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Estimation of sediment yield by using Soil and Water Assessment Tool for an agricultural watershed in Eastern India

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ABSTRACT

Soil erosion due to accelerating runoff in various land cover types poses a serious threat to the long term sustainability of the fragile Chotki Berghi watershed in Jharkhand. Estimation of sediment yield is needed to study the reservoir sedimentation, river morphology and taking up any soil and water conservation measures. The study was aimed at delimitation of the zones of high runoff and consequently soil erosion in the agricultural dominated Chotki Berghi watershed. Identification of such zones could help in the implementation of better land management practices. The Soil and Water Assessment Tool (SWAT) was applied to simulate stream flow and sediment yield. The model was calibrated for the period 2004–2006 and validated for 2007–2008. Nine highly sensitive parameters were identified of which base flow alpha factor was the most sensitive one. The results were satisfactory for the gauging station with coefficient of determination, R^2 = 0.75 and Nash–Sutcliffe model efficiency coefficient, NSE = 0.78 for calibration and R^2 = 0.62 and NSE = 0.68 for validation period. Sub-basin 5 contributed highest sediment load to the outlet and thus need immediate attention. The SWAT model could be effectively used to predict stream flow and sediment yield in order to effectively design irrigation system and water resources planning and management at large scale.

1. INTRODUCTION

Erosion is a serious problem for productive agricultural land and sustainable development. Effective control and management of the sediment yield must be an integral part of any soil conservation and management system to improve water and soil quality. A comprehensive understanding of hydrological process in the watershed is the pre-requisite for successful water management and environmental protection. Mathematical models are nowadays very helpful and used to expedite the process of decision making. Several water quality computer simulation models have been developed and applied to simulate complex hydrological processes within the agricultural watershed. These models are classified as lumped or distributed parameter models. A model provides the basis for developing water allocation policy and efficient watershed management plan that ensures environmental protection, sustainable development 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 (Goodchild, 1992).

There are numerous hydrological models but in the present study, SWAT model was chosen. 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). Several hydrologic components, currently in SWAT, have been developed and validated at smaller scales within the EPIC (Izaurralde *et al.,* 2006), GLEAMS (Leonard *et al.,* 1987) and SWRRB (Arnold and Williams, 1987) models. SWAT model has been chosen in this study due to its simplicity in handling spatial inputs and independency of GIS platform after certain operations. 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). 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 (White and Chaubey, 2005; Cao *et al.,* 2006; Singh *et al.,* 2013; Chandra *et al.,* 2014). Few findings of application of SWAT model are discussed in next section.

Jain *et al.* (2010) estimated runoff and sediment yield from an area of Suni to Kasol, an intermediate watershed of Satluj river, located in Western Himalayan region of India by using SWAT model. They determined the coefficient of determination for the daily and monthly runoff as 0.53 and 0.90, respectively for the calibration period, and 0.33 and 0.62 respectively for the validation period. Chandra *et al.* (2014) calibrated and validated the SWAT model for Upper Tapi catchment in India and found Nash-Sutcliffe Efficiency (NSE) and RSR for sediment yield 0.85 and 0.36, respectively. Tyagi *et al.* (2014) concluded that SWAT is capable of estimating the discharge and sediment yield from Himalayan forested watersheds and suggested it to be a useful tool for assessing hydrology and sediment yield response of the watersheds in the region. Wu and Chen (2015) compared the Sequential Uncertainty Fitting Algorithm (SUFI-2), Generalized Likelihood Uncertainty Estimation (GLUE) method and the Parameter Solution (ParaSol) method within the SWAT modeling frame-work. They observed that SUFI-2 method provided more reasonable results than the other two methods. Mohammad *et al.* (2014) simulated the yearly surface runoff and sediment load for the main three valleys on the right bank of Mosul Dam Reservoir. The simulation considered for the twenty one year begins from the dam operation in 1988 to 2008. They opined that in order to minimize the sediment load entering the reservoir, a check dams is to be constructed in suitable sites especially for valley one. SWAT studies in India include identification of critical or priority areas for soil and water management in a watershed (Tripathi *et al.,* 2003; Kaur *et al.,* 2004; Singh *et al.,* 2013, 2014; Chandra *et al.,* 2014). Though SWAT application in India has increased in the past 10 years but it needs proper validation for more watersheds so that SWAT model application for the planning purpose can be emphasized. Main objective of the study is to simulate the sediment yield in a watershed of Chotki-Berghi by using SWAT model and identify the high sediment producing zone of the watershed for taking up any remedial measures. The uncertainty analysis of the model output was carried out by using SUFI-2 algorithm.

