International Journal of Latest Engineering Research and Applications (IJLERA) ISSN: 2455-7137

Volume – 02, Issue – 04, April – 2017, PP – 05-13

Estimation of SWAT model output uncertainty

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Abstract: The problem of soil erosion exists in Chotki-Bherghi watershed in Eastern India and requires immediate attention. The watershed includes mostly agricultural land and rainfall is the major source of irrigation in the region. The objective of the study is to priorities the parameters and simulates the stream flow by using SWAT model and analysing the output uncertainty with SUFI-2 algorithm. The SWAT model was simulated for the period of 2004-2006 and validated for 2007-2008. R^2 and NSE values were found to be 0.88 and 0.82 for calibration, and 0.80 and 0.78 during validation period, respectfully. P-factor of 0.70 during calibration indicates that 70% of observed data were captured very well. The calibrated model can be used for further analysis of the effect of climate and land use change as well as other different management scenarios on stream flow and soil erosion.

Keywords: SWAT, SWAT-CUP, SUFI-2, Hydrological Modelling, Stream flow

1. Introduction

Watershed is a hydrologic unit which receives water as an end-product of the interaction of atmosphere, land surface and ocean systems. Seasonal variations in stream flow, coupled with increased and competing demands for water by a growing population, place considerable pressure upon efficient management of available water resources. Mathematical models applications in water resources design, management and decision support systems have been in consideration since early sixties. Having longer years of historical records for hydrological modelling often provide a better model representation which is common in the developed world because of good data collection techniques, whereas, developing country such as India is gearing up to manage hydrological database. Water quantity and quality problems are of great concern everywhere in the world and especially in watersheds located in sub-humid and subtropical climate regions of India that are dominated by monsoon climate conditions (Singh et al. 2013). Most of the rainfall occurs in 18–38 events of high magnitude which generate significant surface runoff during the monsoon period from June to October (Thapliyal 1997). These heavy rains cause floods and severe erosion of the top soil layer which ultimately leads to degradation of soil resources and pollution of surface water bodies that are used for irrigation, power generation, sanitation, recreation and other purposes. Extensive soil erosion and its associated problems have already deteriorated land and water resources of India. Mathematical models can be of great help in overcoming challenges of decision making. Many water quality computer simulation models have been developed to simulate complex hydrologic processes and determine surface flow from agricultural watershed (Maidment 1991). These models are classified as lumped or distributed parameter models. Hydrological modeling linked with geographical information systems helps water resources managers by allowing them to do their work more quickly and efficiently (Goodchild 1992). A model can provide the basis for developing policy intervention and for developing sound watershed management scheme that ensures environmental protection and economic sustainability. Non point source pollutant modeling is the most widely used and effective approach for soil conservation planning and design due to the difficulty in monitoring the influence of each specific agricultural and land management practice in a diverse ecosystem.

There are many process based hydrological models but in the present study, Soil Water Assessment Tool (SWAT) was selected. SWAT is recognized by the US Environmental Protection Agency (EPA) and has been incorporated into the EPA's BASINS (Better Assessment Science Integrating Point and Non-point Sources) (Di Luzio et al. 2002). The SWAT model was chosen because the model itself remains independent of GIS. The model interfaces with GIS facilitate pre and post processing such as watershed delineation, manipulation of the spatial and tabular data. Another reason for choosing SWAT is its ability to perform water quality modeling, which would be investigated in our further research work. Early origin of SWAT can be traced to previously developed models by United States Department of Agriculture. These models are the Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) model (Knisel 1980), the Groundwater Loading Effects on Agricultural Management Systems (GLEAMS) model (Leonard et al. 1987) and the Environmental Impact Policy Climate (EPIC) model (Izaurralde et al. 2006). The current SWAT model is a modified and improved version of the Simulator for Water Resources in Rural Basins (SWRRB) model (Arnold and Williams 1987) which was designed to simulate impacts of management on water and sediment movement. Many researchers across the world have calibrated and validated the SWAT model for various watersheds and proved the effectiveness of the SWAT model in simulating hydrological processes (Van Liew & Garbrecht 2003; Govender & Everson 2005; Cao et al. 2006; White & Chaubey 2005). The SWAT model offers the most comprehensive representation of hydrological processes that can be of great help to take decisions on the land use management alternatives impacting water quality.

