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Identification of sensitive parameters and uncertainty analysis for simulating streamflow in Jaraikela catchment of Brahmani river basin using SWAT model

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ABSTRACT

The Soil and Water Assessment Tool (SWAT) is a widely accepted semi-distributed model for watershed hydrological analysis. The facility of uncertainty analysis with the help of SWAT-Calibration and Uncertainty Procedures (SWAT-CUP) model is now capable to bring a variety of calibration and analysis techniques in one single platform, namely ParaSol, sequential uncertainty fitting (SUFI-2), Generalized Likelihood Uncertainty Estimation (GLUE), particle swarm optimization and Markov Chain Monte Carlo (MCMC). In the present study, the SWAT model has been calibrated for the period 1987-2000 considering initial 3 years as the warm-up period (1987–89) and validated from 2001-2010 for monthly streamflow simulation. Uncertainty analysis was carried out using SUFI-2 algorithm at Jaraikela gauging station of Bramhani river basin, India. The sensitivity of the parameters was determined according to the t-stat and p-value. Nine distinguished parameters were selected for sensitivity analyses. The performance of the model was evaluated satisfactorily on monthly time scale streamflow simulation using Nash–Sutcliffe Efficiency (NSE), the coefficient of determination (R^2) and Percentage BIAS (PBIAS). The P and R factors were used to assess the degree of uncertainty. The values of NSE, R^2, and PBIAS were found to be 0.84, 0.85 and -0.08 during the calibration period and 0.71, 0.73 and -0.17 during the validation period, respectively. The values of P and R factors were observed to be 0.79 and 0.92, respectively during calibration, and 0.89 and 0.86 during the validation period, respectively. The simulated streamflow also well fitted within the 95 percentage prediction uncertainty (95PPU) band of SUFI-2 algorithm during the calibration and validation periods indicating a satisfactory performance of the model under parameter uncertainty.

1. INTRODUCTION

Water is the most precious and prime natural resource and a major constituent of all living matters on the planet Earth. As the quantity of available water is constant and there is over-use of the same due to population rise and growing urbanization, it has progressively emerged as the most important national and international concern today. Hence, proper management of water resources is imperative to meet the need of current and future demands of the civilization (Panigrahi *et al.,* 1992). Assessment of potential of water resources at basin or sub-basin scale may be a prerequisite to achieve it. Hydrological modeling is a key tool for water resource assessment and management in watershed scale. Several watershed models starting from simple empirical models to more complex physically based distributed models have been developed for the purpose by this time. Although, the physical principle of any hydrologic process is considered in formulating a model structure, the final design invariably is only an approximation of the natural system. This is because the modeler combines existing knowledge of physical processes with some conceptual representations of unknown principles underlying the process being modeled. Therefore, applications of any type of model are associated with several kinds of uncertainties with respect to model structure, parameters, input data and natural randomness.

These uncertainties finally lead to considerable error in model simulation. Hence, it is very much necessary to quantify the degree of uncertainty associated with model results before drawing any conclusion and giving recommendation. Hence, researchers now prefer to use joint stochastic and deterministic model having a deterministic core within a stochastic frame.

Out of all types of uncertainties, the primary problem in any hydrological modeling is the uncertainty in quantifying the model parameters. Further complications arise owing to the mismatch between model complexity and data availability to parameterize a model (Zhang *et al.*, 2012; Song *et al.,* 2015). Sensitivity analysis (SA) is one such method that helps to identify the parameters that have a strong impact on the model outputs, thereby influencing the efficiency of any model. In hydrological modeling, SA can be simply defined as the change in the output responses to the change in one or more model inputs or parameters. It is also worthwhile to mention that SA takes into account the effect of parameters as well as the uncertainties in model forcing (D'Agnese *et al.,* 1999; Hill and Tiedeman, 2006). In a calibration process, the highly sensitive parameters are quickly and closely optimized than the less sensitive parameters. SA based on automatic calibration procedures are generally divided into two types, *i.e.* local and global search strategies (Sorooshian and Gupta, 1995). The local approaches deal with assessing the effect of parameters on the output by varying each parameter, one at a time around any base case, and global approaches assess the change in output by varying all the parameters simultaneously over the entire feasible range. The application of SA methods in hydrological modeling, although very limited (Blasone *et al.,* 2007), has been gaining attention in the recent past.