2. MATERIALS AND METHODS

SWAT Model Description

The SWAT model was developed to evaluate the effects of alternative management practices on water resources and nonpoint-source pollution in large river basins. The model is process based, computationally efficient, and capable of continuous simulation over long time periods (Arnold *et al.,* 1993). Major model components include weather, hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management. In SWAT, a watershed is divided into multiple sub watersheds, which are then further subdivided into Hydrologic Response Units (HRUs) that consist of homogeneous land use, management, topographical, and soil characteristics. The HRUs are represented as a percentage of the sub watershed area and may not be contiguous or spatially identified within a SWAT simulation. For climate, SWAT uses the data from the weather station nearest to the centroid of each sub-basin. Calculated flow, sediment yield, and nutrient loading obtained for each sub-basin are then routed through the river system. Channel routing is simulated using the variable storage or Muskingum method (Arnold *et al.,* 1998). The model computes evaporation from soils and plants separately. Potential evapotranspiration can be modeled with the Penman-Monteith, Priestley-Taylor or Hargreaves methods, depending on data availability. More detailed descriptions of the model can be found in Arnold *et al.* (1998). Simulation of hydrology of a watershed is done in two separate components. One is the land phase of the hydrologic cycle that controls the water movement in the land and determines the water, sediment, nutrient and pesticide amount that will be loaded into the main stream. Hydrological components simulated in land phase of the hydrological cycle are canopy storage, infiltration, redistribution, and evapotranspiration, lateral subsurface flow, surface runoff, ponds and tributary channels return flow. The second component is routing phase of the hydrological cycle in which the water is routed in the channels network of the watershed, carrying the sediment, nutrients and pesticides to the outlet. In the land phase of the hydrologic cycle, SWAT simulates the hydrological cycle based on the water balance equation:

$$SW_t = SW_0 + \sum(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \quad ...(1)$$

Where, SW_t is the final soil water content (mm), SW_0 is the initial soil water content for day I (mm), t is in days, R_{day} is the day precipitation (mm), Q_{surf} is the surface runoff (mm), E_a is the evapotranspiration (mm), W_{seep} is the seepage from the bottom soil layer (mm) and Q_{gw} is the groundwater flow on day i (mm). Once the runoff part is finished, soil erosion is assessed by Modified Universal Soil Loss Equation (Wischmeier and Smith, 1978). Sediment generation from each HRU is calculated by the following equation:

$$Sed = (Q_{surf}.q_{peak}.area_{hru})^{0.56} K_{USLE}\, C_{USLE} P_{USLE} LS_{USLE} CFRG \; ...(1)$$

Where, Sed is the sediment generation (metric ton), Q_{surf} is the surface runoff (mm), q_{peak} is the peak runoff rate (m^3/s), $area_{hru}$ is the HRU area (ha), K_{USLE} is the USLE soil erodibility factor, C_{USLE} is the USLE cover and management factor, P_{USLE} is the USLE support practice factor, LS_{USLE} is the USLE topographic factor, and $CFRG$ is the coarse fragment factor. Sediment generation is calculated separately for each HRU and then summed to determine total sub-basin fluxes (Arnold *et al.,* 1998).

Sequential Uncertainty Fitting (SUFI)