Numerous research works have been carried out for simulating hydrological process by using SWAT model across the world (Frede et al.2002; Van Liew et al. 2003; Setegn et al. 2010). Srivastava et al. (2006) found that an artificial neural network (ANN) model was more accurate than SWAT for stream-flow simulations of a small watershed in southeast Pennsylvania. Abbaspour et al. (2007) used SWAT model to simulate all the processes affecting water quantity, sediment and nutrient loads in the Thur watershed in Switzerland.

SWAT (Soil and Water Assessment Tool) is a comprehensive, semi-distributed river basin model that requires a large number of input parameters, which complicates model parameterization and calibration. SWAT-CUP was recently developed and provided a decision-making framework that incorporates a semi-automated approach (SUFI2) using both manual and automated calibration and incorporating sensitivity and uncertainty analysis. Singh et al. (2013 a) applied SWAT for the measurement of the stream flow to the Tungabhadra catchment in India. They described a methodology for calibration and parameter uncertainty analysis for distributed model based on generalized likelihood measures. Performance of the SUFI-2 and GLUE techniques was evaluated using five objective functions, namely P-factor, R-factor, coefficient of determination R^2, Nash–Sutcliffe (NS) and coefficient of determination divided by coefficient of regression bR^2 calculated on daily and monthly time-steps. The obtained results showed that the observed and simulated discharge were not significantly different at the 95% level of confidence (95PPU). Singh et al. (2013 b) evaluated the process-based SSWAT model and the data-driven radial basis neural network (RBNN) model for simulating sediment load for the Nagwa watershed in Jharkhand, India, where soil erosion is a severe problem. Comparison of the results of the two models showed that the value of r factor (r = 0.41) in the RBNN model is less than that of SWAT model (r = 0.79), which means there is a wider prediction interval for the SWAT model results. More values of observed sediment yield were bracketed by the 95PPU in the RBNN model. Ridwansyah et al. (2014) examined the applicability of SWAT model for modeling mountainous catchments, focusing on Cisadane catchment Area in West Java Province, Indonesia. There are many more studies on simulation of hydrological processes by using SWAT model. The objective of the present study is to calibrate and validate the SWAT model for stream flow simulation for a relatively small Chotki-Berghi watershed in Damodar Basin in Jharkhand. Calibration of watershed model is a challenging task because of input data uncertainties, model structure and algorithms, parameterization and output ambiguity. Sources of model output uncertainty emanates from processes not accounted for during the model development and inaccuracy due to over-simplification of the processes considered in the model. Input uncertainty is normally due to inaccurate or spatial measurements of model input parameters such as elevation data, land-use data, rainfall data and temperature data. Several methodologies and techniques have been developed to estimate the parameters and assess prediction errors in the hydrological modelling.

Since these hydrological models are used to study the alternate agricultural management programs, construction of water harvesting structures and irrigation planning, it is important to calibrate the models with their prediction uncertainty before being considered for decision making. In the present study, we have calibrated and validated a process-based semi-distributed SWAT model for simulating the stream flow for Chotki-Berghi watershed in Eastern India. Estimating uncertainties in the outputs of the SWAT model, which originates from different sources, has been the main focus of this paper. SUFI-2 algorithm was used for calibration and uncertainty analysis in case of the SWAT model.

2. Materials and Methods

2.1 SWAT model description

The SWAT model is a physically based, semi-distributed parameter and watershed-scale model that works on a continuous daily time step. It simulates hydrological processes, sediment yield, nutrient loss, and pesticide losses into surface and groundwater and the effects of agricultural management practices on water in large watersheds (Arnold et al. 1993). The SWAT model incorporates the effects of weather, surface runoff, evapotranspiration, crop growth, irrigation, groundwater flow, nutrient loading, pesticide loading and water routing as well as the long-term effects of varying agricultural management practices (Neitsch et al. 2005)). In the hydrologic component, runoff is estimated separately for each sub-watershed or hydrological response unit (HRU) of the total watershed area and routed to obtain the total runoff for the watershed. Runoff volume is estimated from daily rainfall using modified SCS-CN (Curve Number Method) and Green–Ampt methods. Sediment yield is estimated from the Modified Universal Soil Loss Equation (MUSLE). The model requires spatial input of DEM, land use and soil maps as well as weather data such as daily rainfall and temperature. In the SWAT model, the watershed is divided into small sub-basins that are further subdivided into HRUs based on unique land cover, soil and topographic conditions. The hydrology component of the model determines a soil water balance at each time step based on daily data of rainfall, runoff, evapotranspiration, percolation, and base flow. Sediment yield from each HRU is computed with the Modified Universal Soil Loss Equation. The simulated variables are routed through the stream network to the watershed outlet.

