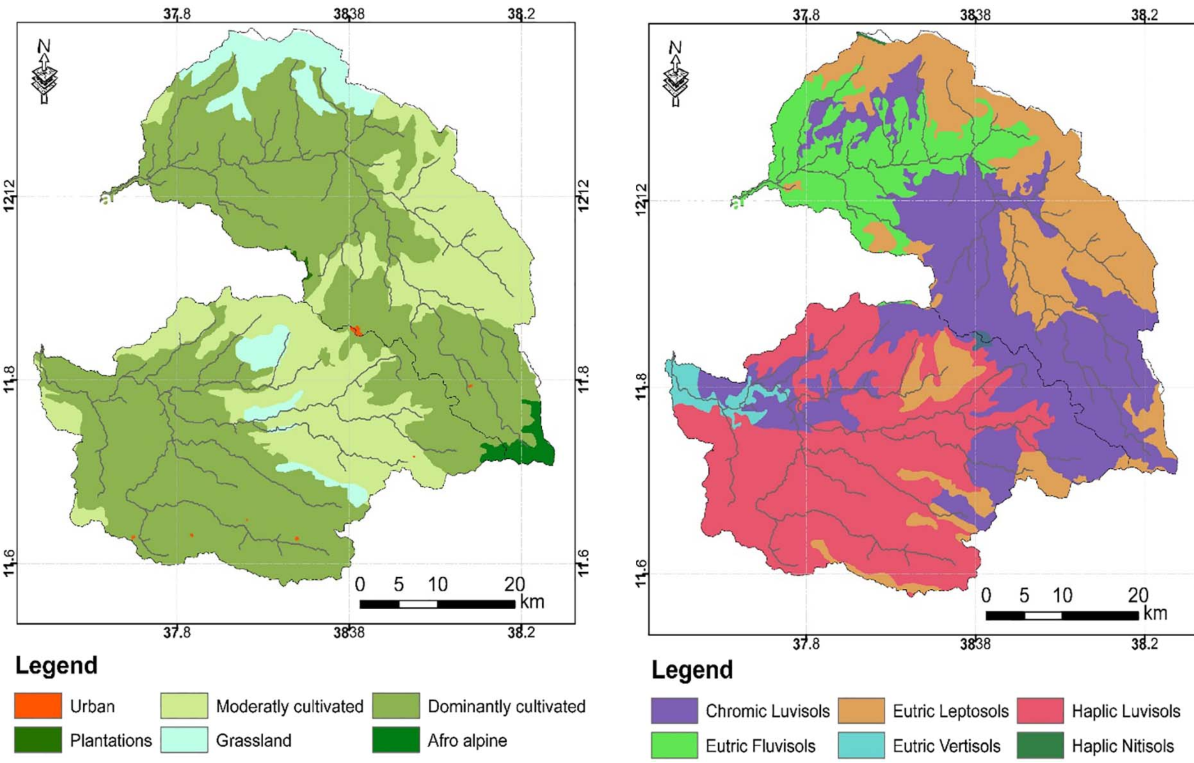

Fig. 3. Land use (a) and soil map (b) of Gumara and Ribb. The upper watershed is Ribb and the lower is Gumara.

baseflow separation was calculated using the digital filter approach of Lyne and Hollick (1979) (Eq. (1)).

$$q_t = \alpha * q_{t-1} + \frac{(1+\alpha)}{2} * (Q_t - Q_{t-1}) \tag{1}$$

where, Q_t is stream flow at time t and q_t is the corresponding quick response component, Q_{t-1} is stream flow at time t-1 and q_{t-1} is the corresponding quick response component, and Alpha (α) is the filter parameter associated with the catchments. Baseflow is the difference between the total discharge and the quick response component. The baseflow index (BFI) which is the ratio of the total volume of mean baseflow to the total volume of mean flow was calculated as a measure of baseflow characteristics of the watersheds.

2.2.3. Description of the hydrologic model

This study used the Soil and Water Assessment Tool (SWAT) model to evaluate the hydrologic responses of the watersheds to different biophysical parameters such as soil data. In SWAT, a watershed is divided into sub-basins based on topography, and then each sub-basin is further conceptually divided into hydrologic response units (HRUs), which have a unique combination of soil, land use and slope. The paired watersheds were delineated with the same drainage threshold of 8000 ha, resulting to 9 sub-basins for Ribb and 11 for Gumara. Without excluding marginal land use groups below a certain threshold percentage, the analysis indicated Ribb and Gumara have 222 and 227 HRUs, respectively. SWAT simulates soil water content, surface runoff, crop growth, sediment yield and management practices at the HRU level which is then aggregated at a sub-basin level (Neitsch et al., 2011b). Detailed descriptions about the simulation strategies and concepts of the model can be found in Arnold et al. (2012). The general water balance equation used in the model is described as Eq. (2).

$$SW_t = SW_{t-1} + \sum_{1}^{t} (P_i - Q_{surf,i} - ET_i - Q_{loss,i} - Q_{gw,i}) \tag{2}$$

where, SW_t is the soil water content above the wilting point at the end of day t. P_i is the amount of precipitation on day i and $Q_{surf,i}$, ET_i, $Q_{loss,i}$ and $Q_{gw,i}$ are the daily amounts of surface runoff, evapotranspiration, percolation into deep aquifer, and lateral subsurface flow, respectively. All components are estimated in the unit of mm.