Choosing the right parameter is an important step in model calibration and should be based on the sound understanding of the hydrological processes and variability in soil, land use, slope, and location as defined by the sub-basin number. In SUFI-2, uncertainty is defined as the discrepancy between measured and simulated variables. It combines calibration and uncertainty analysis to find parameter uncertainties that result in prediction uncertainties bracketing most of the measured data, while producing the smallest possible prediction uncertainty band. Hence, these parameter uncertainties reflect all sources of uncertainties, *i.e.* conceptual model, forcing inputs, and parameter (Abbaspour *et al.,* 2007). In SUFI-2, uncertainty of input parameters is depicted as a uniform distribution, while model output uncertainty is quantified at the 95% prediction uncertainty (95PPU). The cumulative distribution of an output variable is obtained through Latin hypercube sampling. The SUFI-2 model starts by assuming a large parameter uncertainty (within a physically meaningful range), so that the measured data initially fall within the 95PPU, then decreases this uncertainty in steps while monitoring the P factor and the D factor. The P factor is the percentage of data bracketed in the 95% prediction uncertainty (95 PPU) calculated at 2.5 and 97.5% intervals of the simulated variables. This factor indicates how much of the uncertainty we are capturing. The D factor, on the other hand, captures the goodness of calibration, as a smaller 95PPU band indicates a better calibration result. In each iteration, previous parameter ranges are updated by calculating the sensitivity matrix, and the equivalent of a Hessian matrix (Neudecker and Magnus, 1988), followed by the calculation of a covariance matrix, 95% confidence intervals of the parameters, and a correlation matrix. Parameters are then updated in such a way that the new ranges are always smaller than the previous ranges, and are centered on the best simulation (Abbaspour *et al.,* 2007). Because this analytical approach considers a band of model solutions (95PPU) instead of a best fit solution, the goodness of fit and the degree to which the calibrated model accounts for the uncertainties are assessed by the above two measures instead of the usual R^2 or Nash-Sutcliffe coefficient (Nash and Sutcliffe, 1970), which only compare two inputs. An ideal situation would lead to a P factor approaching 100% and a D factor approaching zero.

Study Area

Chhotki-Berghi watershed is located under Damodar-Barakar Basin in the district of Giridih, Jharkhand, India. The study area is situated between 24°03'30" (N) - 24°08'00" (N) latitude and 85°59'30" (E) - 86°04"10" (E) longitude. Maximum rainfall occurs from July to September accounting for more than 1,400 mm spread across the whole region. This watershed has three types of topographical areas *viz.,* central plateau having moderate elevation, lower plateau having lower elevation and the trough basin of Damodar. The lower plateau area has relatively rough terrain having an elevation of 390 m. In the North and North West there is a table land having an elevation of 250 m, where steep scarp is found. Location of study area is shown in Fig. 1. The mean temperature ranges from 7^{0}C in winters to 37 ^{0}C in summer. There are two main streams in the study area namely, Chotki nala (stream) and Berghi nala. These two streams serve as the main source of water for irrigation and domestic purposes in Chotki-Berghi region. Agriculture is the mainstay of more than 75% people in the study area and major food crops are rice, wheat, potato, seasonal vegetable *etc.*

SWAT model input and implementation

SWAT model is data driven, which requires several data ranging from topography, land use, soil, climate, *etc.* Digital Elevation Model (DEM) is one of the main inputs of SWAT Model (Fig. 2). For preparation of DEM, the vector map with contour lines (from topographic maps) was converted to raster format (Grid) before the surface was interpolated. Land use/land cover map was prepared using remote sensing data of Landsat ETM+ (Fig. 3). In the present study, the unsupervised classification method was used for preparation