SWAT input parameters are process based and must be held within a realistic range, which may represent watershed condition. The first step in the calibration and validation process in SWAT is the determination of the most sensitive parameters for a given watershed or sub-watershed. Sensitivity analysis is the process of determining the rate of change in model output with respect to changes in model inputs (parameters). It is necessary to identify key parameters and the parameter precision required for calibration. Calibration is an effort to better parameterize a model to a given set of local conditions, thereby reducing the prediction uncertainty. Model calibration is performed by carefully selecting values for model input parameters (within their respective uncertainty ranges) by comparing model predictions (output) for a given set of assumed conditions with observed data for the same conditions. The final step is validation for the component of interest. Model validation is the process of demonstrating that a given site-specific model is capable of making sufficiently accurate simulations, although “sufficiently accurate” can vary based on project goals. Validation involves running a model using parameters that were determined during the calibration process, and comparing the predictions to observed data not used in the calibration. In general, a good model calibration and validation should involve: (1) observed data that include wet, average, and dry years; (2) multiple evaluation techniques; (3) calibrating all constituents to be evaluated; and (4) verification that other important model outputs are reasonable. In general, graphical and statistical methods with some form of objective statistical criteria are used to determine when the model has been calibrated and validated (Abbaspour et al. 2007).

Latin Hypercube One–factor-At-a-Time (LH-OAT) method of the sensitivity analysis, implemented in SWAT, was used. The parameters affecting stream flow were tested such as base flow alpha factor, channel effective hydraulic conductivity (mm/hr), curve number, plant uptake compensation factor, soil evaporation compensation factor, groundwater "revap" coefficient, threshold water depth in the shallow aquifer for "revap" (mm), available water capacity (mm/mm), saturated hydraulic conductivity of soil (mm/hr) and surface runoff lag time (days). SWAT model was run for several simulations with different values of the input parameters to get an adequately calibrated model. All the values of the input parameters were chosen within the defined limit of the parameter and care was taken so that it could represent the true characteristics of the watershed. The monthly calibration and validation of the SWAT model for stream flow were performed after conducting sensitivity analysis. The model was calibrated manually for reasonable ranges and then automatic calibration was performed. The auto-calibration option provides a powerful, labor-saving tool that can be used to substantially reduce the time and uncertainty that often characterize manual calibrations (Van Liew et al. 2005). The sensitivity analysis and calibration currently available in the SWAT-CUP (SUFI 2 method) were performed to determine optimal parameter values for output variable for the watershed based upon observed data at a single gauge. Five years of meteorological and measured stream flow data were used for calibration and validation. The periods 2004- 2006 and 2006-2007 were used for calibration and validation, respectively. After each parameter adjustment, the simulated and measured stream flows were compared to judge the improvement in the model prediction. The performance of the model for simulating hydrologic variables was evaluated with the help of statistical tests such as coefficient of determination (R^2) and Nash-Sutcliffe model efficiency (NSE).

