water

MDPI

Article

Uncertainty in a Lumped and a Semi-Distributed Model for Discharge Prediction in Ghatshila Catchment

Aradhana Yaduvanshi [1,*], Prashant Srivastava [2], Abeyou W. Worqlul [3] and Anand Kr Sinha [4]

1. Centre of Excellence in Climatology, Birla Institute of Technology, Mesra, Ranchi, Jharkhand 835215, India
2. Institute of Environment and Sustainable Development, Banaras Hindu University, Varanasi, Uttar Pradesh 221005, India; prashant.just@gmail.com
3. Blackland Research and Extension Center, Texas A&M Agrilife Research, Temple, TX 76502, USA; abeyou_wale@yahoo.com
4. Civil and Environmental Engineering, Birla Institute of Technology, Mesra, Ranchi, Jharkhand 835215, India; aksinha@bitmesra.ac.in

* Correspondence: aradhanayaduvanshi10@gmail.com

Received: 13 November 2017; Accepted: 20 March 2018; Published: 25 March 2018

check for updates

Abstract: Hydrologic simulations of different models have direct impact on the accuracy of discharge prediction because of the diverse model structure. This study is an attempt to comprehend the uncertainty in discharge prediction of two models in the Ghatshila catchment, Subarnarekha Basin in India. A lumped Probability Distribution Model (PDM) and semi-distributed Soil and Water Assessment Tool (SWAT) were applied to simulate the discharge from 24 years of records (1982–2005), using gridded ground based meteorological variables. The results indicate a marginal outperformance of SWAT model with 0.69 Nash-Sutcliffe (NSE) for predicting discharge as compared to PDM with 0.62 NSE value. Extreme high flows are clearly depicted in the flow duration curve of SWAT model simulations. PDM model performed well in capturing low flows. However, with respect to input datasets and model complexity, SWAT requires both static and dynamic inputs for the parameterization of the model. This work is the comprehensive evaluation of discharge prediction in an Indian scenario using the selected models; ground based gridded rainfall and meteorological dataset. Uncertainty in the model prediction is established by means of Generalized Likelihood Uncertainty Estimation (GLUE) technique in both of the models.

Keywords: SWAT; PDM; GLUE; model structure; discharge

1. Introduction

Disaster risks will continue to rise in many countries of the Asia-Pacific region as more number of people and resources are open to weather extremes [1]. Within the Asia-Pacific region, the countries of South Asia have the most prominent risk for disasters that are associated with water and face the lowest resilience [2]. India is also highly vulnerable to floods. 40 MHa is affected by flood out of the total area of 329 MHa. In recent years, annual damages that are caused by floods has been around Rs. 4745 crore (790 million USD), whereas the average loss during the last 53 years has been around Rs. 1805 crore (300 million USD). This can be ascribed to rapid growth in population and urbanisation integrated with mounting developmental and economic actions in the inundation plains, together with global warming [3].

A high frequency of floods in recent years has compelled researchers to find methods for the improvement of runoff dynamics prediction and flood forecasting. To attain consistent outcomes of basin response, the calibration practice of watershed against discharge is indispensable in order to know some parameters, which are not directly measurable. Many models are now available in the technical literature domain for rainfall runoff analysis. Based on spatial representation, rainfall runoff can be classified as lumped model, semi-distributed, and distributed [4–8]. Until recently, less attention has been given to test the efficiency of models with respect to model structure and parameter uncertainty for catchments. Semi distributed models, such as SWAT, require detailed spatial data for model setup and calibration, leading to a relatively expensive field data collection when compared to lumped models [9]. Complexity and size of the model either inversely or proportionally related to the uncertainty associated with model parameters [10]. The difficulty in reducing uncertainties is severe in the hydrologic modelling. A complex model precisely reflects the physical process of system, but adding more parameters causes uncertainty in the modeling. Mathematical equations representing the physical processes and oversight of parameters brings uncertainty in the structure. A substantial extent of uncertainty with ominous consequences on water resources is caused by spatio-temporal variability in standard value of parameters [7,11]. Therefore, vigorous calibration and uncertainty analysis is the way to effectively calibrate the models for an efficient forecast and reducing the uncertainty in the models Model parameter uncertainty is the compounding of the uncertainty in these processes. In many cases, the best parameters for one period will not be acceptable for the other periods. Thus, optimum parameter value should not be the only focus during calibration. Uncertainty is a major challenge that is emerging in recent periods. Nowadays, requisite of already occurring methods to cope with growing uncertainty associated with structure, parameters type and range along with observations is obligatory for the evaluation process of model. Recently, in hydrologic studies there have been ample studies focusing on input, output, and parameter uncertainty [11–14]. It includes GLUE structure [5], dual state-parameter estimation methods [15], the Shuffled Complex Evolution Metropolis algorithm [16], and the Bayesian recursive estimation technique [17]. In an obvious and consistent way, these processes fully reveal the three precarious facets of uncertainty analysis: understanding, quantification, and reduction of uncertainty.

In this study, a semi distributed model, SWAT, and a lumped Probability Distribution Model (PDM), are used to assess the performance and the output uncertainty of simulated flow in the Ghatshila Catchment, India. SWAT model is increasingly used in discharge prediction, nutrient and sediment load assessment, and to quantify the fluxes from lakes [18–21]. In SWAT, auto-calibration gives a rigorous loom via algorithms of optimization [22]. PDM is an extension of lumped model developed in 1960 by Moore and Clark [23]. One advantage of this model is the improved illustration of storage variability in a catchment. Association between the incidences of rain events and magnitudes of peak flow can be studied with the PDM model [24]. In this study, the focus is to compare the lumped model and semi-distributed model for the discharge prediction in the data scarce region.

In the face of growing uncertainties, the main aims of the study were focused on the following objectives (1) to appraise the suitability of hydrological model system for predicting discharge in an data scarce Indian catchment, (2) to quantify parameter uncertainty for discharge prediction of a semi distributed hydrological model (SWAT) and lumped hydrological model (PDM) using GLUE, and (3) to assess the variation in the outcomes of two models over the study area. In an endeavor to answer the above-mentioned research questions, the paper is arranged into three main sections. Following the introduction, the second section provides the details of the study site, data, and the modelling approaches. The third section provides the results and discussion. The final section reports the main outcomes of this study.

2. Study Area and Datasets

2.1. Watershed Description

The Ghatshila catchment lies between the geographical co-ordinates of 86°27′ E and 22°35′ N (Figure 1), found in the middle lower part of Subarnarekha River. Subarnarekha is the most tenacious east flowing inter-state river, which drains 32,647 km^2 areas. Ghatshila is sited on the banks of

Subarnarekha River, at a distance of almost 45 km from Jamshedpur. Average elevation is recorded about 103m. Population of Ghatshila is 37,850. The catchment comes under the tropical region of India. Monsoon is the adequate source of rainfall during the monsoon period from May to October [25]. Rainfall in the winter season is caused by the North East monsoon. The average temperature in Ghatsila is 26.7 °C. The average annual rainfall is 1241 mm. The temperature in May averages 33.3 °C. At 19.5 °C on average, January is the coldest of all the months.

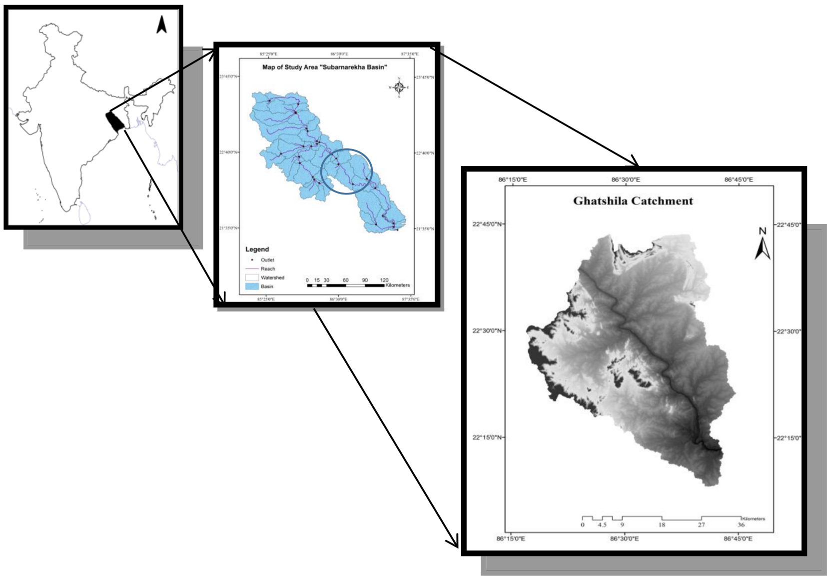

Figure 1. Location map of the Ghatshila Catchment.