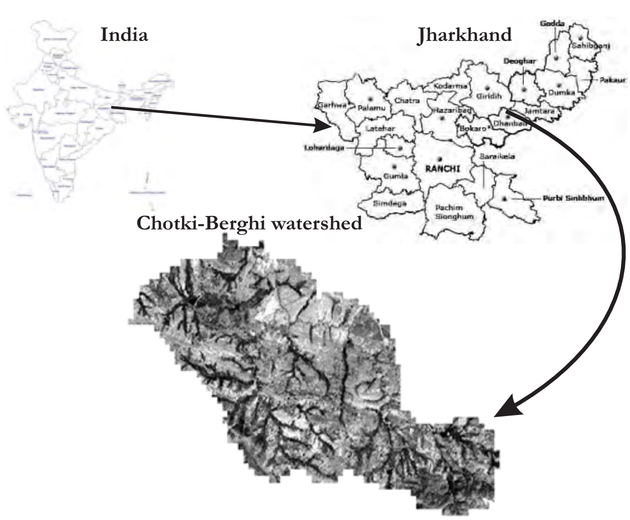

Fig. 1. Location of the study area

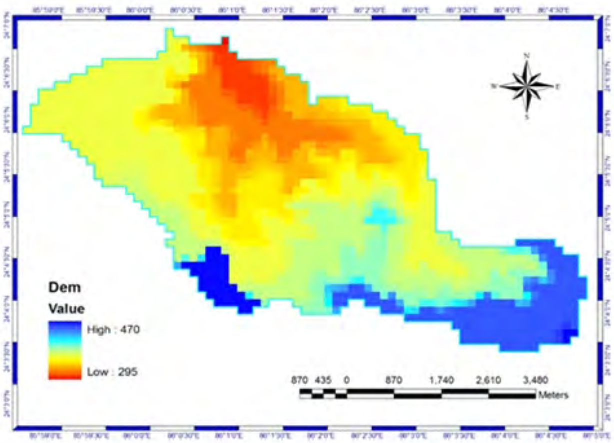

Fig. 2. DEM of study area

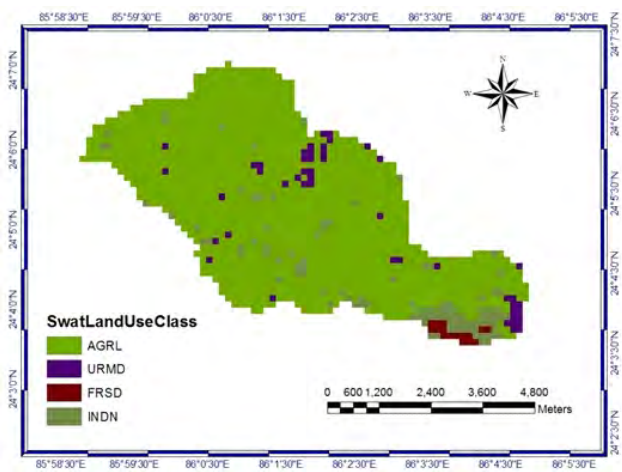

Fig. 3. Land use and land cover of the study area

of the land use map. The soil map was collected from Damodar Valley Corporation (DVC), Hazaribagh. SWAT requires daily values of precipitation, maximum and minimum temperature, solar radiation, relative humidity and wind speed. Daily rainfall and temperature data for the period 2004-2008 were collected by DVC, Hazaribagh.

Geographic information systems data for the SWAT model were preprocessed by two separate functions watershed delineation and determination of hydrologic response units (HRUs). SWAT uses DEM to automatically delineate the watershed into several hydrologically connected sub-watersheds. The initial stream network and sub-basin outlets were defined based on drainage area threshold approach. The threshold area defines the minimum drainage area required to form the origin of a stream. The interface lists a minimum, maximum and suggested threshold area. The smaller the threshold area, the more detailed the drainage network delineated by the interface but the slower the processing time and the larger memory space required. In this study, threshold drainage area has been defined using the threshold value. HRUs are lumped land areas within the sub-basin comprise unique land cover, soil, slope and management combinations. The runoff is estimated separately for each HRU and routed to obtain the total runoff for the watershed. This increases the accuracy in flow prediction and provides a much better physical description of the water balance. The model was calibrated for simulating the sediment yield for the periods 2004-2006 and validated for the periods 2007-2008.

3. RESULTS AND DISCUSSION

The model delineated watershed area is 32 km^2 which was much closer to actual area (33.04 km^2) provided by DVC Hazaribagh. Whole watershed was divided into five sub-basins and 23 HRU's. The area coverage of each land use type is presented in Table 1. Maximum area of the watershed consists of agricultural land, which accounts for 89% of the watershed area. The dominant soil type in the watersheds is sandy loam soil. It was analyzed that 28% of the area in Chotki-Berghi had a slope less than 1%. Results of sensitivity analysis with observed data showed that most sensitive parameters are base flow alpha factor (ALPHA_BF), Curve number (CN_2), GW_DELAY, the delay time, which cannot be directly measured and a threshold depth of water in the shallow aquifer to allow for water flow (GW_QMN). The flow of underground water into the river can occur if the water depth in the shallow aquifer is equal or greater than the value GW_QMN. It is a significant parameter in a watershed that represent saturated zone which are located not far from the surface of the soil or vegetation which have roots deep enough. GW_REVAP value approaching 0 indicates that the movement of water from the shallow aquifer to the root zone is limited. GW_REVAP value close to 1 indicates that the movement of water from the shallow aquifer to the root zone close to the average potential evapotranspiration. The obtained value after the calibration was 0.01 which indicates the limited movement of water from the aquifer to the root. Soil evaporation compensation factor (ESCO), available water capacity of the soil layer (SOL_AWC), saturated hydraulic conductivity (SOL_K) and the soil depth (SOL_Z) were found the sensitive parameters which affected sediment yield loss of the watershed (Table 2).