2.2.4. Model calibration and validation

The calibration parameters were selected based on literature recommendation and expert opinion (Bitew and Gebremichael, 2011; Dile et al., 2013; Setegn et al., 2009; Setegn et al., 2010). A global sensitivity analysis was implemented to identify parameters significantly influencing streamflow. In global sensitivity analysis all paramters are allowed to change at the same time followed by estimating the standardized regression coefficients (Alfano et al., 2015). The sensitivity analysis provided insight into the parameters contributing the most to the variance of the output variable, and helps to identify the most dominant parameters that should be used for calibration. The t-stat and p-value were used to evaluate the significance of the relative sensitivity. The t- stat provides a measure of sensitivity, a larger absolute t-stat means greater sensitivity and p-value determines the significance of the sensitivity, p-value close to zero represents higher significance (Abbaspour et al., 2007). The list of parameters and their respective parameter space is described in Table 1. The type of change applied to calibrate the parameters were by replacing a given value (v_), or by relative change ('r_'), in this case, the existing parameter will be multiplied by (1 + initial value) (Table 1, Abbaspour et al., 2007).

The Integrate Parameter Estimation and Uncertainty Analysis Tool (IPEAT, Yen et al., 2014b) was applied to calibrate the SWAT model parameters. IPEAT is developed based on the Dynamically Dimensioned Search (DDS) algorithm. DDS is an optimization algorithm for automatic calibration base on based heuristic global search algorithm (Tolson and Shoemaker, 2007). It is efficient to locate a parameter set that provides the best performance statistics and identify behavioral parameter sets that give an equally acceptable performance (Yen et al., 2014a). One thousand parameter sets were sampled to identify a set of parameters that provide the maximum Nash-Sutcliff efficiency (NSE) for the calibration period.

Table 1
SWAT model calibration model parameters, their description and parameter space.

Parameter	Name	Parameter space
SCS runoff curve number	r_CN2.mgt	− 0.35–0.35
Soil evaporation compensation factor	v_ESCO.hru	0.01–1.0
Average slope length	r_SLSUBBSN.hru	− 0.5–0.5
Manning's "n" value for overland flow	v_OV_N.hru	0.01–0.3
Surface runoff lag time	v_SURLAG.bsn	0.0001–1.0
Depth to impervious layer for modeling perched water tables	v_DEP_IMP.hru	0.0–6000
Baseflow alpha factor (days)	v_ALPHA_BF.gw	0.0–1.0
Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	v_GWQMN.gw	0.0–5000
Groundwater "revap" coefficient	v_GW_REVAP.gw	0.02–0.2
Manning's "n" value for the main channel	v_CH_N2.rte	0.01–0.3
Average slope of main channel	r_CH_S2.rte	− 0.5–0.5
Available water capacity of the soil layer	r_SOL_AWC ().sol	− 0.25–0.25
Depth from soil surface to bottom of layer	r_SOL_Z ().sol	− 0.25–0.25
Saturated hydraulic conductivity	r_SOL_K ().sol	− 0.25–0.25
Average slope of tributary channels	r_CH_S1.sub	− 0.5–0.5
Manning's "n" value for the tributary channels	v_CH_N1.sub	0.001–0.3

Note: The parameter calibration for this study is constructed based on 'v_' and 'r_' meaning a replacement and a relative change to the initial parameter value respectively. *t*-Value is a measure of sensitivity (larger *t*-value means more sensitive). p-Value indicates the significance of the sensitivity (the smaller the p-value, the less chance of a parameter being by chance assigned as sensitive).