2.2 Uncertainty Analysis Procedures (SUFI-2)

The Sequential Uncertainty FItting ver. 2 (SUFI-2) algorithms follows a methodology to obtain posterior parameters from priors. In SUFI-2, parameter uncertainty accounts for all sources of uncertainties such as uncertainty in driving parameters, conceptual model, parameters, and measured data. The degree to which all uncertainties are accounted for is quantified by a measure referred to as the p-factor, which is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU). The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin 1599 hypercube sampling. As all forms of uncertainties are reflected in the measurements (e.g., discharge), the parameter uncertainties generating the 95PPU account for all uncertainties. Another measure quantifying the strength of a calibration/uncertainty analysis is the so called d-factor, which is the average thickness of the 95PPU band divided by the standard deviation of the measured data. SUFI-2, hence seeks to bracket most of the measured data with the smallest possible d-factor. SUFI-2 starts by assuming a large parameter uncertainty (within a physically meaningful range), so that the measured data initially falls within the 95PPU, then decreases this uncertainty in steps while monitoring the p-factor and the d-factor. In each step, previous parameter ranges are updated by calculating the sensitivity matrix (equivalent to Jacobian), and equivalent of a Hessian matrix, followed by the calculation of covariance matrix, 95% confidence intervals of the parameters, and correlation matrix. Parameters are then updated in such a way that the new ranges are always smaller than the previous ranges, and are centered around the best simulation (Abbaspour et al. 2007). The goodness of fit and the degree to which the calibrated model accounts for the uncertainties are assessed by the above two measures. An ideal situation would lead to a p-factor of about 100% and a d-factor near zero. When acceptable values of d-factor and p-factor are reached, then the parameter uncertainties are the desired parameter ranges. Further goodness of fit can be quantified by the R^2 and/or Nash Sutcliff coefficient (NSE) between the observations and the final best simulation. If initially a set of parameter ranges cannot be found where the 95PPU brackets most of the data, SUFI-2 can currently handle 6 different objective functions (two types of root mean square error, Chi square, Nash-Sutcliffe, R^2, and bR^2, where b is the slope of the regression line between measured and simulated variable).

2.3 Description of Study area and data preparation

The study area of Chotki-Bergi watershed is located in the Barakar Basin near Bargi Nala stream between $24^0$03’30” (N) to $24^0$8’00” (N) and $85^0$85’30” (E) to $86^0$41’0” (E) in the Hazaribagh and Girdih district of Jharkhand State. The Damodar Barakar catchment, with an area of 17.61 Mha, is the second most seriously eroded area in the world (El- swaify et al., 1982). The high intensity rainfall in the region makes it highly susceptible to soil erosion and the region faces serious challenges to control this problem which also causes high siltation at reservoirs in the catchment. It belongs to the Chhotanagpur plateau and experiences erratic and uneven rainfall. The area has experienced 16 serious floods between 1923 and 1943. After the 1943 floods, the Government of India prepared a unified river basin development plan, including provision for flood control, irrigation, power generation, navigation and soil conservation. This led to the construction of five dams namely Tilaya, Maithon, Panchet, Konar and Tenughat, by the Damodar Valley Corporation (DVC). Throughout the catchment, the general picture is that of long stretches of gently sloping uplands. About 24% of total area is well terraced, where paddy is grown. Of the rest, about 23% is under forest, 12.2% is cultivable wastelands, 155.73% is uplands; 13% current fallows and about 5.13% and 6.19% are uncultivable wastelands and habitations respectively. About 34.5% of the total area is subjected to severe sheet and gully erosion. Signs of erosion are conspicuous in cultivated fields. About 86% of the area has a slope range of 1-6 %. The soils are mainly of sandy loam type. The area experiences sub-humid, sub-tropical monsoon type of climate, characterized by hot summers (40^oC) and mild winters (4^0C). The total annual precipitation of 1206mm is distributed mainly between June and September, with about 20 rainy days per month during monsoon period. The main agricultural crops grown during the Kharif season (June to September) are rice and maize and during Rabi season (October to March) are wheat, gram and mustard. But much of the catchment is single cropped with paddy rice as the major crop and maize as the second most common crop. Agriculture is mostly rainfed (about 80% of the area). The remaining 20% receives irrigation mainly from wells. This together with the prevalence of conventional tillage or no tillage, low fertilizer/manure consumption and local crop varieties, is mainly responsible for low crop productivity in the area. The location of the study area is given in Fig. 1.

DEM at 90m resolution was obtained from the website of the CGIAR- Consortium for Spatial Information (CGIAR-CSI). It was used to delineate the watershed and to analyse the drainage patterns of the land surface terrain. Sub-basin parameters such as slope and the stream network characteristics such as slope, length and width were derived from the Demote Value Ranges from 290m to 470 m. Land use is one of the most important factors that affect surface erosion, runoff and evapotranspiration in watershed. The land use map of the study area was obtained from DVC. The figure shows that the majority part of the study area is agricultural land. SWAT model requires different soil textural and physicochemical properties such as soil texture, available water content, hydraulic conductivity, bulk density and organic carbon content for different layers of each soil type. Only two predominant types of soil is found in the region; sandy Soil and Sandy Loam. SWAT requires daily meteorological data that can either be read from measured data set or be generated by a weather generator model. The weather variables used in this study for driving the hydrological balance are daily precipitation, minimum and maximum air temperature for the period 2004-2008. Daily precipitation, maximum, minimum temperature and river discharge data were obtained from DVC, Hazaribagh.