Model Calibration and Uncertainty Analysis

The SUFI-2 method was used for calibration and 500 simulation runs were performed. Both NSE and R^2 of the

Table: 1
Land use and land cover of the study area

Watershed	SWAT Land use codes	Land Use	Area km^2	% Area
Chotki-Berghi	AGRL	Agricultural Land-Generic	29.14	88.95
	RNGE	Range grass	2.25	6.87
	FRSE	Forest-Evergreen	0.34	1.05
	URML	Residential	1.02	3.14

Table: 2
Sensitive parameter ranking and final auto-calibration result

Rank	Aggregate Parameters	Min. Value	Max. Value	Fitted Value
1	CN_2	-0.2	0.2	0.160
2	ALPHA_BF	0.0	1.0	0.500
3	GW_DELAY	30.00	450.00	324.000
4	GW_QMN	0.00	2.00	0.89
5	GW_REVAP	0.00	0.2	0.09
6	ESCO	0.10	1.00	0.40
7	SOL_AWC	0.2	0.4	0.25
8	SOL_K	0.00	0.80	0.56
9	SOL_Z	300	500	450
10	RCHRG_DP	0	1.0	0.26

best simulation were selected to evaluate the simulation performance to improve the reliability of the analysis in this study. The scatter plots of simulated and observed runoff during the calibration and validation period are shown in Fig. 4 and Fig. 5, respectively. The NSE and R^2 of the best simulation were found to be as 0.78 and 0.75 for the calibration period, and 0.68 and 0.62 for the validation period, respectively. After the acceptable simulation was obtained, uncertainly analysis can be further conducted. It is observed from Fig. 5 that most of the lower values are closer to the line of best fit. Higher values of runoff have not been captured well by the model. The reason may be attributed to inconsistency in the input data or lack of proper base flow simulation.

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. Fig. 6 shows the dot plots of NSE against four selected parameters in the iterations (with 500 runs each). Because other parameters are not quite sensitive to the simulation results (no special trends or patterns for dotplots), the dotplots of four parameters (CN_2, ALPHA_BF, GW_DELAY and GW_QMN) with special and typical trends for NSE against parameter ranges were shown in Fig. 6. (a-d) as examples of visualization of the optimization direction, respectively. From Fig. 6, 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 0.78 and 0.68.

Due to certain unreasonable parameter ranges, NSE values of some simulation results are much lower than the threshold value. For the parameter CN_2, 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,

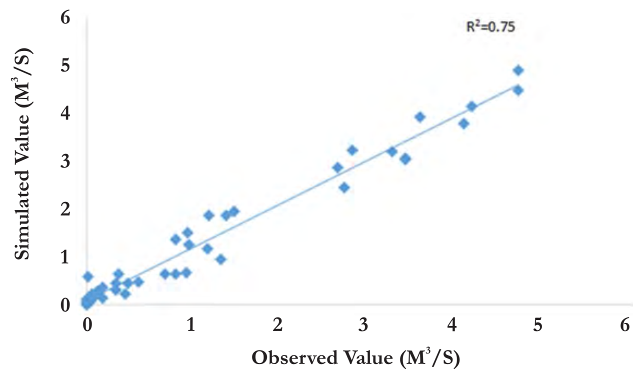

Fig. 4. Scatter plot of monthly simulated and observed surface runoff for the calibration period

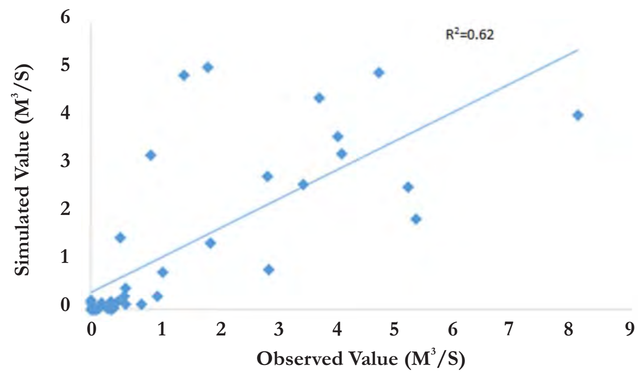

Fig. 5. Scatter plot of monthly simulated and observed surface runoff for the validation period