2.2. Datasets

2.2.1. Hydro-Meteorological Data

The Government of India implemented the Hydro-meteorological data dissemination policy. The river discharge data can be downloaded from the Central Water Commission (CWC) site. These data include gauge height, discharge, silt, and water quality parameters up to the period 2012. In the Ghatshila catchment, continuous discharge data are available from 1982–2005. Detailed description of CWC discharge site of river basin is as follows: Site name is Ghatshila encompassed in 22°35′08″ latitude and 86°27′42″ longitude. Catchment area is 14,176 km^2. The longest path of flow is approximately 187 km. In the current study, gridded rainfall data (0.25° × 0.25° lat. /long.) over the Subarnarekha basin during 1982 to 2005 has been used at a daily scale. These data sets are prepared at 0.25 degree resolution for the India using 6955 daily reporting stations of National Data Centre at India Meteorological Department (IMD) [26]. Geographic location, elevation information, and coding error have been checked in order to meet standard quality. Interpolation has been done by using the Inverse Distance Weighting (IDW) technique of power two with a spatial grid of 0.25° × 0.25° resolution to estimate areal rainfall [27]. IDW method was selected due to its simplicity and acceptable performance in capturing the areal rainfall [28–30]. Relative humidity, Temperature, Wind speed, and solar radiation data are taken from the given site (http://globalweather.tamu.edu/) of Global weather data for SWAT on daily scale since 1979–2014 [31]. The list of model inputs is presented in Table 1.

Table 1. Model input details with simulations for semi distributed hydrological model (SWAT) and Probability Distribution Model (PDM) model.

	Input Variables and Model Setup	Simulation Period and Input Data Resolution
1	Simulation length (years)	24
2	Warm up (years)	2
3	Rainfall (Gridded)	0.25^0
4	Streamflow data	Daily Scale
5	Land use Land cover (SWAT)	1 km
6	Soil Type (SWAT)	10 km
7	Temperature (SWAT)	1°
8	Calibration Period	1982–1996
9	Validation Period	1997–2005

2.2.2. Spatial Data

Topographic parameters, including Slope, area, field slope length, and other of the sub-basin are analysed using Digital Elevation Model (DEM). Cotter [32] suggested that the resolution of data should be in the range of 100 to 200 to reduce the error for the flow (Figure 2A). Here, 3 arc-second resolution of DEM is used to cover land at 60° N and 56° S. (http://csi.cgiar.org). The amount of runoff is majorly affected by the Land use, land cover (LULC) of the region (Figure 2B). Soil datasets and LULC are taken from Water Base, which is a project of the United Nations University. The land cover map that is accessed for this research is from the Global Land Cover Characterization database (GLCC) of the U.S. Geological Survey and has a 1 km resolution (USGS, 2008). 1-km Advanced Very High Resolution Radiometer (AVHRR) data spanning (USGS, 2008) is used to derive the data set. Flexible structure of data base and seasonal land cover concepts are used for its basis (Figure 2C). Soil raster data are available at 10 km resolution [33] (http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/).

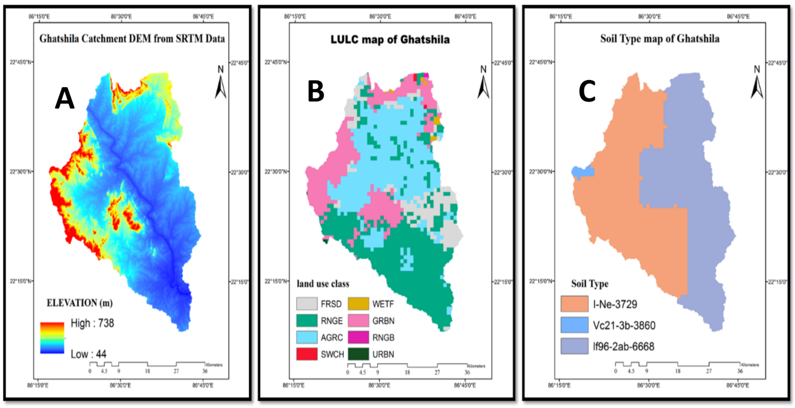

Figure 2. SWAT model inputs (**A**) Topography, (**B**) Land use/land cover, and (**C**) Soil type.

3. Methodology

3.1. Watershed Models

The precipitation was converted to streamflow at the watershed outlet using two hydrological models the SWAT and PDM models. Those two models were selected to represent a semi-distributed and lumped model, respectively. A brief description of the models is given below:

3.1.1. SWAT Model

The direct outgrowth of simulator for water resources in rural basin (SWRRB) model results into development of SWAT model by USDA-ARS. It was developed to simulate the management practices over an ungauged catchment to check sediment measurement. SWAT is a non-proprietary, physically dependent, continuous, and basin scale model. Hydrologic responses that were simulated by the model are based on the process based equation (Figure 3). GIS interface, computation efficiency, and incorporation of easily available input data, such as soil, weather, and land use makes it more efficient to capture small changes in hydrologic behavior of basins. Water balance is the key factor for all hydrologic models. In SWAT, it is calculated by including several components such as ET, Base flow, Surface runoff, snow melt, and snow cover and infiltration, etc. [34]. The SWAT model uses a principal water balance method (Equation (1)) to calculate the runoff volumes and peak flows [18], expressed as:

$$SW_t = SW_o + \sum_{i=1}^{t}\left(R_{day} - Q_{SURF} - E_a - W_{seep} - Q_{gw}\right) \tag{1}$$

where, SW_o is initial soil water content and SW_t is the final soil water contents on particular day i. All of the other measurements are given in millimetres and time (t) is in days. The equation subtracts all forms of water loss on day i from precipitation on day i (R_{day}), including surface runoff (Q_{surf}), evapotranspiration (E_a), loss to vadose zone (W_{seep}), and return flow (Q_{gw}) [35]. By operating this equation, the model can expect variations in variables of concern, like return flow and runoff. The performance of semi distributed model SWAT has been analysed over wide areas with a quite satisfactory performance. The uniqueness of the semi distributed model lies in the fact that calibration does not need much time as they integrate physical and meteorological parameters into sub basins, which is easy to set up.

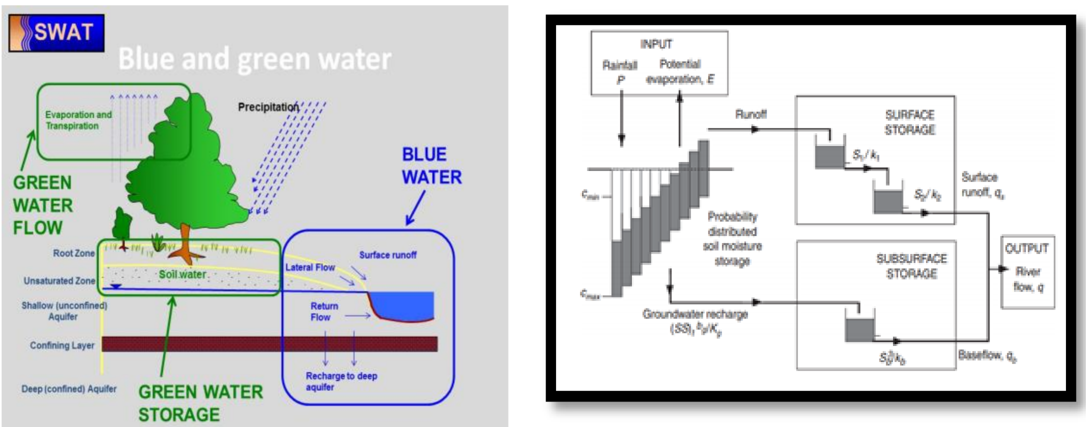

Figure 3. Schematic representation of SWAT [36] and PDM model (Source: Hydrology in Practice 2011).

3.1.2. PDM Model

In this study, PDM model which was developed in the 1980s by Moore and Clarke [23] at the Institute of Hydrology at Wallingford, UK center is used. PDM model can be illustrated as a kit of tools that collectively treat a catchment as a single unit by representing the diverseness of hydrological behaviour in the basin [8]. The heterogeneity in soil and runoff characteristics is not measurable in the real scenario. Moore [23] found out that local storage deficit is needed to be satisfied before fast runoff generation, which is an approximation of probability distribution. Soil moisture accounting is done by distributing soil moisture storage capacities [37–39]. Basic concept of the model lies in of runoff generation using rainfall and evapotranspiration (ET) data as an input [40]. The most governing factor during the runoff generation along the gradient of catchment is absorption capacity of soil.