The simulation was divided into three periods: warm-up (1994), calibration (1995 to 2004) and validation (2005 to 2008). The performance of calibrated flow of the SWAT was evaluated using multiple statistics such as percentage bias (PBIAS, %, Eq. (3)), coefficient of determination (R-Squared) and Nash-Sutcliff efficiency coefficient (NSE, Eq. (5)). PBIAS varies between negative infinity and positive infinity but performs best when a value of zero is generated. R-squared values can range from zero to one, where zero indicates no correlation and one represents perfect correlation. NSE values can range between negative infinite and one. A NSE value of one indicates a perfect fit between the simulated and observed flow, and negative NSE values mean that use of an average of observed time series is better than the model predictions.

$$\mathrm{PBIAS} = \left(\frac{\sum_{i=1}^{n} Q_{Obs(i)} - \sum_{i=1}^{n} Q_{sim(i)}}{\sum_{i=1}^{n} Q_{Obs(i)}}\right) * 100 \tag{3}$$

$$\mathrm{R-Squared} = \left(\frac{n\sum Q_{Obs(i)}Q_{sim(i)}) - (\sum Q_{Obs(i)})(\sum Q_{sim(i)})}{\sqrt{[n(\sum Q_{Obs(i)}{}^2) - (\sum Q_{Obs(i)})^2][n(\sum Q_{sim(i)}{}^2) - (\sum Q_{sim(i)})^2]}}\right)^2 \tag{4}$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n} (Q_{sim(i)} - Q_{Obs(i)})^2}{\sum_{i=1}^{n} (Q_{Obs(i)} - \overline{Q}_{obs(i)})^2} \tag{5}$$

where $Q_{sim(i):}$ simulated flow, $Q_{obs(i):}$ observed flow and n: number of simulated and observed data pairs and $\overline{Q}_{obs(i):}$ average of observed flow.

3. Results and discussion

3.1. Comparison of watershed characteristics

The watershed characteristics of the Gumera and Ribb watersheds are compared in Table 2. The difference for a specific catchment characteristic (5th column Table 2) is obtained by dividing the absolute difference of the characteristics by the average of the characteristics of the two watersheds. Percentage differences in climate, topography, and land uses of the watersheds are generally less than 20%. The annual average areal rainfall computed from 1994 to 2008 indicated that there is only 225 mm/year more rain in the Gumara than in the Ribb. The drainage areas of the watersheds are similar; the drainage density is slightly greater in the Ribb than in the Gumara, likely, because it is slightly steeper. Both Gumara and Ribb have approximately the same large portion of over 80% cropland (Table 2). There are difference in areas of the woody savanna, grassland, and urban, but these cover less than 10% of the watershed. However, differences in the soils and discharge were significant; the percentage difference can reach up to 200%.

Table 2
Physical catchment characteristics of Ribb and Gumara Watersheds.

Main catchment characteristics	Catchment characteristic	Ribb	Gumara	Percentage difference (%)
Climate (from 1994 to 2008)	Areal rainfall (mm/year)	1210	1435	17.0
	Areal Evaporation (mm/year)	1225	1234	0.7
	Climate index	1.1	1.2	9.6
Topography	Catchment area (km^2)	1302	1284	1.4
	Longest flow path length (km)	84	100	17.0
	Average slope (degree)	21.6	17.9	18.6
Soil	Drainage density (m/km^2)	301	284	5.8
	% Chromic Luvisols	39.7	24.4	47.7
	% Eutric Fluvisols	23.9	0.5	191.8
	% Eutric Leptosols	36.2	8.2	126.1
	% Eutric Vertisols	0.0	3.5	200.0
	% Haplic Luvisols	0.0	63.4	200.0
	% Haplic Nitisols	0.2	0.0	200.0
Land use/land cover	% Afro-alpine	1.7	0.4	123.8
	% Dominantly cultivated	63.6	64.2	0.9
	% Moderately cultivated	25.5	31.4	20.7
	% Grass Land	8.9	3.9	78.1
	% Urban and Build up	0.3	0.1	66.7
Discharge (1994 to 2008)	Baseflow index (BFI)	0.49	0.45	8.5
	Average stream flow (m^3/s)	16.0	38.4	200

A large difference in soil types between the two watersheds was observed, especially in Eutric Fluvisols, Eutric Leptosols and Haplic Luvisols (Table 2). The soil properties of the different soil groups including soil texture, bulk density, available water content, saturated hydraulic conductivity and hydraulic soil group is shown in Table 3. The dominant soil in Ribb Chromic Luvisols and Eutric Leptisol covering 76% of the watershed are characterized as a shallow clay loam soil (Michéli et al., 2006). While the majority of soil in Gumara (87%) is covered by Haplic Luvisols and Chromic Luvisols, which have a high clay content (i.e. ~60%). The amount of water recharging groundwater will be affected by the soil properties. The soil properties suggest that, Ribb is likely to possess a greater air space or voids between soil particles, which will facilitate infiltration, and storage between voids.

Finally, the discharge in the Gumara is more than twice that in the Ribb (Table 2). The baseflow separation results showed that Gumara had average daily baseflow of 17.3 m^3/s is similarly more than twice that in the Ribb with is 7.8 m^3/s. The ratio of baseflow to total discharge (baseflow index, BFI) of Ribb is slightly larger than that of Gumara, indicating that the contribution of groundwater to Ribb is slightly greater than that of Gumara.