the updated parameter range could not be the main reason to generate so many non-behavioral simulations. Nonetheless, for the parameter GW_QMN, when the parameter ranges shifted from [0, 2] to [0,1], 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. It demonstrates that the parameter in this range can cause more non-behavioral simulations when the parameter values are close to 0.89. The dot plots of parameter GW_DELAY is very similar to that of parameter GW_QMN, which can lead to the same conclusion: both dot plots of GW_QMN and GW_DELAY 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 GW_QMN and GW_DELAY have been adjusted to [0,450] and [50, 150] in the next iteration, respectively. 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 curve was generated for years 2004-2006. The remaining 2 years monthly runoff data (2007-2008) were used for validation, and the curve of the validation results is shown in Fig. 7. The 95PPU represented a combined model prediction uncertainty including parameter uncertainty resulting from the non-uniqueness of effective model,

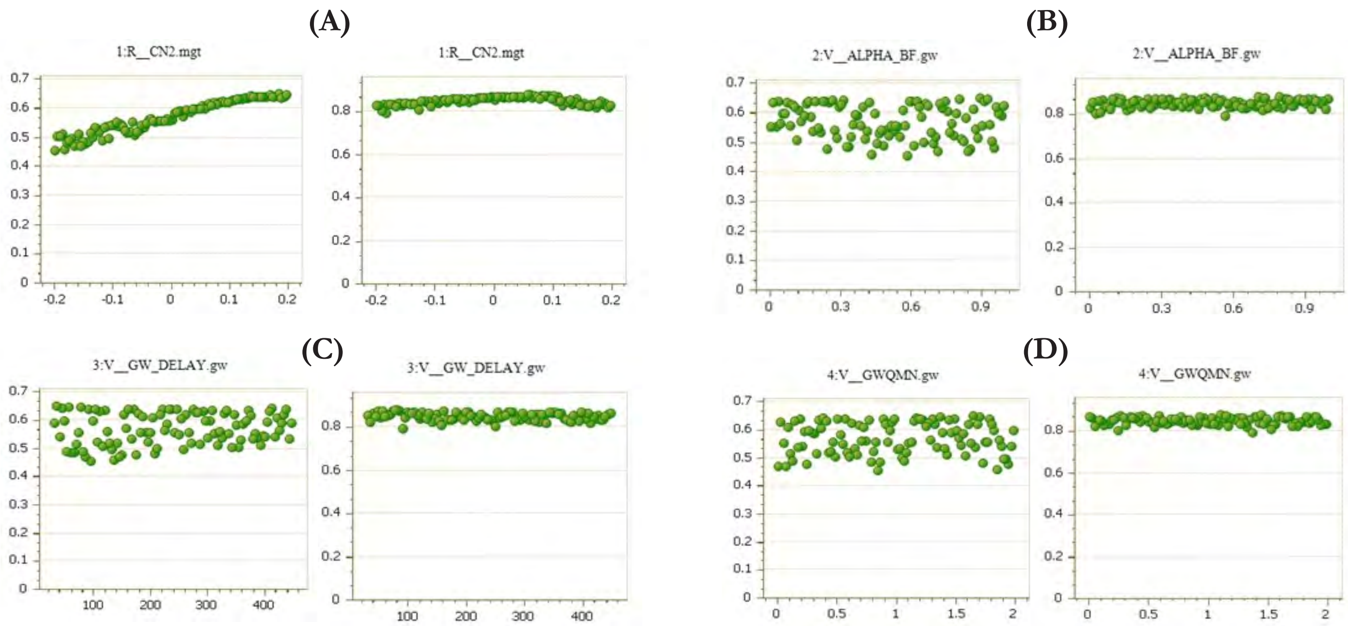

Fig. 6. Dotplots for NSE against different parameters: (a) CN2, (b) ALPHA_BF, (c) GW_DELAY, and (d) GW_QMN. On left is for calibration and on right is for validation ; Note: The Y-axis indicates the NSE values, and the X-axis indicates the value of parameters

conceptual model uncertainties, and input uncertainties. 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 Fig. 7 and Fig. 8.