Since diverse points in a unit have different storage capacity and a PDM can illustrate the spatial disparity of a capacity, therefore the entire catchment surface runoff in surface storage is integrated by combining the point's runoff in PDM (Figure 3). The PDM model is balanced by the apprising methods for real-time flow predicting applications [41]. Apprising methods are based on state-correction approaches and error prediction. Input data for PDM model includes daily rainfall, evaporation, and discharge data for calibration.

Essentially, the PDM assumes that at any point and at any time step, storm flow will be produced whenever any local storage deficit is filled so that

$$q(i) = r(i) - D(i) - e_a(i) \tag{2}$$

where $r(i)$ is the rainfall at time i, $D(i)$ is local storage deficit at time i and $e_a(i)$ is actual evaporation. The maximum possible storage capacity will vary throughout the catchment in a dry condition. The approach is reserved from statistical distribution in form of spatial variation.

3.2. Model Perfromance Evaluation

To assess the performance of SWAT and PDM simulated flow, Nash Sutcliffe Efficiency (NSE) has been used as objective function [42]. The inclusive fit of a hydrograph can be best reflected by this objective function [43]. It ranges between $-\infty$ to 1. The optimum value of NSE = 1. Undesirable performance is showed when the NSE value is less than 0.0, which points out that the mean value of observed data is a better predictand than the simulated one. It expresses the relative amount of residual discrepancy related to the calculated data variance ("noise"). Simulated versus observed data fitted in 1:1 line displays the significance of NSE [44]. The given equation is used to compute NSE

$$NSE = 1.0 - \frac{\sum_{i=1}^{N}\left(Q_{obs(i)} - Q_{sim(i)}\right)^2}{\sum_{i=1}^{N}\left(Q_{obs(i)} - \overline{Q_{obs}}\right)^2} \tag{3}$$

where, $Q_{sim(i)}$: the ith simulated flow, $Q_{obs(i)}$: the ith observed flow and N: number of simulated and observed data pairs and $\overline{Q}obs(i)$: average of observed flow. The performance of the simulated flow of both the models was also evaluated by comparing the respective flow duration curve (FDC) with the gauged flow over the simulation period. The FDC curve indicates the percentage of time that the simulated or observed flow is likely to equal or exceed a specific value of interest. The FDC curve provides a compact summary of the variability of the daily simulated and observed flow.

3.3. Output Uncertainty Evaluation

The GLUE [5] is used for calibration and uncertainty analysis of both PDM and SWAT models. The Monte Carlo simulation technique can be extended by using the goodness of fit of each run of the simulation. This is referred to as the Glue procedure. In hydrological modeling, unlike most calibration approaches, the GLUE technique discards the hypothesis of unique universal finest parameter set and upholds justification of distinct parameter sets that can be developed to fit the model predictions. This concept is termed 'equifinality', and it can be undertaken by an assessment of various parameters sets contained by the GLUE method [45]. The GLUE procedure gives a number of possibilities for getting optimal results in the simulations. So, instead of a single calibrated set of parameters, we obtain a collection of parameter sets, each of which gives acceptable model output. Regulating a set of models that are satisfactory on the grounds of available data is the function of GLUE system. To estimate uncertainty of modeling, the GLUE method wields prediction interval at every time step with higher and lower limits. In the proceedings of the method, first of all, the objective function is defined and a 'likelihood weight' is obtained for all of the parameters. Reasonable ranges are assigned to the parameters in relation to their physical denotation and current understanding, and then the Monte

Carlo scheme is applied. In GLUE, uniform distribution of parameters before the modeling is generally adopted, with the assumption that choice of prior density does not predominantly impact information that is extracted from posterior distribution [46]. Subsequently, random sets of parameters are selected as an input for SWAT model simulation to get output in the form of surface runoff, which comes under parameter uncertainty analysis. In GLUE, a set of discrete 'behavioral' parameters along with assigned 'likelihood weights' are combined and are termed as parameter uncertainty [5].

$$w_{i=}\frac{L(\theta_i)}{\sum_{k=1}^{N}L(\theta_k)} \tag{4}$$

where $L(\theta)$ is likelihood measure and N is number of behavioral parameter sets. Model prediction uncertainty analysis is performed. The simulation results are utilized by considering the lower and upper limit of model prediction outputs. The time series of predicted uncertainty lies under the well-defined confidence level. It can be calculated by arranging the likelihood values in an increasing order within simulations in harmony with the assumption of threshold [47,48].

4. Results and Discussion

4.1. Evaluation of Rainfall, ET and Discharge Datasets

Visualization of hydro-meteorological variables that are intended for the better understanding is the essential step in modelling. The calculated ET from the temperature and sunshine hour data are plotted as time series for the 24 years that is from 1982 to 2005. The discrepancy in the series can be seen in the Figure 4. Temperature is an imperative factor in ET when it is calculated by Hamon method [49] Seasonal variation occurred in all three meteorological parameters. The lowest temperature is found in December and January, whereas the highest is found in June and July. The range of temperature in this catchment is 32.9 °C to 11.3 °C. ET varies from 5.2 mm to 1.21 mm. The rainfall amount varies from 0 mm to 276.06 mm per day. The highest rain in a single day (276 mm) occurred in the year 1997. Most of the rainfall comes in monsoon season that is from June to September. The variability of meteorological parameters has large impact on runoff characteristics.

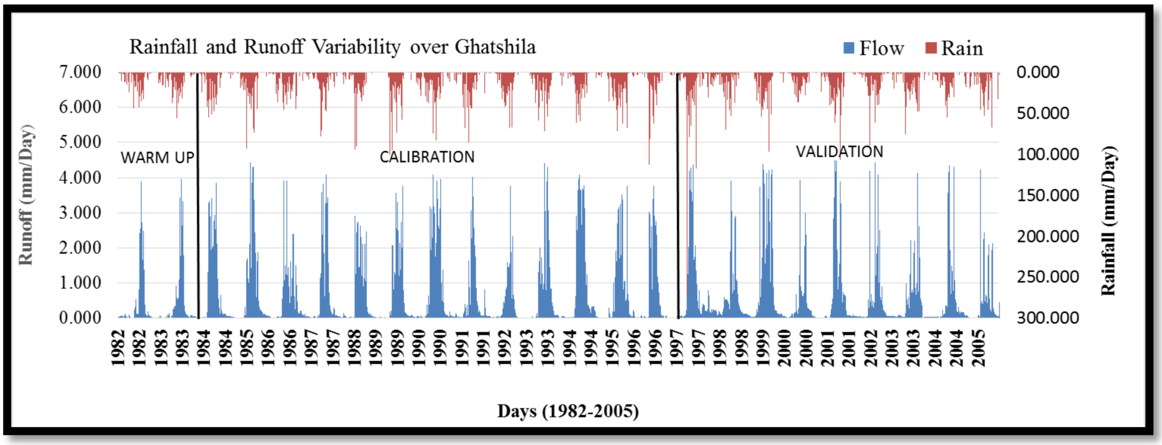

Figure 4. Time series of runoff in the primary y-axis and areal rainfall in the secondary y-axis.

Long term monthly variability of Hydro-meteorological parameters is given in Figure 5. Variability of ET and flow series shows a similar type of pattern for entire hydrological year. A markable seasonal cycle with sharp peak in mid-May to September is also observed. Low ET during post monsoon season is due to the significantly wet profile of soil. During the pre-monsoon and monsoon period (April to mid-September), due to high evaporation and temperature, there is liberal aeration of the soil. Wetness in soil enlarges just after the monsoon rain in a particular region. This leads to a decrease in ET by the end of November and December. Rainfall events lead to the nonlinear processes of runoff generation, this behavior can be easily marked by understanding the lag time response between rainfall and flow. Soil moisture is nearly equal to the field capacity in most of the time from August to October. Subsurface and surface response of the earth during high ET values for the period from April to August reveals the impact of temperature conditions and the amount of net radiation. Monsoon period overlaps the period of higher temperature and is enough to support rain-fed crops without affecting the flow significantly, irrespective of high ET.