3. Result and Discussions

3.1 Model Calibration and validation

The model parameterization was derived using the ArcGIS interface for SWAT2012 and initially the whole watershed was divided into 5 sub-basins based on DEM. Dominant land use and soil type, more than 5% within each sub-basin, were considered during HRUs generation. The major parameters affecting stream flow were modified to increase agreement between the simulated and observed monthly stream flow. During the calibration processes the curve number was adjusted within the range of ±10% from the curve number value for moisture condition II. These curve numbers were also adjusted for slopes greater than 4%. For simulation of the base flow in the watershed, the base-flow recession constant was adjusted to 0.05. It is directly proportional to groundwater flow response to changes in recharge. Groundwater delay time was adjusted to 35 days. This represents the lag between the times that water exits the soil profile and enters the shallow aquifer. This slightly reduced the overall stream flow and shifts the monthly timing. Groundwater revap coefficient that indicates the rate of transfer of water from the shallow aquifer to the root zone was adjusted to 0.02. The soil evaporation compensation factor was adjusted to 0.87. The calibrated values represent the response of land cover, land management practices, soil properties, and topographic condition of the watershed. The calibration process significantly reduced the difference between the measured and simulated stream flows. These parameters were adjusted to the level where they could represent the characteristics of the existing land use and topographic condition of the watershed. The final fitted values are listed in Table 1. The Hargreave method of evapotranspiration computation (Hargreaves & Samani 1982) and Muskingum method of routing were observed to give best performance during calibration of the SWAT model under sub-humid region.

The time series of the observed and simulated monthly stream flow for SWAT model is compared graphically in Fig. 2 and 3 for calibration and validation periods, respectively. It is observed from the figures that the simulated stream flow follows the trend of the observed stream flow. The magnitudes of the simulated stream flow are higher than that of observed stream flow for most of the years during high rainfall events. In case of normal rainfall events the prediction matches with the measured values. This may be due to inaccurate spatial input or ponding of water has not been well accounted. Majority of rainfall is converting into runoff. It is observed that the stream flow mainly depends on the nature of rainfall. Heavy and continuous rainfall in a short span of time produces more runoff. The major portion of the scatter plot is well distributed about the regression line indicating the model capability of estimating stream flow for well-distributed normal rainfall events. The R^2 value during the calibration period shows a good correlation between observed and simulated values of runoff. The R^2 and NSE values were found to be as 0.88 and 0.82, respectively (Fig. 2). The validation result of monthly stream flow is presented graphically in Fig.3. The SWAT model over predicted almost all the years of validation except in 2007 when rainfall received was highest. This year has seen more frequent and intense rainfall as compared to remaining years. Most of the compared points are evenly distributed around the regression line except a few events of lower magnitudes of stream flow. The R^2 and NSE values were found to be as 0.80 and 0.78, respectively during validation periods.

3.2 Uncertainty analysis

The results from the last iteration were used for uncertainty analysis. The original parameter ranges were set based on the available information and physical meaning of parameters. Each iteration could provide the best estimation of parameter sets and then suggest new ranges of the parameters for the next iteration based on the evaluation of simulation performance. To be noticed, some suggested ranges were outside the physically meaningful parameter ranges during the iterations, and manual adjustments have been made to those parameters to make them not exceed the maximum/minimum absolute range values. The suggested ranges were further adjusted to agree with the physical meaning and the requirements of the SWAT model. From Fig. 4 it is shown that the NSE values were approaching their greater values in the last iteration. The values of NSE of the best simulation for calibration and validation iterations are 0.82, 0.78, and the number of behavioral simulation are 500 in both iterations respectively, demonstrating the improvement of simulation during two iterations.