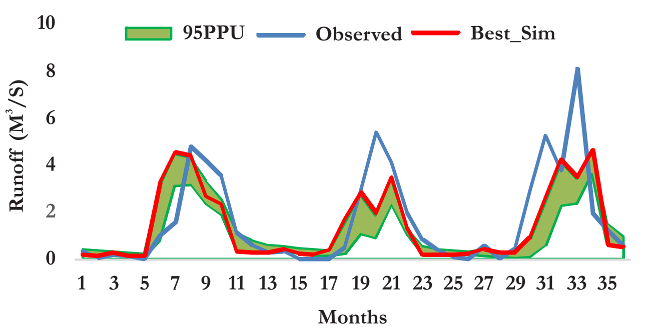

Fig. 7. Best-simulated surface runoff with 95PPU for calibration by using theSUFI-2 method

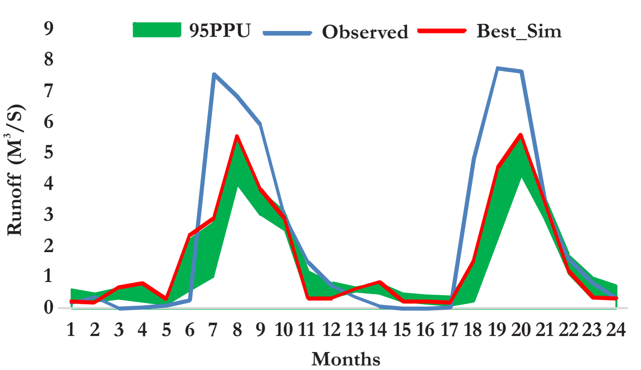

Fig. 8. Best-simulated surface runoff with 95PPU against observed runoff for validation by using theSUFI-2 method

Fig. 7 shows the curve 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 sets can achieve NSE = 0.65. 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 0.68, 0.62, 0.65 and 0.62, respectively. As shown in Fig. 7, 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. To quantify the fit between simulation results, expressed as 95PPU, and observation expressed as P-factor and R-factor. P-factor is the percentage of observed data enveloped by modeling result, the 95PPU. R-factor is the thickness of the 95PPU envelop. In SUFI2, reasonable values of these two factors are tried to be noted. While most of observations are tried to be captured in the 95PPU curve, at the same time we would like to have a small curve. P-factor, as suggested a value of >70% for discharge, while having R-factor of around 1 is quite reasonable and good for result. For sediment, a smaller P-factor and a larger R-factor could be acceptable. The calibrated SWAT model for runoff was applied to simulate sediment yield (results not presented).

Surface Runoff, Sediment Yield and Sediment Distribution

The water yield was simulated for the year 2004 to 2008 on monthly time step. The result was summarized as intermediate (Feb-May), wet (Jun-Sep), dry (Oct-Jan) and on yearly basis after calibration of sensitive parameters for flow obtained during the auto-calibration of Chotki-Berghi station. The result is shown in Table 3. Based on simulation results, the total average annual sediment yield at the outlet of watershed (all the sub-basins) was observed in the range of 9.259 to 30.451 tha^{-1} during the years 2004 to 2008. The detail is presented in Table 4. The spatial variability of sedimentation rate was identified and shown in Fig. 9 and based on which the potential area of intervention can be identified. The output of model showed that Sub-basin 5 of Chotki-Berghi at the existing condition generates a maximum annual average sediment yield of 2.70 t ha^{-1} whereas the minimum annual average sediment yield of 1.39 tha^{-1} was observed in case of sub-basin 4. This is attributed due to the topographic slope and land use of this sub-basin. It was an agricultural land with slope more than 4%. The minimum yield of less than 1.5 tha^{-1} was obtained for sub-basin 3, it has a slope <2% and it is covered by agriculture. Precipitation data is used as dominant climatic factor in the study of sediment yield, because it affects vegetation and runoff. However, the effectiveness of a given amount of annual precipitation is not everywhere the same. Variations in temperature, rainfall intensity, number of storms and seasonal and areal distribution can also affect the yield of sediment. The effect of temperature, which controls the loss of water by evapotranspiration, can also been taken into account.