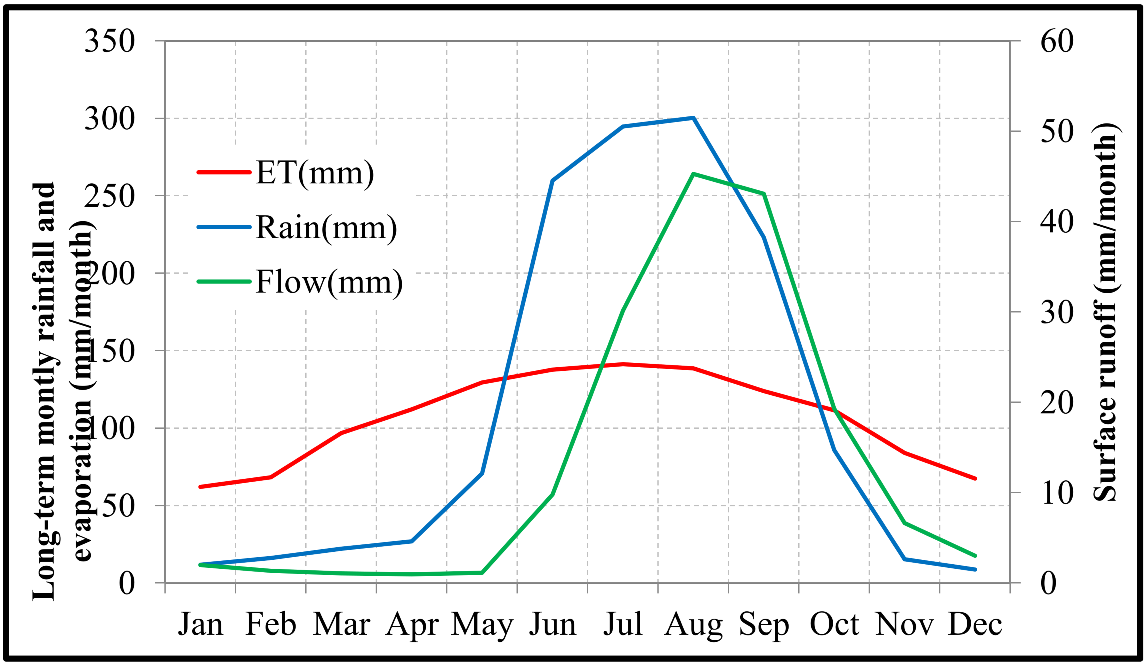

Figure 5. Monthly long term average rainfall, potential evaporation and river flow.

4.2. Performance of PDM and SWAT

PDM and SWAT model are simulated using GLUE Optimization technique. These models are calibrated for Ghatshila gauge station's daily-observed discharge data. 10,000 iterations are performed to calibrate the both of the models. The whole time series is divided into the calibration and validation period. Calibration period is considered from 1982–1996 and validation period is from 1997–2005, along with two years warm up period under SWAT Calibration and Uncertainty Procedures (SWAT-CUP). Model initialization starts with a warming up of data sets, which precedes realistic preliminary values of the formal variable of the particular model. Many studies emphasised a 2–3 years of warm up period for the satisfactory results [47,50]. In Ghatshila, the calibration period is for sixteen years and the validation period is nine years. The first step in the model simulation process is calibration, wherein identifying the sensitive parameters is essential for the catchment (Table 2).

Table 2. Description of stream flow parameters for SWAT and PDM models.

Serial No	Parameters	Description of Parameters
	SWAT	
1	r__CN2.mgt	Curve number
2	v__ALPHA_BF.gw	Base flow alfa factor
3	v__GW_DELAY.gw	Groundwater delay time
4	r__SOL_AWC .sol	Soil available water capacity
5	v__ESCO.hru	Soil evaporation compensation factor
	PDM	
1	Cmax	Maximum Store Capacity
2	b	Exponent of Pareto Distribution
3	g	Ground water recharge time constant
4	Kf	Fast Flow Component
5	Ks	Slow Flow Component

To appraise the uncertainty in the model to replicate the measured flow over the Ghatshila gauge station, generally used goodness-of-fit indicator is considered as NSE. The better assessment of model during calibration and validation can be analysed by computing P and R factor. P factor reflects the percentage of the observed data that are wrapped by modelling results, whereas R factor defines thickness of the 95PPU.

Storage time constants, parting between runoff generated by slow response system of ground water and direct runoff through channels and the translational flow are the main focus of calibration in PDM model. The approach that was taken by Moore and Clarke is to assume that the spatial variation takes the form of a statistical distribution function. A suitable function is the Pareto distribution, which does have a maximum capacity. Maximum soil storage capacity in a grid square is related to the regional maximum gradient and storage capacities, while the exponent b is treated as a function of mean slope angle. PDM uses functional forms to represent the non-linearity of storm flow generation based on an interpretation of spatially distributed storage deficits. PDM initialisation is being done by taking fie parameters into consideration viz g (groundwater recharge time constant), $C_{\max}$ (maximum store capacity), b (exponent of pareto distribution), K_s (slow flow component) and K_f (fast flow component). Table 3 displays the min and max range of the parameters that are used in this study with optimal values.

A comparison of simulated and observed flow time series is shown for the better interpretation of behavior. The complete analysis shows a NSE value of 0.62 for the validation and 0.58 during the calibration after analysing 10,000 simulations. In the case of PDM, we see a satisfactory performance. However, it clearly misses a couple of peaks in the wet season of 1997. Despite the aforementioned result, the overall hydrograph is a good match during the complete period. It is difficult to understand the pattern of the hydrograph, especially in the lower portion where there are weak events, especially in the winter months. The evidence of incapability of model structure can be seen in the peak flows. Overall performance of PDM model is comparatively sensible. Time series plots of calibration and validation, generated by PDM using rainfall and runoff data are shown in Figure 6. Uncertainty analysis in PDM is done using GLUE algorithm [51], which gives quite good results like any other auto calibration methods that are used to perform uncertainty analysis.

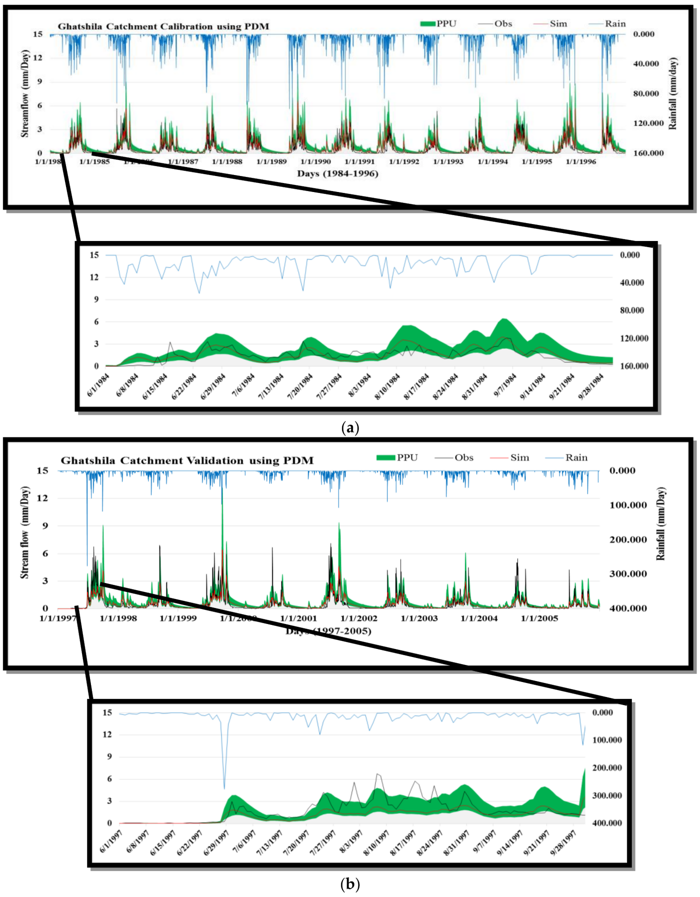

Figure 6. Comparison of simulated flow with observed flow of Ghatshila catchment. (**a**) Comparison PDM simulated flow vs. observed flow (**b**) comparison of PDM simulated flow vs. observed flow.

For the Ghatshila catchment, the sensitive parameters are identified during the calibration process. We have analysed the sensitivity of the parameters during the model calibration. Tables 3 and 4 shows the min and max ranges of the parameters fitted for the daily calibration in the GLUE uncertainty techniques.

Table 3. Stream flow calibration parameter ranges in SWAT.

Serial No	Parameters	Fitted Value	Minimum Value	Maximum Value
1	Cmax	1525	1200	1800
2	b	0.27	0.24	0.30
3	g	0.47	0.30	0.60
4	Ks	0.40	0.32	0.41
5	Kf	0.012	0.008	0.015

Table 4. Stream flow calibration parameter ranges in PDM.