Table 3
Soil texture and soil properties of Ribb and Gumara watersheds.

Soil name	Soil depth	Bulk density (g/cm^3)	AWC (mm)	SAT (mm/h)	Clay	Silt	Sand	Texture	Hydraulic soil group
Chromic Luvisols	800	1.40	0.15	7.1	29.4	38.1	32.5	Clay loam	C
Eutric Fluvisols	1500	1.19	0.09	3.0	62.0	32.2	5.9	Clay	D
Eutric Leptosols	350	1.32	0.14	4.6	38.8	34.8	26.4	Clay loam	C
Eutric Vertisols	1450	1.19	0.07	1.8	68.0	24.6	7.3	Clay	D
Haplic Luvisols	1400	1.23	0.10	3.2	54.4	30.7	14.9	Clay	D
Haplic Nitisols	1550	1.24	0.11	2.0	56.7	28.6	13.5	Clay	D

Where AWC is available water content (mm), SAT is saturated hydraulic conductivity (mm/h).

Table 4
Sensitivity analysis of SWAT model parameters for Gumara and Ribb River watersheds.

Parameter name	Gumara			Ribb		
	t-Stat	p-Value	Rank	t-Stat	p-Value	Rank
v_ALPHA_BF.gw	14.28	0.00	1	2.31	0.02	7
r_CN2.mgt	13.77	0.00	2	− 29.97	0.00	1
v_DEP_IMP.hru	− 9.08	0.00	3	4.91	0.00	2
v_SURLAG.bsn	7.97	0.00	4	− 3.70	0.00	5
v_GWQMN.gw	− 3.34	0.00	5	2.95	0.00	6
v_ESCO.hru	2.76	0.01	6	− 3.74	0.00	4
r_SLSUBBSN.hru	− 2.01	0.04	7	− 1.40	0.16	11
r_CH_S1.sub	1.89	0.06	8	− 1.48	0.14	10
r_SOL_Z().sol	− 1.82	0.07	9	0.34	0.74	14
v_CH_N2.rte	− 1.78	0.08	10	− 1.03	0.30	12
v_CH_N1.sub	− 1.66	0.10	11	3.80	0.00	3
r_SOL_AWC().sol	− 1.03	0.30	12	0.72	0.47	13
v_GW_REVAP.gw	− 0.69	0.49	13	0.31	0.76	16
r_CH_S2.rte	− 0.23	0.82	14	− 1.63	0.10	8
v_OV_N.hru	− 0.10	0.92	15	− 1.54	0.12	9
r_SOL_K().sol	0.00	1.00	16	0.33	0.74	15

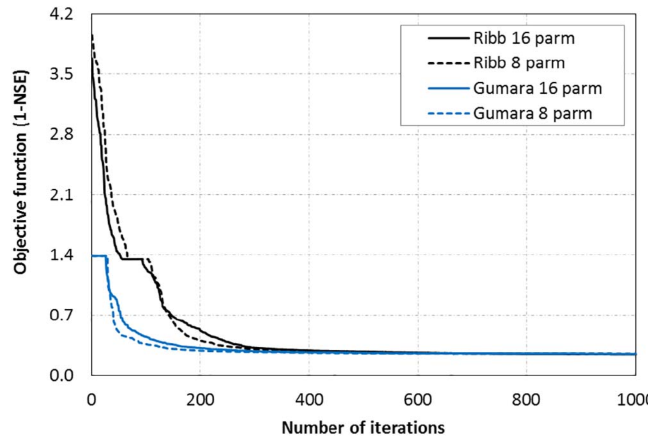

Fig. 4. Convergence of iterations to the objective function (1-NSE) for daily river flow simulation using sixteen and the most sensitive (eight) parameters. (The result of the iteration with all the parameters is denoted as "16 parm" where the result of the iteration using the most sensitive parameters is denoted as "8 parm").

Table 5
Sensitivity and performance of the eight most sensitive parameters and good-ness-of-fit performance during the calibration and validation period.