4. CONCLUSIONS

In this study, SUFI-2 was used for model calibration and to perform the uncertainly analysis for number of parameter. The SWAT model created HRUs from the combination of land use/soil types and runoff was modeled on the basis of Curve Number (CN) defined for HRU. SWAT model was highly sensitive to CN for the runoff; minor change in the value of CN affected the runoff amount significantly. ALPHA_BF was the second sensitive parameter, adjustment of the parameter resulted into better simulation of runoff. For sediment yield support practice factor was most sensitive because of the defining of the tillage practice for the crops in the watershed. Slope steepness and vegetation cover factor were the other important factor which affected the sediment yield. Notwithstanding the data scarcity, the result is very satisfying and provides notable insight into the runoff availability and the associated uncertainties in this susceptible

Table: 3
Simulated monthly surface runoff (mm)

Month	Year					
	2004	2005	2006	2007	2008	Average
Jan	5.45	4.66	8.56	0.98	7.98	5.76
Feb	2.66	12.38	0.91	12.77	2.08	6.16
Mar	7.51	7.40	22.24	1.01	0.74	7.78
Apr	5.36	1.93	0.39	1.59	0.43	1.94
May	1.02	0.76	19.77	3.78	1.91	5.45
Jun	40.76	3.00	116.49	10.83	184.47	71.11
Jul	66.91	89.14	193.70	287.48	283.84	184.21
Aug	177.27	131.12	144.96	252.44	288.71	198.90
Sep	155.71	166.59	286.76	217.17	133.21	191.89
Oct	135.96	60.07	80.16	119.35	67.53	92.61
Nov	44.63	30.36	46.75	58.85	32.85	42.69
Dec	23.23	13.83	22.42	28.89	13.19	20.31
Total	674.00	531.68	938.39	1000.82	1023.08	833.58

Table: 4
Simulated monthly sediment yield (t ha^{-1})

Month	Year					
	2004	2005	2006	2007	2008	Average
Jan	0.01	0.22	0	0	0.81	0.20
Feb	0	0.41	0	1.52	0.00	0.38
Mar	1.43	0	1.87	0.02	0	0.66
Apr	0.08	0	0	0.00	0.00	0.01
May	0.00	0	1.38	1.22	0.03	0.52
Jun	0.29	0.09	4.79	2.61	3.99	2.36
Jul	0.86	2.05	8.36	7.30	7.92	5.30
Aug	6.93	2.45	2.32	4.17	12.55	5.68
Sep	9.01	4.01	11.70	4.88	3.80	6.68
Oct	9.47	0	0	0.401	0	1.97
Nov	0	0	0	0	0	0
Dec	0.04	0	0	0	0	0.008
Total	28.15	9.25	30.45	22.16	29.13	23.83

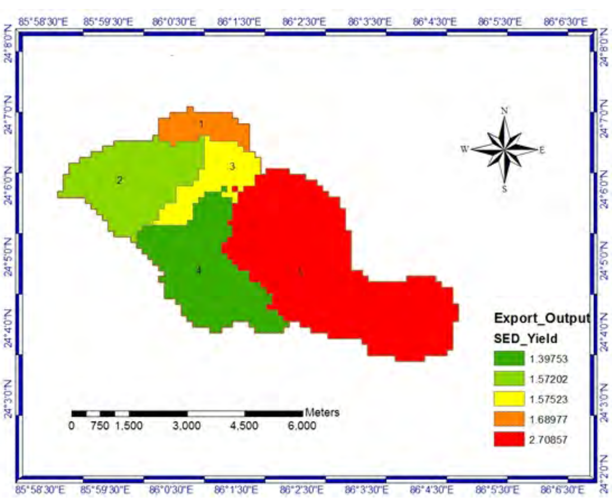

Fig. 9. Sediment yield distribution (t ha^{-1}) with respect to sub-basin

region. Sub-basin no. 5 of Chotki-Berghi at the existing condition generates a maximum annual average sediment yield of 2.70 t ha^{-1}, this can be reduced by using sediment yield intervention strategies such as land slope stabilization, construction bench terraces, changing the land use of steepy area and afforestation. The model gives relatively good result in Chotki-Berghi basin. Given the complexities of a watershed and the large number of interactive processes taking place simultaneously and consecutively at different times and places within a watershed, it is quite remarkable that the simulated results comply with the measurements to the degree that they do. Based on the results obtained in this study, SWAT is assessed to be a reasonable model to use sedimentation and water quantity studies in the Chotki-Berghi watershed.

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