Serial No	Parameters	Fitted Value	Minimum Value	Maximum Value
1	r__CN2.mgt	0.06	−0.2	0.2
2	v__ALPHA_BF.gw	0.002	0.0	0.2
3	v__GW_DELAY.gw	394	200.00	400.00
4	r_SOL_AWC.sol	−0.07	−0.2	0.4
5	v__ESCO.hru	0.11	0.0	0.2

During iteration, the calibration of the model is mostly governed by the parameters that are given in Table 1. Parameters are adjusted by continuous iterations and the best fitted range provides the well settlement with observed values. SWAT Model is run using twenty four years hydro meteorological data are provided on daily scale (two years warm up period, 13 years calibration, and nine years validation), DEM, Soil type, and LULC. SWAT initialisation is being done using five parameters viz curve number (CN2), base flow alpha factor (ALPHA_BF), ground water delay time (GW_DELAY), soil available water capacity (SOL_AWC), and soil evaporation compensation factor (ESCO). Table 4 lists the SWAT model parameters, initial ranges, and acceptable fit. Daily scale stream flow is simulated and then calibrated and validated for the uncertainty analysis. 10,000 simulations are performed to choose the best parameters for the validation period. NSE value for the calibration period is found to be 0.67 and for the validation period, it is 0.69. Overall agreement between the observed and simulated data is consistent for calibration and validation. For SWAT, in the calibration period, the PPU in the dry season is very large. Peaks are smoothly captured in the calibration and validation period. In many previous studies it is found that the Semi-distributed modeling approach is better in capturing extreme because of the higher resolution spatial data and the analysis at grid scale [21]. During post monsoon and winter months, the performance of the model is not satisfactory, but the overall results are up to the mark. Time series of calibrated and validated runoff data with the areal rainfall variability is given in Figure 7.

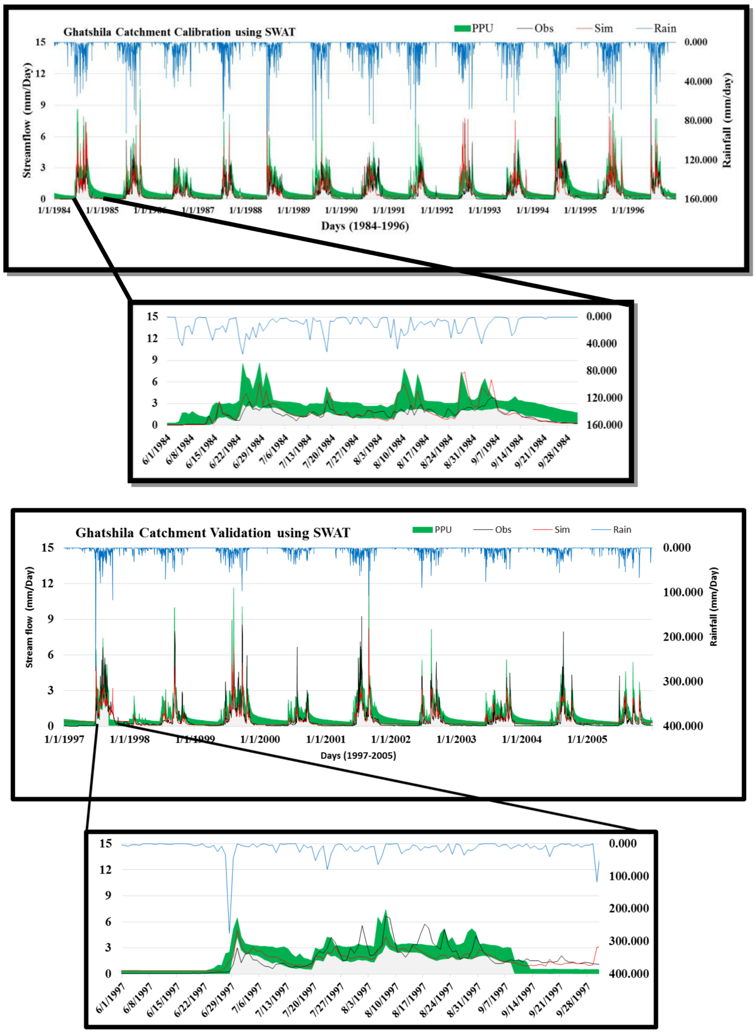

Figure 7. Comparison of simulated flow with observed flow of Ghatshila catchment. Comparison SWAT simulated flow vs. observed flow.

The flow duration curve developed for observed and simulated flow is depicted in Figure 8a,b. The FDC curve indicated that the PDM model was not able to estimate the extremely high flows of the hydrograph effectively. The PDM model over predicted the recession part of the hydrograph. SWAT simulated flow captured the extreme high flows, whereas low performance of recession part of the hydrograph.

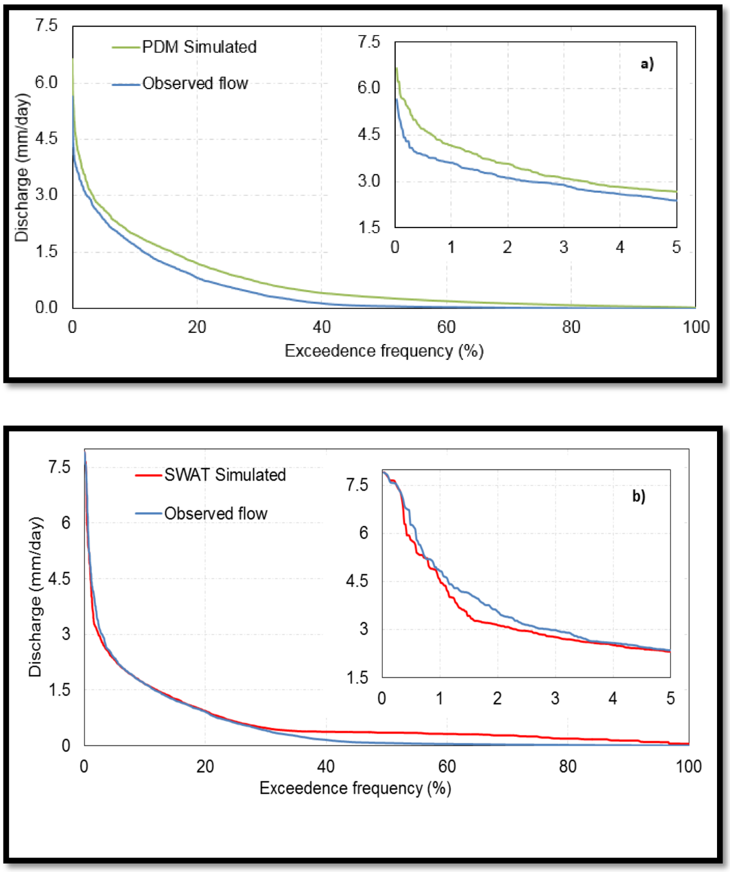

Figure 8. Flow duration curve of SWAT and PDM simulated flow compared with observed data. (**a**) Flow duration curve of PDM simulated vs. observed flow (mm/day). (**b**) Flow duration curve of SWAT simulated vs. observed flow (m^3/s). In both figures the top right corner indicates a zoomed in on the higher flows (the flow exceeded 5% of the time).

4.3. Output Uncertainity of SWAT and PDM Models

The GLUE approach is used in this study, followed by Monte Carlo simulations. The connotation of the variables that are used in present study is assessed by means of two hydrologic models. The sets of variable used in this study vary as per the choice of model structure and topography. Performance measure of PDM model that is considered for the uncertainty analysis is completely related to the regional condition of the catchment. Five parameters have been chosen, which shows the maximum storage capacity, fast and slow component, groundwater recharge time constant, and exponent of Pareto distribution for the complete hydrologic year analysis. Under the natural flow condition, NSE is a possible measure for the uncertainty estimation in the validation and calibration period. Threshold value in the current study for the GLUE performance is considered as 0.5, which means that the iterations with NSE greater than 0.5 are significant, or are otherwise non-significant. It begins with the analysis to ensure how parameters are corresponding to the threshold value. As per the suggestion, initially, values are chosen for the zero thresholds and then it is gradually increased. An appropriate NSE can be attained with excellent behavioral variables at this threshold limit. 10,000 iterations are performed for the all of the GLUE simulations. Whole monitoring period is examined in order to get good NSE. The complete performance shows 0.58 NSE during calibration and 0.62 in validation for the PDM model. Understanding of the spread of variables and sharp peak is the features to determine the sensitivity of parameters. The dotty plots representing the behavioral responses of all the five parameters of PDM are shown in Figure 9. The sensitivity of parameters can be assessed by understanding the cumulative parameter distributions and sharp peak (as in this case is represented by blue dots as shown in Figure 9). Here, Ks (slow flow component) have shown small variability in relation to the highest likelihood with clear peak resulting into highly sensitive parameter. In the Ghatshila catchment, Ks is the most sensitive parameter obtained followed by Cmax (Maximum Store Capacity), Kf (Fast flow component), and b (Exponent of pareto distribution). "g" (Ground water recharge time constant) falls under the category of least sensitive parameter shown in dotty plots (Figure 9). Parameter g is less capable of obtaining information due to the structural scantiness of the variable or may be during time of downturn. The land use and soil type of the area influences more than the model structure itself. 95 PPU (Percent prediction uncertainty) bands in the plot is having narrow region, the thickness of band is explained by the p factor, which indicates that the number of parameters lies in the band. However, the p factor for this study is 64% in calibration and 72% in validation. R factor defines the width of the 95PPU band. The band in Figure 6 has 70% and 78% of R factor for calibration and validation, respectively. In addition to parameter uncertainty, the structure of the model has large impact on the outputs. A noticeable difference is observed in the flow while changing the input datasets. Therefore, it can be summarized that uncertainty in the modelling is a combination of parameters uncertainty and structure uncertainty. In the plot this is noticeable that, in dry season, attention should be paid as there is as overestimation of prediction uncertainty.