Due to certain unreasonable parameter ranges, NSE values of some simulation results are much lower than the threshold value. For the parameter CN2, there is an increasing trend within the range [−0.2, 0.2] for NSE values in the first iteration. Therefore, the parameter ranges were shifted to bigger values based on calculation results. Because the dots almost spread out in the whole space for the second iteration, the updated parameter range could not be the main reason to generate so many non-behavioural simulations. Nonetheless, for the parameter GWQ_MN.gw, when the parameter ranges shifted from [0, 1] to [0, 2], many non-behavioral simulations occurred in the range starting from 0.4 up to 1. The bigger values of the parameter within the range are, the lower NSE values were obtained. The dotplot of parameter GW_DELAY.gw is very similar to that of parameter GWQ_MN.gw, which can lead to the same conclusion: both dotplots of GWQ_MN.gw and

GW_DELAY.gw show that the inappropriate parameter ranges of these two parameters could be the main reasons to obtain a great number of dots below the threshold value in the second iteration. Therefore, the ranges for GWQ_MN.gw and GW_DELAY.gw have been adjusted to [0, 2] and [30, 450] in the next iteration. When ranges of all parameter have been updated and reduced, the NSE values are approaching their optimized values.

The simulated and observed results were compared and the associated hydrograph was generated for years 2004–2006.The remaining 2 years monthly runoff data (2007–2008) were used for validation, and the hydrograph of the validation results is shown in Fig.11. The 95PPU as represented a combined model prediction uncertainty including parameter uncertainty resulting from the non-uniqueness of effective model, conceptual model uncertainties, and input uncertainties (Abbaspour et al., 2007). The SUFI-2 combined effect of all uncertainties is described by the estimates of parameter uncertainties. The 95PPU derived by SUFI-2 on Chotki-Berghi gauge is presented on Figs. 4 and 5. Fig. 4 shows the hydrograph of the simulated runoff with 95PPU against the observed runoff by using SUFI-2 for the calibration period. The green band region is the 95% prediction interval for the parameter set of the best estimation, and it can cover most of the peak flow periods and dry periods. After two iteration, the best estimation parameter set achieve NSE = 0.82. The simulated runoff was compared with the observed runoff. The overall performance for the 2-year period of validation in terms of NSE, R^2, P-factor and R-factor are 0.78, 0.80, 0.70 and 0.62, respectively. As shown in Fig.4, the calibrated model always underestimated the runoff rate in summer and monsoon (from April to August).

From each figure, the simulated runoff matches with the trend of precipitation better than the observed runoff, especially from April to August. According to the local water resource report, it may be caused by some unknown human activities in the upper reaches of the watershed (irrigation channels or weir, dams). The underestimation of evaporation also could lead to relatively small amount of runoff during spring and summer each year. Other possible reasons for the mismatch could be the general issues of hydrological modeling, such as limited meteorological data, incomplete soil and land use database, inaccurate GIS information, etc. Those uncertainties can significantly affect the simulation results, and lead the relatively poor simulation performance. It is evident that the NSE values for monthly runoff produced by the model were greater than 0.75 for the calibration period. Similarly, the NSE values obtained for monthly runoff during the validation periods were also greater than 0.75. The NSE values for daily runoff acquired for the calibration and validation periods were between 0.82 and 0.80. Inspections of the monthly and daily hydrographs in this study show that the SWAT model was generally able to predict the pattern of runoff for both the calibration and validation periods. However, examination of monthly and daily hydrographs and scatter plots for Chotki-Berghi watershed revel that there is a large discrepancy between the observed and predicted runoff for many of the peak flows, particularly for daily runoff.

4. Conclusions

The SWAT model is successfully calibrated and validated for simulation of streamflow in the Chotki-Berghi watershed in Eastern India. Uncertainty analysis was made by SUFI-2 algorithm. The sensitivity analysis of the model, subbasin delineation and HRU definition thresholds showed that the flow is more sensitive to the HRU definition thresholds than subbasin discretization effect. A SUFI-2 algorithm is an effective method but it requires additional iterations as well as the need for the adjustment of the parameter ranges. P-factor of 0.70 during calibration indicates that 70% of observed data were captured very well. More than 45% of losses in the basin are through evapotranspiration. Despite data uncertainty, the SWAT model produced good simulation results for daily and monthly time steps. The calibrated model can be used for further analysis of the effect of climate and land use change as well as other different management scenarios on stream flow and of soil erosion.