Parameter name	Gumara		Ribb	
	t-Stat	p-Value	t-Stat	p-Value
r_CN2.mgt	13.8	0.0	− 30.0	0.00
v_DEP_IMP.hru	− 21.1	0.0	16.9	0.00
v_CH_N1.sub	− 2.6	0.0	3.8	0.00
v_ESCO.hru	2.8	0.0	− 3.7	0.00
v_SURLAG.bsn	8.0	0.0	− 3.7	0.00
v_GWQMN.gw	− 3.3	0.0	3.0	0.00
v_ALPHA_BF.gw	14.3	0.0	2.3	0.02
r_SLSUBBSN.hru	− 2.0	0.0	− 1.4	0.03
Calibration	NSE	0.74		0.75
(1995–2004)	R-square	0.87		0.86
	PBIAS (%)	3.72		− 1.12
Validation	NSE	0.75		0.72
(2005–2008)	R-square	0.82		0.75
	PBIAS (%)	8.20		1.54

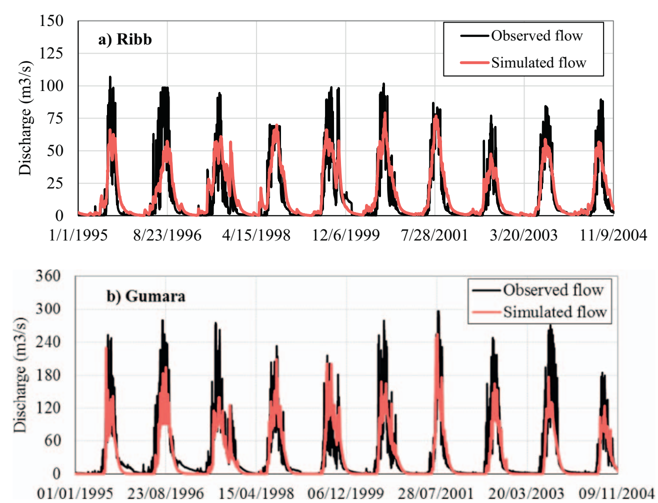

Fig. 5. Daily simulated and observed streamflow for the period 1995 to 2004. a) Simulated vs. observed streamflow of Ribb and b) simulated vs. observed streamflow of Gumara.

3.2. Hydrologic modeling

3.2.1. Model parameter sensitivity analysis

A sensitivity analysis of the model parameters was implemented to identify the parameters that significantly influence the simulated daily flow. The selected 16 parameters (Table 1) were used to simulate runoff within the model parameter space. The effect of the parameters on the simulated variable was evaluated with t-stat which provides a measure of sensitivity and p-value which determines the significance of the sensitivity.

The sensitivity test, *t*-value ranged from 14 to − 9 for Gumara and from 4 to − 29 for Ribb (Table 4). The most sensitive parameters are common for both watersheds with a similar order of sensitivity. Sensitive parameters with their relative order of sensitivity were CN2, DEP_IMP, ALPHA_BF, SURLAG, ESCO, GWQMN, CH_N1 and SLSUBBSN.

3.2.2. Model calibration, and validation

The SWAT model calibration and uncertainty analysis were done using the IPEAT framework. The program allows calibration of models parameters based on hydrologic group, soil, land use and sub-basin. Daily discharge of Gumara and Ribb was simulated with SWAT model for a thousand model parameter sets selected randomly for the calibration period (1995 to 2004). The model calibration was implemented

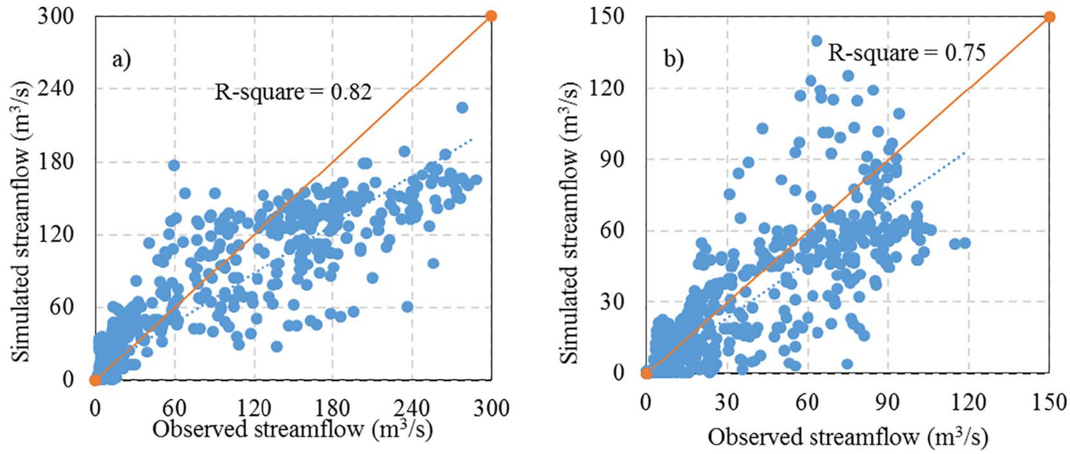

Fig. 6. Scatter plot of simulated vs. observed streamflow Ribb and Gumara watersheds for the validation period (2005–2008). a) Ribb simulated streamflow performance for the validation period b) Gumara simulated streamflow performance for the validation period.