Now, the Soil and Water Assessment Tool (SWAT) model is gaining popularity as a joint stochastic and deterministic model due to the development of SWAT-CUP model for both sensitivity and uncertainty analysis (Agrawal *et al.,* 2011). Basically, SWAT is a physically based semi-distributed hydrologic model initially developed to simulate streamflow in an un-gauged basin (Arnold *et al*., 1998). Nowadays, it is widely used for simulating stream-flow, sediment yield, evapotranspiration, soil moisture, crop yield etc. at watershed scale (Zhang *et al.*, 2010; Yesuf *et al.,* 2016; Bhatt *et al*., 2016; Kumar *et al.,* 2017). The impact of climate change on streamflow (Faramarzi *et al*., 2013; Dahal *et al*., 2016) and estimation of blue and green water resources together (Faramarzi *et al*., 2009) can also be successfully analyzed using this model. Thus, it shows the wide applicability of the SWAT model in land, water and agricultural system simulation and management.

Uncertainty is always associated with model results because of the difficulty in elimination of spurious data collected from several sources. However, this can be minimized through intensive field investigation, adequate and efficient monitoring network, efficient parameter estimation tools and techniques (improved data collection), careful data handling, and efficient manufacturing and maintenance. A realistic assessment of the various sources of error is important for science-based decision making as well as to direct the research towards model structural improvements and uncertainty reduction. It is an accepted fact that hydrological model simulations should explicitly include an estimate of their associated uncertainty.

Both sensitivity and uncertainty analysis are essential processes to reduce the uncertainties developed by the variations of model parameters and structure. Recently developed calibration and uncertainty analysis techniques for watershed models include: MCMC method (Vrugt *et al*., 2003), GLUE method (Beven and Binley, 1992), ParaSol (Parameter Solution) method (Yang *et al*., 2008), and SUFI-2 method (Abbaspour *et al*., 2004). These techniques (GLUE, ParaSol, SUFI-2 and MCMC) have been linked to SWAT model through SWAT-CUP (Abbaspour *et al.,* 2007), and enable sensitivity and uncertainty analysis of model parameters as well as the structure (Rostamian *et al*., 2008). SWAT model calibration and uncertainty analysis using these techniques have been emphasized and confirmed through various studies worldwide, but also needs more investigations in different agro-climatic situations for enhancing the degree of confidence level. Abbaspour *et al*. (2004) and Yang *et al*. (2008) applied the SUFI-2 technique for evaluation of SWAT model. The SUFI-2 technique needs a minimum number of model simulations to attain a high-quality calibration and uncertainty results as compared to other techniques (Yang *et al*., 2008). In this study, stream-flow simulation of Brahmani river basin, India was carried out at Jaraikela gauging station using the SWAT model. Sensitivity and uncertainty in streamflow were evaluated using the SUFI-2 algorithm of SWAT-CUP model.

2. MATERIALS AND METHODS

Study Area

Jaraikela catchment under Brahmani river basin lies between 83°30' to 85°40'E longitude and 21°90' to 23°30'N latitude (Fig. 1). Jaraikela is a small catchment of Brahmani basin having a drainage area of 8995 km^2. The majority of the catchment area is present in Jharkhand and only few portions are present in Odisha. Cultivable land area is dominant among other land uses. Major crops grown in this catchment are rice, groundnut, sugarcane, millet, and vegetables. The average annual precipitation of the catchment is 1320 mm. The maximum temperature is recorded in the month of May *i.e.* 48^{0}C, whereas the minimum temperature is experienced during the month of December *i.e.* 4^{0}C.

Data Used

SWAT needs various field data to set-up the model for simulating streamflow. Soil, land use, weather, discharge and elevation databases were collected from different sources/agencies and are listed in Table 1. The detailed soil and land use maps are shown in Fig's 2 and 3, respectively.

Land Use and Soil

The land use/land cover (LU/LC) mainly affects the runoff and infiltration processess of the hydrological cycle (Singh *et al.,* 2014). LU/LC map used in this study was obtained from the National Remote Sensing Centre (NRSC), Hyderabad, India in 1:250000 scale. The LU is mainly classified into four dominent classes as shown in Fig. 2. Out of the total catchment area agriculture occupies 55.5%, followed by forest, built-up and water bodies in 39.9, 3.2 and 1.4%, respctively. Soil type also plays a prominent role in governing the hydrological response of a catchment. Soil map of the study area was clipped from the harmonized world soil database (HWSD) developed by FAO. The major soil types of the catchment area are clay (59.1%) and loam (33.7%). The northen part of the study area is dominated by clay soil whereas sourthen part is larglely covered with loam soil. Besides these, sandy-loam and clay-loam soils are also persent in few patches of the catchment (Fig. 3).