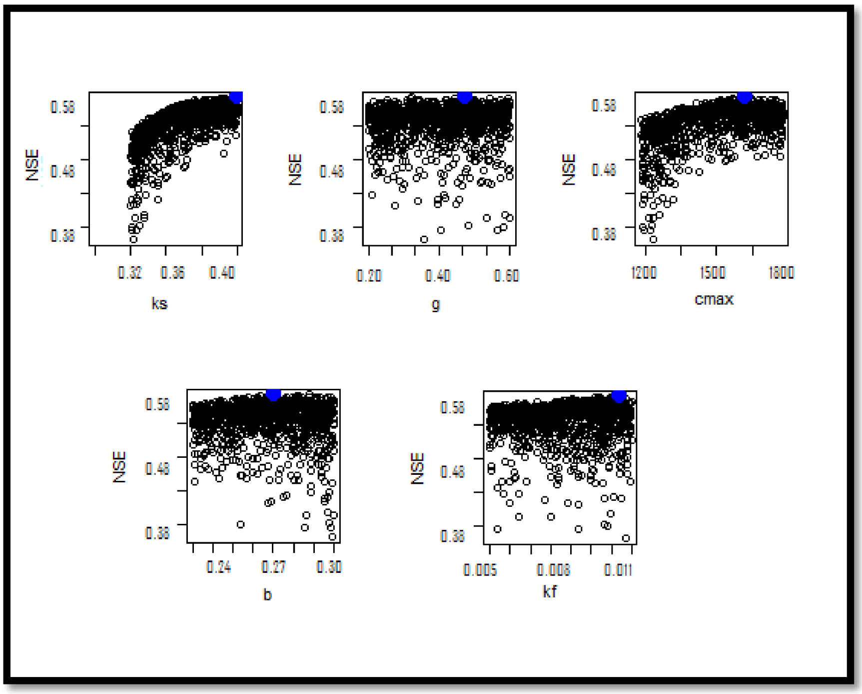

Figure 9. The dotty plot maps for stream flow simulations using PDM *x* axis: Sensitive Parameters Range, *y* axis: NSE.

For the SWAT model, by keeping in mind the widespread literature on key susceptible factors playing major role in governing the runoff processes, the five most influencing parameters are selected from literature [52,53]. Curve number, soil evaporation compensation factor, base flow alpha factor, groundwater delay time, and soil available water capacity are considered as sensitive parameters in the Ghatshila catchment. The dotty plots are showing that curve number is the most sensitive parameter (Figure 10). Functions of the model parameters with detail description are given in the [54]. Model interface has an acceptable range of parameters, which is adjusted as per the local condition. Initially it is the average of the parameter. A few significant parameters, such as evaporation coefficient and runoff curve number, play a key role in SWAT, others inputs of model are mostly process based and remaining are not physically defined. Initially in calibration process, the model's input parameters are adjusted based on the characteristic of soil, weather, and land use, as guided by the uncertainty analysis, to get constructive output from the model. Simulated and measured flow with varying rainfall is shown in the plot for better understanding. The trend and peaks of the observed flow is nicely followed by the simulated flow in given plot (Figure 7). Analysing from hydrograph, it can be summarized that reproduction of observations is quite reasonable, with coefficients of NSE being 0.69 for the calibration period and 0.67 for validation. Observed and simulated discharge show that the coefficients of the NSE behavioral parameters reveal high NSE in the calibration as compared to validation. When considering the uncertainty outcome, the P-factors in the calibration and validation period are 0.74 and 0.68, i.e., 74% of the total observed data lie under the 95PPU band during calibration period, whereas, in validation, it is 68%. The R factor thickness, during calibration and validation, is 76% and 72%, respectively. Figure 11 shows scatter plot of monthly observed flow against simulated flow for SWAT and PDM in the validation period. PDM under-predicted the flow as the model captured only 55% of the observed flow variability, whereas in SWAT, the model over-predicted the observed flow variability with 66% of capture.

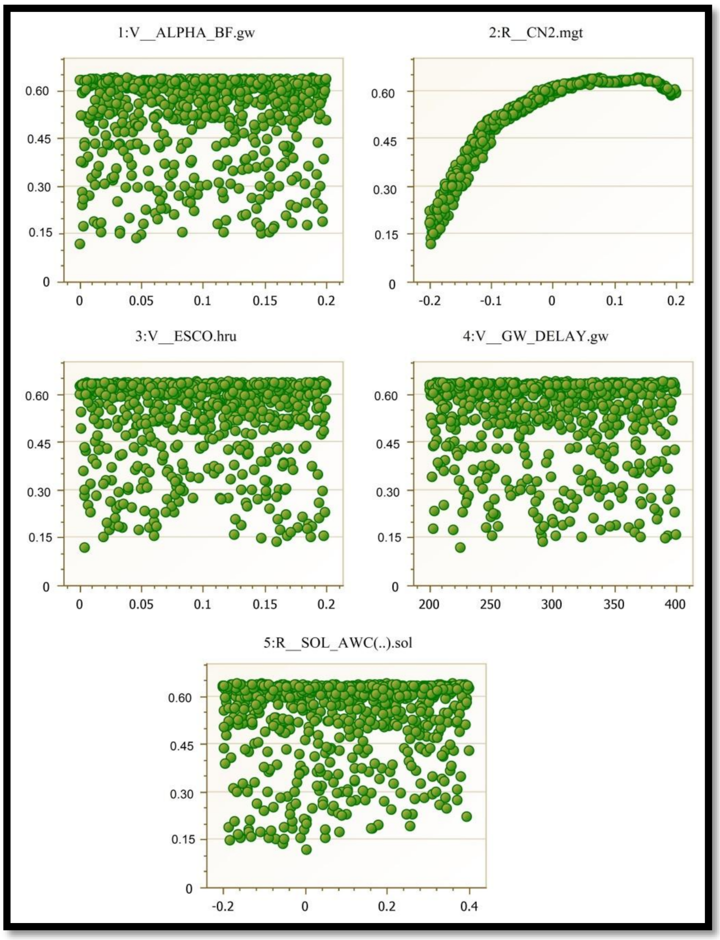

Figure 10. The dotty plot maps for stream flow simulations using PDM *x* axis: Sensitive Parameters Range, *y* axis: Nash Sutcliffe Efficiency (NSE).