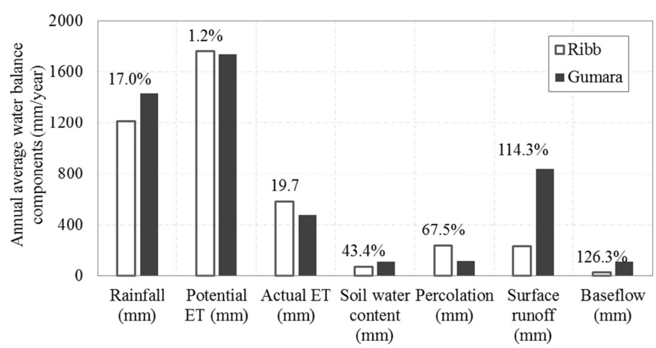

Fig. 7. Water balance components of the Gumara and Ribb. The numbers over the bars display the percentage difference of the water balance components between Gumara and Ribb.

with two different parameter settings. The first one includes the most sensitive eight parameters (8_parm) which includes CN2, DEP_IMP, CH_N1, ESCO, SURLAG, GWQMN, ALPHA_BF and SLSUBBSN (Table 4) and the second one includes all of the selected sixteen parameters (16_parm, Table 5). Nash-Sutcliff efficiency was used as an objective function. At the beginning of the iteration, the model performance of Ribb was lower than Gumara watershed (Fig. 4). As the number of iteration increased the model performance improved and the difference in the model performance reduced significantly. After 300 iteration, the performance of both watersheds and model parameter sets (8 parm and 16 parm) reached optimal value (maximum NSE). Fig. 4 also indicated that removing least sensitive model parameter did not affect the overall performance of the simulation.

The calibrated model provided a streamflow simulation for the calibration period with an NSE of 0.74 and 0.75 and PBIAS of 3.7% and − 1.1% for Gumara and Ribb, respectively (Table 5). The hydrograph between the daily observed and simulated streamflow for the calibrated SWAT model of Gumara and Ribb (Fig. 5a and b) provided reasonable agreement. The validation of the model from 2005 to 2008 also showed a performance of NSE of 0.75 and 0.79 and a PBIAS of 8.2% and 1.5% for Gumara and Ribb, respectively (Fig. 6). According to Moriasi et al. (2007) model performance rating of SWAT, the model performance is "very good" for both calibration as well as validation periods.

The average of the water balance components of Ribb and Gumara watersheds are presented in Fig. 7. The percentage difference of the water balance components (i.e. the ratio of the absolute difference and the average of the components) is displayed over the bars. On average Gumara watershed receives more rainfall and evaporates less by 225 mm and 21 mm, respectively. However the differences in the rainfall and evaporation accounted less than half of the annual runoff difference of 560 mm/year. The while soil water content, percolation, surface runoff and baseflow for the watersheds showed substantial differences (Fig. 7).

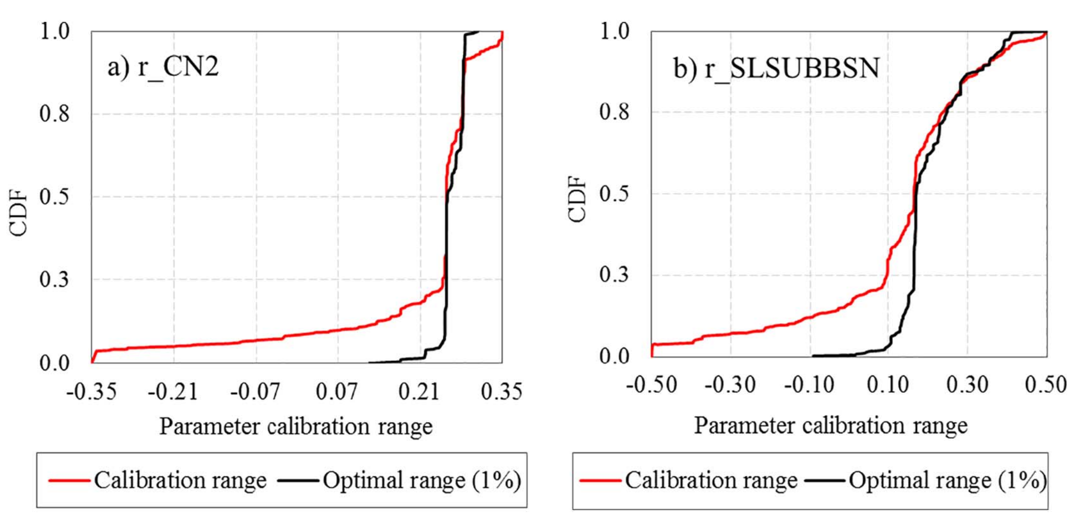

Fig. 8. Cumulative distribution function of the least and the most sensitive parameters for the behavioral and for the whole parameter space: a) r_CN2 and b) r_SLSUBBSN.