SWAT Model

The SWAT model (Arnold *et al.,* 1998) is a semi-distributed hydrological model developed by the United States Department of Agriculture, Agricultural Research Service (USDA-ARS). It can simulate the streamflow, sediment and nutrients load reasonably from a large un-gauged basin (Neitsch *et al.,* 2011). It simulates runoff

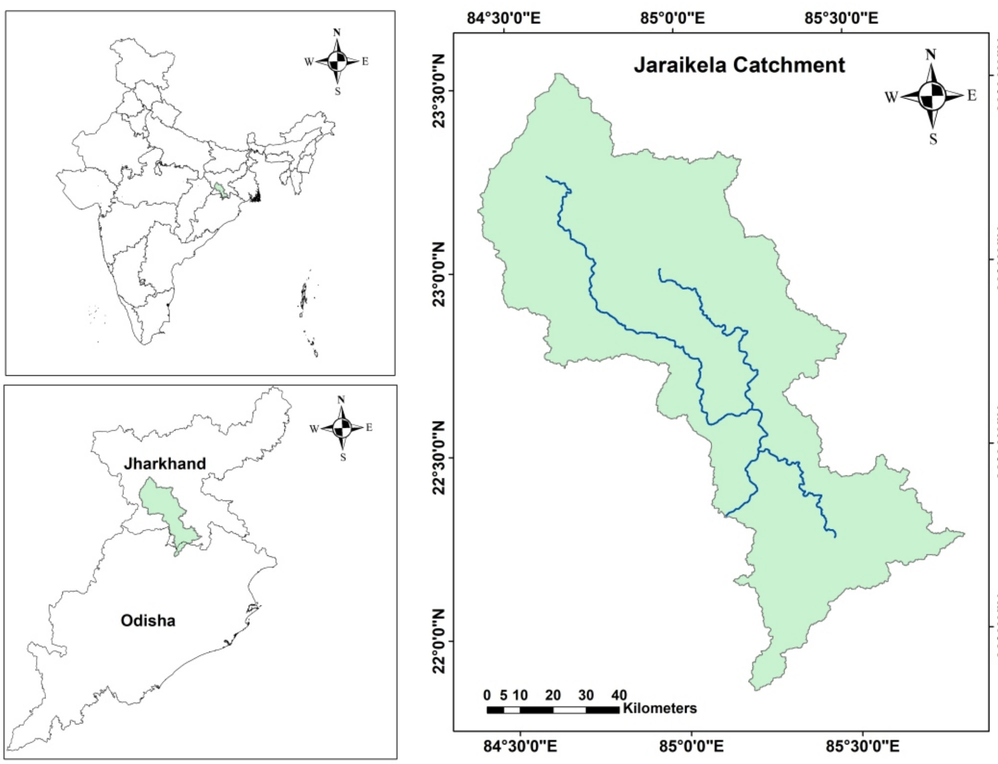

Fig. 1. Location of Jaraikela catchment

Table: 1
Sources of input data

Data	Source
Soil	The soil map obtained from the harmonized world soil database (HWSD) developed by the Food and Agriculture Organization of the United Nations (http://www.fao.org/geonetwork/srv/en/metadata.show%3Fid=14116).
Land use	The land use map collected from National Remote Sensing Centre (https://www.nrsc.gov.in/).
Rainfall and Temperature	Daily rainfall and temperature (1980-2013) gridded (1°*1°) data were collected from the India Meteorological Department (IMD), Pune.
Discharge	Daily discharge data (1980-2013) was collected from the Water Resources Information System of India (India-WRIS), CWC.
DEM	The Digital Elevation Model (DEM) was collected from Shuttle Radar Topography Mission (SRTM 90) of USGS (http://srtm.csi.cgiar.org/).