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Table 1. SWAT flow sensitive parameters and fitted values after calibration using SUFI-2

Sl. No.	Sensitive Parameters	Parameters Description	Lower and Upper Bound	Final Fitted Value
1.	CN2	Curve Number	± 20%	0.16
2.	ALPHA_BF	Base flow alpha factor	0 –1	0.5
3.	GW_DELAY	Ground water Delay (days)	30 – 450	324
4.	GWQMN	Threshold depth of water	0 – 2	0.45

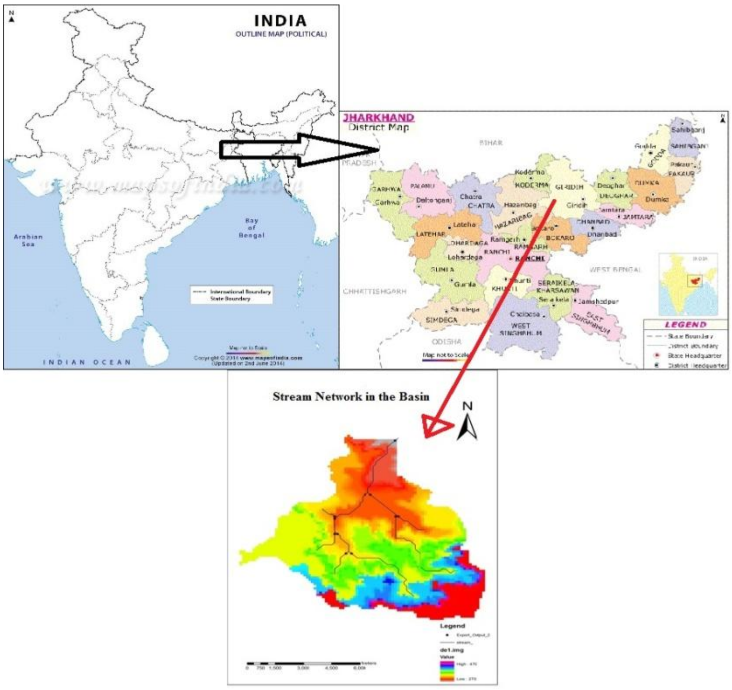

Fig. 1. Location of study area in the Girdih district of Jharkhand, India.

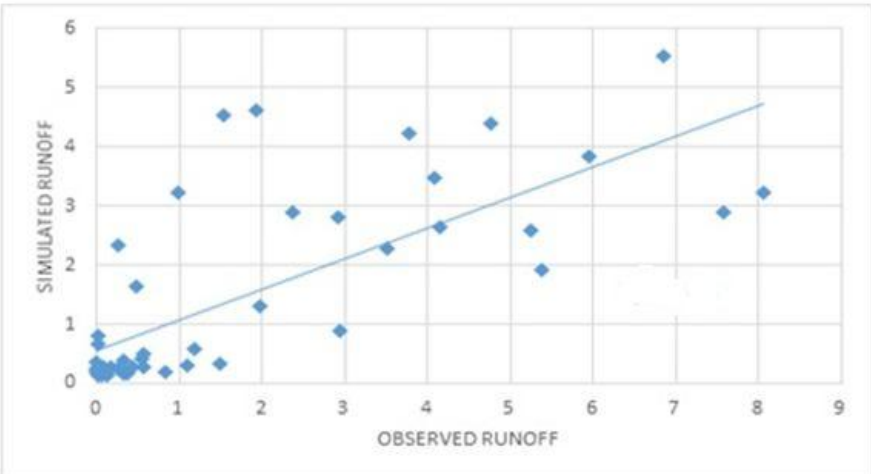

Fig. 2. The scatter plot of monthly simulated and observed runoff (m^3/s) for the calibration period, where R^2=0.88.