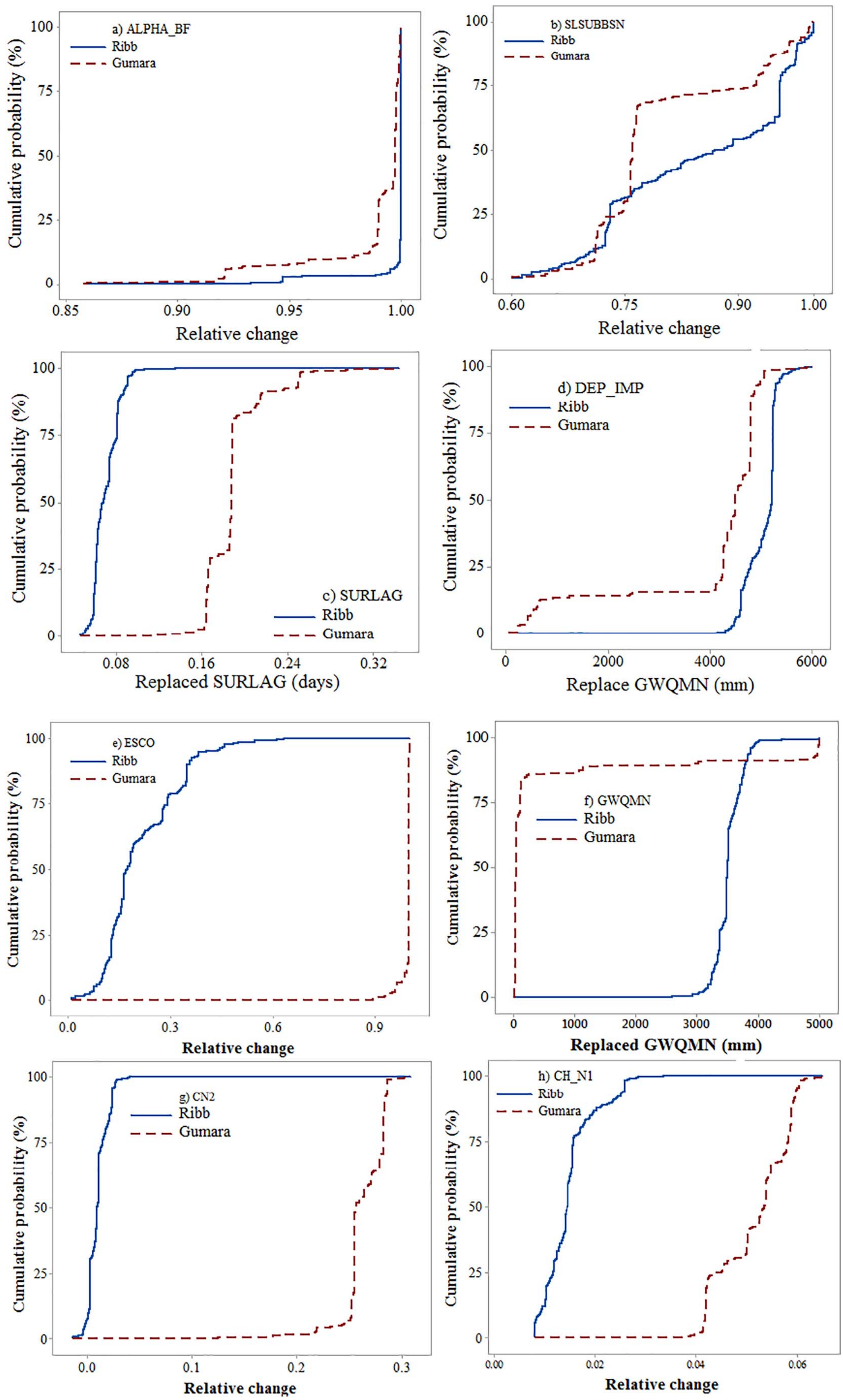

Fig. 9. K-S test of the behavioral model parameter sets of Ribb and Gumara watershed. The selected behavioral parameters were within 1% of the maximum NSE value for the respective watersheds.