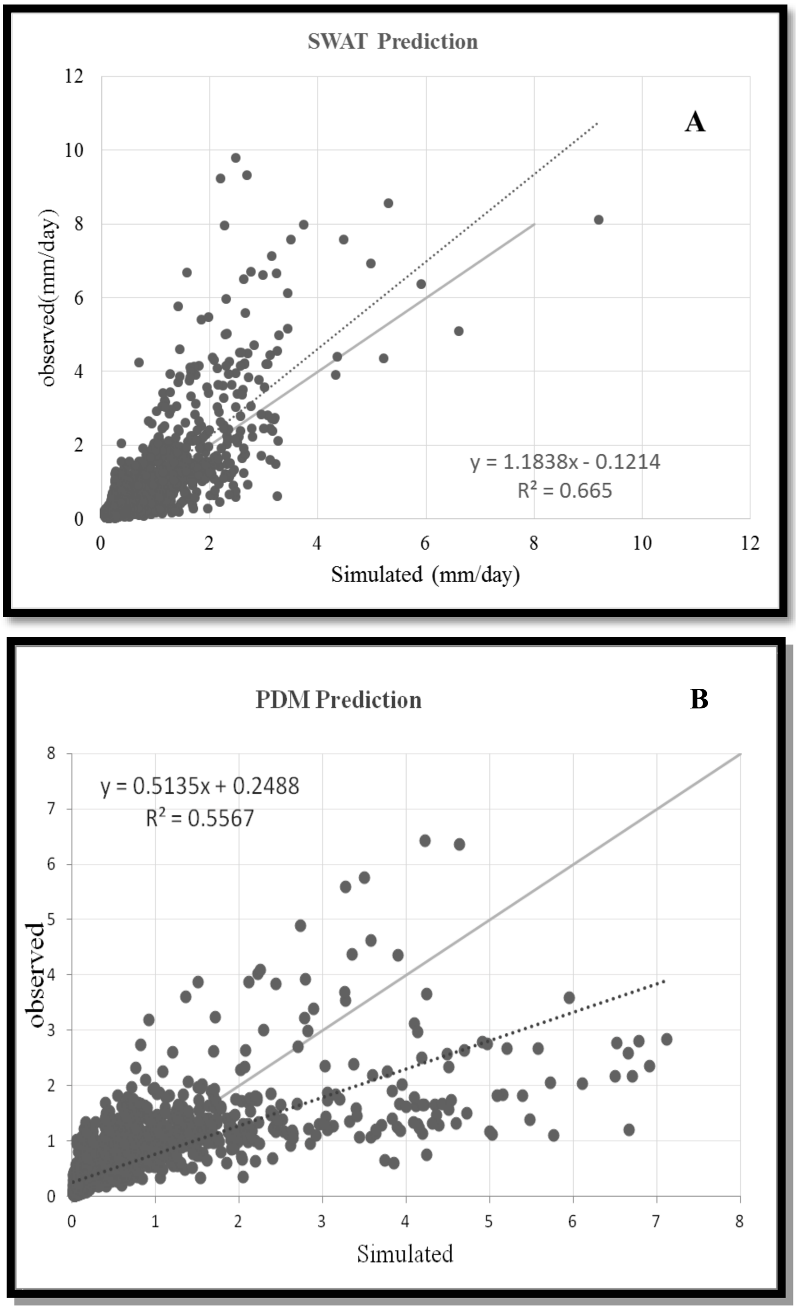

Figure 11. Scatter plots of monthly simulated verses observed flow (1997 to 2005). (**A**). SWAT simulated vs. observed flow and (**B**) PDM simulated vs. observed flow.

5. Conclusions

The understanding of model sensitivity towards the input parameters is the major foundation of model development, which helps to solve the problem that is associated with water resources management. This work accessed the possibility of two hydro models that have difference in depiction of processes that are associated with model, such as surface flow, base flow, and runoff generation, and are appraised for their capability to simulate stream flow with less uncertainty. SWAT (semi distributed) and PDM (lumped model) are applied over Ghatshila catchment for the period of twenty four years. The study is performed over Ghatshila catchment of Subarnarekha river basin in Eastern India. Parameter uncertainty is checked using the GLUE method in the SWAT and PDM model. We first analysed that preferred hydrological models are appropriate for replicating the hydrology of the catchment in tropical regime. Performance of both the models is satisfactory during the simulations of stream flow. Statistical valuation of the model expressed satisfactory values of NSE. The presented period of data showed adequate results for both of the models. The SWAT model illustrated quite a good performance in simulating the daily measured flow of the Ghatshila catchment with NSE coefficient 0.69. The model captured more than 60% of the observed flow of Ghatshila catchment in its 95 PPU plots. However, PDM showed average performance while simulating discharge. NSE value for PDM is 0.62. Nonetheless, minute dissimilarity existed: (1) SWAT is more precise than PDM in the simulation of stream flow, when a local region is having major impact of saturation excess runoff, and (2) SWAT simulated stream flow quite accurately than PDM during the time of peak and low runoff generation. The relative analysis suggested that in spite of the unlikeness in runoff processes over the Ghatshila, there is conformity in the overall performance of models. PDM, being a lumped model with only temperature, rainfall, and runoff as inputs, gave quite satisfactory results during normal flow generation. In India, the data availability in river basin is an issue that needs more attention for the implementation of management practices, and so a model with less input is always preferred.

Author Contributions: Aradhana Yaduvanshi developed methodology, model set up, calibration and validation of semi-distributed and lump models. Aradhana Yaduvanshi and Prashant Srivastava wrote the paper. Abeyou W. Worqlul and Anand Kr Sinha supervised the research.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Field, C.B. (Ed.) *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*; Cambridge University Press: Cambridge, UK, 2012.
2. Asian Development Bank. *Asian Water Development Outlook*; Asian Development Bank: Mandaluyong, Philippines, 2013.
3. National Disaster Managemnt Authority Government of India. *National Disaster Management Guidelines*; National Disaster Managemnt Authority Government of India: New Delhi, India, 2013.
4. Abbaspour, K.C.; van Genuchten, M.; Schulin, R.; Schla, E. A sequential uncertainty domain inverse procedure for estimating subsurface flow and transport parameters. *Water Resour. Res.* **1997**, *33*, 1879–1892. [CrossRef]
5. Beven, K.J.; Binley, A.M. The future of distributed models: Model calibration and uncertainty prediction. *Hydrol. Process.* **1992**, *6*, 297–298. [CrossRef]
6. Duan, Q.Y.; Sorooshian, S.; Gupta, V. Effective and efficient global optimization for conceptual rainfall–runoff models. *Water Resour. Res.* **1992**, *28*, 1015–1031. [CrossRef]
7. Shen, Z.Y.; Chen, L.; Chen, T. Analysis of parameter uncertainty in hydrological and sediment modeling using GLUE method: A case study of SWAT model applied to Three Gorges Reservoir Region, China. *Hydrol. Earth Syst. Sci.* **2012**, *16*, 121–132. [CrossRef]
8. Srivastava, P.K.; Han, D.; Rico Ramirez, M.; Islam, T. Sensitivity and Uncertainty analysis of Mesoscale model downscaled hydro-meteorological variables for discharge prediction. *Hydrol. Process.* **2014**, *28*, 4419–4432. [CrossRef]
9. Gupta, H.V.; Sorooshian, S.; Yapo, P.O. Towards improved calibration of hydrologic models: Multiple and non commensurable measures of information. *Water Resour. Res.* **1998**, *34*, 751–763. [CrossRef]
10. Vano, J.A.; Udall, B.; Cayan, D.R.; Overpeck, J.T.; Brekke, L.D.; Das, T.; Hartmann, H.C.; Hidalgo, H.G.; Hoerling, M.; McCabe, G.J.; et al. Understanding uncertainties in future Colorado River streamflow. *Bull. Am. Meteorol. Soc.* **2014**, *95*, 59–78. [CrossRef]
11. Zhang, X.; Srinivasan, R.; Zhao, K.; Liew, M.V. Evaluation of global optimization algorithms for parameter calibration of a computationally intensive hydrologic model. *Hydrol. Process.* **2009**, *23*, 430–441. [CrossRef]
12. Cho, J.; Bosch, D.; Lowrance, R.; Strickland, T.; Vellidis, G. Effect of spatial distribution of rainfall on temporal and spatial uncertainty of SWAT output. *Trans. ASAE* **2009**, *52*, 1545–1555. [CrossRef]
13. Li, Z.; Shao, Q.; Xu, Z.; Cai, X. Analysis of parameter uncertainty in semi-distributed hydrological models using bootstrap method: A case study of SWAT model applied to Yingluoxia watershed in northwest China. *J. Hydrol.* **2010**, *385*, 76–83. [CrossRef]