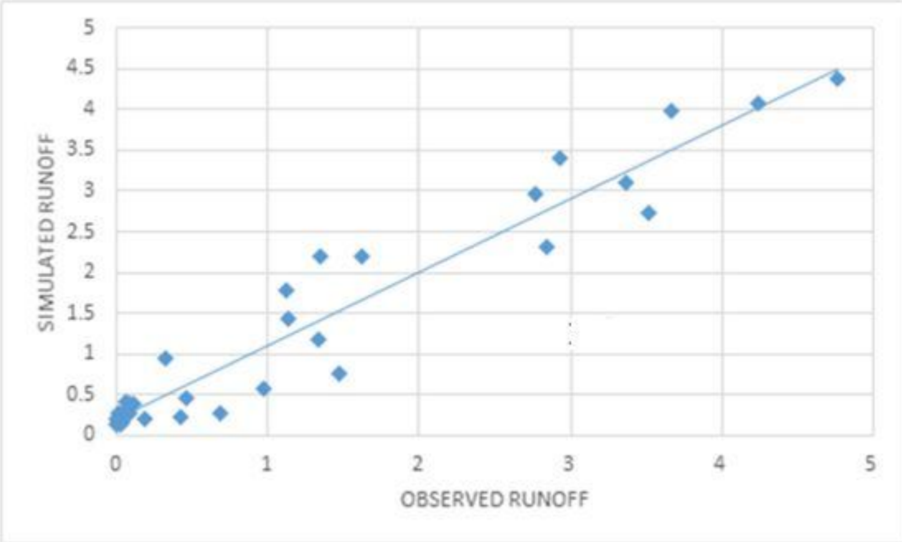

Fig. 3. The scatter plot of monthly simulated and observed runoff (m^3/s) for the validation period, where R^2=0.80.

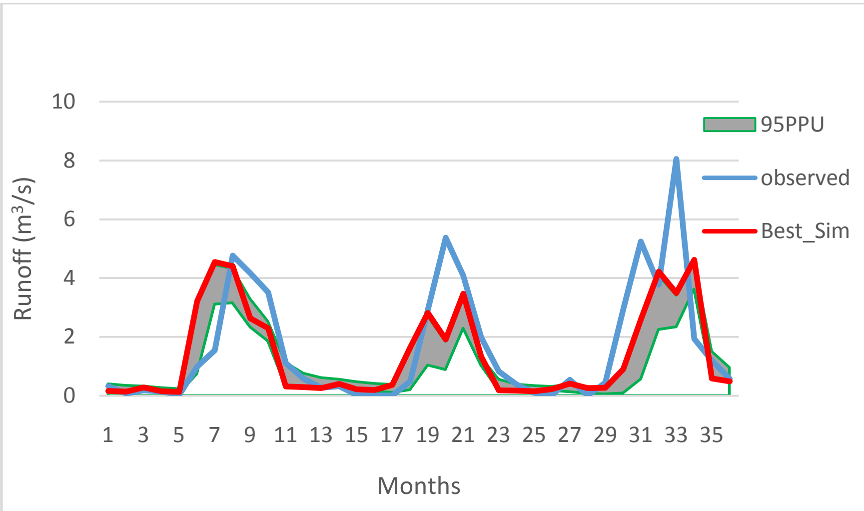

Fig. 4. The best-simulated runoff with 95PPU for calibration by using the SUFI-2 method

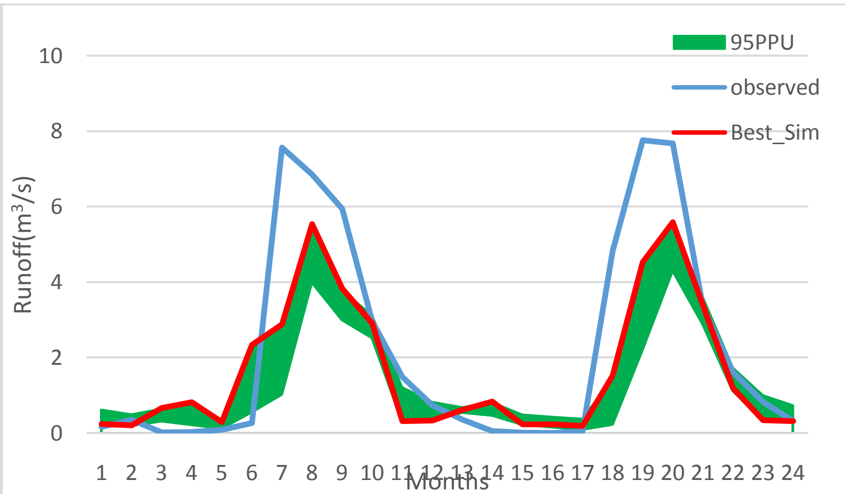

Fig. 5. The best-simulated runoff with 95PPU against observed runoff for validation by using theSUFI-2 method.