3.2.3. Model parameter uncertainty

The cumulative distribution functions (CDFs) was constructed for the full and 'behavioral' model parameter sets to show the distribution of behavioral solutions. The 1000-parameter samples were divided into behavioral and non-behavioral with a 1.0% threshold from the optimal parameter set (maximum NSE). The behavioral model parameter sets contains all the model parameter sets which performed by up to 1.0% less from the maximum NSE in the respective watersheds. Within the 1% thresholds, there were 478 and 337 behavioral parameter sets providing NSE values greater than 0.73 and 0.74 for Gumara and Ribb, respectively. Fig. 8a and b shows the cumulative distribution function of the most and least sensitive model parameters out of the eight parameters (r_CN2 and r__SLSUBBSN). The CDF plotted for the behavioral solution of CN2 indicated a narrow range, which was in the range of 12% to 31% plus the default value (Fig. 8a). While the relatively less sensitive model parameter (SLUSBBSN) among the calibration parameters has a wider range of optimal solutions ranging between − 10% and 50% from the default parameter value. The CDF plot indicated a consistent narrow band solution for the relatively sensitive model parameters such as r_CN2 while indicating a higher uncertainty for the least sensitive model parameters. As the output model uncertainty is dependent on the shape and distribution of the behavioral model parameters, the communitive distribution indicates of the parameters indicated a narrow output uncertainty.

3.3. Hydrologic response to the watershed characteristics

The distributions of the 'behavioral' parameters of Ribb and Gumara watersheds were compared statistically to understand the hydrologic responses of the watersheds. A non-parametric test K-S test was used to determine if response of the watershed parameters were significantly different or not (Fig. 9). The posterior distributions of the baseflow recession constant (ALPHA_BF, which is determined by geological characteristics) and average slope length (SLSUBSN) indicated no significant difference at alpha value of 0.05 between Gumara and Ribb (Fig. 9a and b). The optimal ALPHA_BF values of both watersheds were concentrated between 0.9 and 1.0 indicating a relatively rapid baseflow response to rainfall in the both watersheds (Neitsch et al., 2011a). The K-S test indicated a significant difference in the behavioral model parameters of surface flow lag time as explained by SURLAG cumulative probability plot in Fig. 9c. SURLAG is influenced by topography, land cover, and soil. The posterior distributions of the calibration parameter of SURLAG indicated that baseflow responses to rainfall events are slower in Ribb implying a delay in release of surface runoff. Likewise a significant difference was observed with the depth of soils to the impervious layer (DEP_IMP). A major difference in the behavioral parameter distribution was observed in ESCO, GWQMN, CN2 and CH_N1. Those model parameters are directly related to soil data. Ribb watershed indicated a lower soil evaporation compensation factor (ESCO), which enables to extract evaporation from deeper soil levels. ESCO also accounts for effect of cracking, crusting and capillary action by adjusting the depth distribution to meet the soil evaporation demand (Hutchinson and Christiansen, 2013). The posterior distribution of the threshold depth of water in the shallow aquifer required for return flow to occur (GWQMN) for Gumara was smaller than Ribb indicating a smaller groundwater reservoir in Gumara. The SCS runoff curve number (CN2) which is a function of soil permeability, land use and antecedent soil water condition indicated a higher value for Gumara. The behavioral solution also indicated a higher Manning's value (CH_N1) for the tributary channels of Ribb than Gumara indicating a higher resistance to flow. This suggests that there are multiple factors that contributed for a significant runoff difference in surface runoff. Among those factors, difference in weather (rainfall and evaporation) is one of them. However, the difference in soil between the two watersheds magnified the difference by causing the watersheds to respond differently.

4. Conclusions

This study presents the effect of watershed characteristics on the hydrologic responses of two paired watersheds (Gumara and Ribb) in the Upper Blue Nile Basin, Ethiopia. The hydrologic response was evaluated using streamflow measurements at the outlets of the watersheds. The quantitative comparisons of the catchment characteristics showed that both watersheds have similar topography and land cover and a minor difference in climate (rainfall and evaporation) but a significant different was observed in soil characteristics. For example, Ribb watershed is dominated by Chromic Luvisols and Eutric Leptosols, which have a similar proportion of sand, silt and clay while Haplic Luvisols, which has a higher proportion of clay soil, dominated Gumara watershed. The difference in soil characteristics magnified the differences in weather by affecting the watersheds response to runoff at the outlet. The calibration parameters were identified from a sensitivity analysis, and the performance of the calibrated model was acceptable with NSE value of greater than 0.70 for a daily streamflow simulation. The evaluations were also acceptable for the validation period. The cumulative probability distribution of the behavioral solution of both watersheds were compared with a K-S test, the parameters showed that the hydrologic modeling reasonably respond to the differences in the watershed characteristics. The simulated water balance components using the calibrated model exhibited that the two watersheds showed significantly different hydrologic response which is related to difference climate characteristics and soil data. It can be justified that the SWAT model has captured the watershed-scale responses caused by the differences in the watershed characteristics. This study demonstrated that in seemingly similar paired watersheds difference in soils found to significantly affect the hydrologic responses of the watersheds. Results suggest that uncertainty in soil data will have considerable impact on water balance estimates. We recommend due emphasis on soil information in hydrologic analysis and reminding of the necessity of developing fine-resolution soil database.

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