14. Sexton, A.; Shirmohammadi, A.; Sadeghi, A.; Montas, H. Impact of parameter uncertainty on critical SWAT output simulations. *Trans. ASABE* **2011**, *54*, 461–471. [CrossRef]
15. Moradkhani, H.; Sorooshian, S.; Gupta, H.V.; Houser, P.R. Dual state-parameter estimation of hydrological models using ensemble Kalman filter. *Adv. Water Resour.* **2004**, *28*, 135–147. [CrossRef]
16. Vrugt, J.A.; Gupta, H.V.; Bouten, W.; Sorooshian, S. A Shuffled Complex Evolution Metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters. *Water Resour. Res.* **2003**, *39*, 1201. [CrossRef]
17. Thiemann, M.; Trosset, M.; Gupta, H.; Sorooshian, S. Bayesian recursive parameter estimation for hydrologic models. *Water Resour. Res.* **2001**, *37*, 2521–2535. [CrossRef]
18. Arnold, J.G.; Srinivasan, R.; Muttiah, R.S.; Williams, J.R. Large area hydrologic modeling and assessment part I: Model development 1. *JAWRA J. Am. Water Resour. Assoc.* **1998**, *34*, 73–89. [CrossRef]
19. Neitsch, S.L.; Arnold, J.G.; Kiniry, J.R.; Williams, J.R. *Soil & Water Assessment Tool Theoretical Documentation—Verion 2009*; Texas A&M University System: College Station, TX, USA, 2011.
20. Nielsen, A.; Trolle, D.; Me, W.; Luo, L.; Han, B.P.; Liu, Z.; Olesen, J.E.; Jeppesen, E. Assessing ways to combat eutrophication in a Chinese drinking water reservoir using SWAT. *Mar. Freshw. Res.* **2013**, *64*, 475–492. [CrossRef]
21. Yaduvanshi, A.; Sharma, R.K.; Kar, S.C.; Sinha, A.K. Rainfall–runoff simulations of extreme monsoon rainfall events in a tropical river basin of India. *Nat. Hazards* **2018**, *90*, 843–861. [CrossRef]
22. Eckhardt, K.; Fohrer, N.; Frede, H.G. Automatic model calibration. *Hydrol. Process.* **2005**, *19*, 651–658. [CrossRef]
23. Moore, R.J.; Clarke, R.T. A distribution function approach to rainfall runoff modeling. *Water Resour. Res.* **1981**, *17*, 1367–1382. [CrossRef]
24. Hosking, J.R.M. L-moments: Analysis and estimation of distributions using linear combinations of order statistics. *J. R. Stat. Soc. Ser. B* **1990**, *52*, 105–124.
25. Yaduvanshi, A.; Ranade, A. Long-Term Rainfall Variability in the Eastern Gangetic Plain in Relation to Global Temperature Change. *Atmos. Ocean* **2017**, *55*, 94–109. [CrossRef]
26. Pai, D.S.; Sridhar, L.; Rajeevan, M.; Sreejith, O.P.; Satbhai, N.S.; Mukhopadhyay, B. *Development and Analysis of a New High Spatial Resolution (0.25° × 0.25°) Long Period (1901–2010) Daily Gridded Rainfall Data Set over India*; National Climate Centre Research Report No. 1/2013; India Meteorological Department: Pune, India, 2013.
27. Pai, D.S.; Sridhar, L.; Rajeevan, M.; Sreejith, O.P.; Satbhai, N.S.; Mukhopadhyay, B. Development of a new high spatial resolution (0.25° × 0.25°) long period (1901–2010) daily gridded rainfall data set over India and its comparison with existing data sets over the region. *Mausam* **2014**, *65*, 1–18.
28. Basistha, A.; Arya, D.; Goel, N. Spatial distribution of rainfall in Indian Himalayas—A case study of Uttarakhand region. *Water Resour. Manag.* **2008**, *22*, 1325–1346. [CrossRef]
29. Chen, F.-W.; Liu, C.-W. Estimation of the spatial rainfall distribution using inverse distance weighting (IDW) in the middle of Taiwan. *Paddy Water Environ.* **2012**, *10*, 209–222. [CrossRef]
30. Tomczak, M. Spatial interpolation and its uncertainty using automated anisotropic inverse distance weighting (IDW)-cross-validation/jackknife approach. *J. Geogr. Inf. Decis. Anal.* **1998**, *2*, 18–30.
31. Dile, Y.T.; Srinivasan, R. Evaluation of CFSR climate data for hydrologic prediction in data-scarce watersheds: an application in the Blue Nile River Basin. *J. Am. Water Resour. Assoc.* **2014**, *50*, 1226–1241. [CrossRef]
32. Cotter, A.S.; Chauby, I.; Costello, T.A.; Soerens, T.S.; Nelson, M.A. Water quality model output uncertainty as affected by spatial resolution of input data. *J. Am. Water Resour. Assoc.* **2003**, *39*, 977–986. [CrossRef]
33. Batjes, A.; Dijkshoorn, K.; Engelen, V.; Fischer, G.; Jones, A.; Montanarella, L.; Petri, M.; Prieler, S.; Teixeira, E.; Wiberg, D.; et al. *Harmonized World Soil Database*; IIASA: Luxemburg, WI, USA, 2009.
34. Narsimlu, B.; Gosain, A.K.; Chahar, B.R.; Singh, S.K.; Srivastava, P.K. SWAT model calibration and uncertainty analysis for streamflow prediction in the Kunwari river basin, India, using sequential uncertainty fitting. *Environ. Process.* **2015**, *2*, 79–95. [CrossRef]
35. Arnold, J.G.; Moriasi, D.N.; Gassman, P.W.; Abbaspour, K.C.; White, M.J.; Srinivasan, R.; Santhi, C.; Harmel, R.D.; van Griensven, A.; Van Liew, M.W.; et al. SWAT: Model use, calibration, and validation. *Trans. ASABE* **2012**, *55*, 1491–1508. [CrossRef]
36. Amatya, D.M.; Jha, M.K.; Williams, T.M.; Edwards, A.E.; Hitchcock, D.R. SWAT model prediction of phosphorus loading in a South Carolina karst watershed with a downstream embayment. *J. Environ. Prot.* **2013**, *4*, 75. [CrossRef]

37. Moore, R.J. The probability-distribted principle and runoff production at point and basin scales. *Hydrol. Sci. J.* **1985**, *30*, 273–297. [CrossRef]
38. Moore, R. The PDM rainfall-runoff model. *Hydrol. Earth Syst. Sci.* **2007**, *11*, 483–499. [CrossRef]
39. Srivastava, P.K.; Han, D.; Ramirez, M.R.; O'Neil, P.; Islam, T.; Gupta, M. Assessment of SMOS soil moisture retrieval parameters using tau–omega algorithms for soil moisture deficit estimation. *J. Hydrol.* **2014**, *519*, 574–587. [CrossRef]
40. Liu, J.; Han, D. Indices for calibration data selection of the rainfallrunoff model. *Water Resour. Res.* **2010**, *46*, W04512. [CrossRef]
41. Bell, V.A.; Moore, R.J. The sensitivity of catchment runoff models to rainfall data at different spatial scales. *Hydrol. Earth Syst. Sci. Discuss.* **2000**, *4*, 653–667. [CrossRef]
42. Nash, J.E.; Sutcliffe, J.V. River flow forecasting through conceptual models part I—A discussion of principles. *J. Hydrol.* **1970**, *10*, 282–290. [CrossRef]
43. Servat, E.; Dezetter, A. Selection of calibration objective fonctions in the context of rainfall-ronoff modelling in a Sudanese savannah area. *Hydrol. Sci. J.* **1991**, *36*, 307–330. [CrossRef]
44. Moriasi, D.N.; Arnold, J.G.; Van Liew, M.W.; Binger, R.L.; Harmel, R.D.; Veith, T.L. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Trans. ASABE* **2007**, *50*, 885–900. [CrossRef]
45. Blasone, R.-S.; Madsen, H.; Rosbjerg, D. Uncertainty assessment of integrated distributed hydrological models using GLUE with Markov chain Monte Carlo sampling. *J. Hydrol.* **2008**, *353*, 18–32. [CrossRef]
46. Croke, B.; Wagener, T.; Post, D.; Freer, J.; Littlewood, I. Evaluating the Information Content of Data for Uncertainty Reduction in Hydrological Modelling. In Proceedings of the 4th International Congress on Environmental Modelling and Software, Catalonia, Spain, 7–10 July 2008.
47. Abbaspour, K.C. *SWAT-CUP4: SWAT Calibration and Uncertainty Programs—A User Manual*; Swiss Federal Institute of Aquatic Science and Technology (Eawag): Dübendorf, Switzerland, 2011.
48. Bastola, S.; Murphy, C.; Sweeney, J. The role of hydrological modelling uncertainties in climate change impact assessments of Irish river catchments. *Adv. Water Resour.* **2011**, *34*, 562–576. [CrossRef]
49. Allen, R.G.; Pereira, L.S.; Raes, D.; Smith, M. *Crop Evapotranspiration—Guidelines for Computing Crop Water Requirements—FAO Irrigation and Drainage Paper 56*; FAO: Rome, Italy, 1998.
50. Daggupati, P.; Pai, N.; Ale, S.; Douglas-Mankin, K.R.; Zeckoski, R.; Jeong, J.; Parajuli, P.B.; Saraswa, D.; Youssef, M.A. Recommended calibration and validation strategy for hydrologic and water quality models. *Trans. ASABE* **2015**, *58*, 1705–1719.
51. Beven, K.; Smith, P.; Freer, J. Comment on 'Hydrological forecasting uncertainty assessment: Incoherence of the GLUE methodology' by Pietro Mantovan and Ezio Todini. *J. Hydrol.* **2007**, *338*, 315–318. [CrossRef]
52. Ghosh, M. Application of SWAT Model to Assess the Impact of Land Use Changes on Daily and Monthly Streamflow of Subarnarekha River Basin. Ph.D. Thesis, National Institute of Technology Rourkela, Odisha, India, 2016.
53. Kumar, P.; Joshi, V. Applications of Hydrological Model SWAT on the Upper Watershed of River Subarnarekha with Special Reference to Model Performance and its Evaluation. *J. Basic Appl. Eng. Res.* **2015**, *2*, 1128–1134.
54. Spruill, C.A.; Workman, S.R.; Taraba, J.L. Simulation of Daily and Monthly Stream Discharge from Small Watersheds Using the SWAT Model. *Trans. Am. Soc. Agric. Eng.* **2000**, *43*, 1431–1439. [CrossRef]