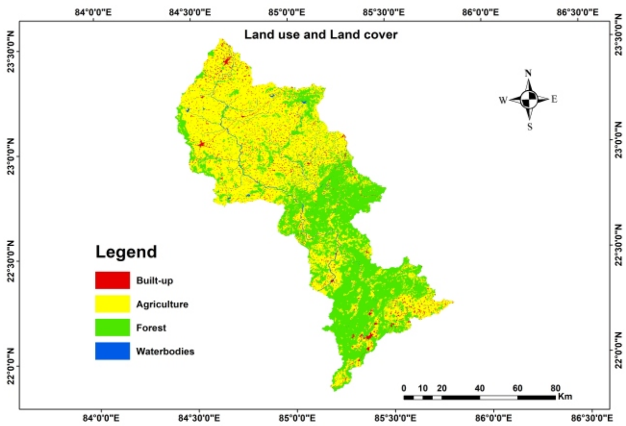

Fig. 2. Land use map of Jaraikela catchment

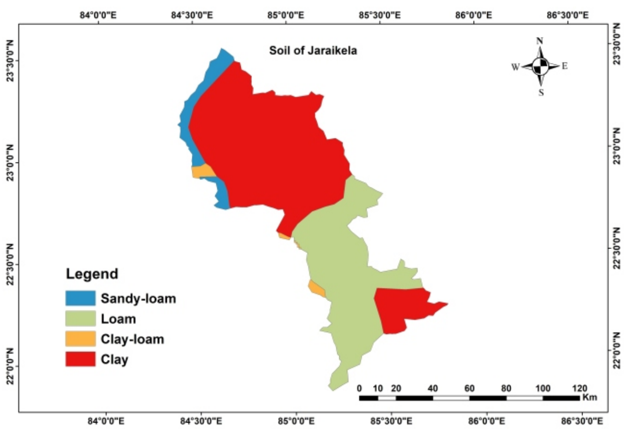

Fig. 3. Soil map of Jaraikela catchment

based on United States Department of Agriculture, Natural Resources Conservation Services-Curve Number Method, 1972 (USDA, NRCS-CN). The water balance equation (Neitsch *et al.,* 2011) has been used for simulating other hydrological components as shown in eq. 1.

$$SW_t = SW_0 + \Sigma_{i=1}^{t} (R_{day,i} - Q_{surf,i} - E_{a,i} - W_{seep,i} - Q_{gw,i}) \quad ...(1)$$

Where, SW_t = Final soil water content (mm), SW_o = Initial soil water content on day i (mm), R_{day} = amount of precipitation on day i (mm), Q_{surf} = Amount of surface runoff on day i (mm), $E_{a,}$ = Amount of evapotranspiration on day i (mm), W_{seep} = Amount of water entering the vadose zone from the soil profile on day i (mm), Q_{gw} = Amount of return flow on day i (mm) and, t = time interval in day.

SUFI-2 Algorithm

SWAT-CUP is especially developed and coupled with the SWAT model by Abbaspour *et al.* (2007) for calibration, sensitivity and uncertainty analysis. Any calibration / uncertainty or sensitivity program can easily be linked to the SWAT model by using this generic interface. SWAT-CUP has various algorithms in one single platform namely, ParaSol, SUFI-2, GLUE, and MCMC. In this study, the SUFI-2 algorithm was used to investigate sensitivity and uncertainty in streamflow simulation. The SUFI-2 technique is based on a Bayesian framework that obtains the posterior parameters from priors as it provides a method of incorporating new information with prior assessments to calculate new values (posterior parameters) for the relative likelihood of events of interest (Haan, 1977).

Several objective functions are used in SUFI-2 technique to reduce the non-uniqueness problem in the model parameterization (Duan *et al.*, 2006). The average change in the objective functions with respect to the consequential changes of each parameter is referred as the relative sensitivities. It provides partial information about the sensitivity of the objective function and is based on linear approximation of the model parameters. Further, to estimate the level of significance between the datasets, a t-test is applied to identify the relative significance of each parameter. The t-test and the p-values were used to provide a measure and the significance of the sensitivity, respectively. The larger absolute value of t-test indicates that a parameter is more sensitive, and lower p-values close to zero show more significance.

In SUFI-2, the uncertainties from all sources are accounted in terms of 'parameter uncertainty' such as uncertainties in driving variables (e.g. rainfall), model conceptualization, parameterization, and measured data. Parameter uncertainty is quantified in terms of 95PPU band. The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of output variables. A 'Latin hypercube' sampling technique (McKay *et al.,* 1979) has been used to draw independent parameter sets. The strength of a calibration and uncertainty analysis is quantified by two additional statistics referred to as the P-factor and R-factor.

Calibration and Validation

SWAT was calibrated and validated for monthly streamflow by comparing the observed streamflow at Jaraikela outlet. The model was run for a period of 24 years (1987–2010) by considering the first 3 years as the warm-up period. Streamflow data from 1990 to 2000 were used for calibration, whereas, the remaining 10 years of the dataset *i.e.* 2001–2010, were used for validating the model. After simulation, SWAT-CUP was used for model sensitivity, calibration and uncertainty analysis. Global SA was performed to distinguish the most sensitive parameters. The objective of the calibration is to optimize the model parameters. Nine parameters were selected for model calibration, sensitivity and uncertainty analysis of streamflow simulation. Recommended ranges of these nine parameters in terms of maximum and minimum values are shown in Table 2.

Performance Indices

Five parameters have been used for evaluation of model performance, namely coefficient of determination

Table: 2
Minimum and maximum value of calibration parameters by SUFI-2

S.No.	Parameter	Description	Minimum	Maximum
1	r_CN2.mgt	Soil Conservation Service curve number for AMC II	-0.05	0.05
2	v_ALPHA_BF.gw	Base flow recession alpha factor (days)	0	1
3	a_GW_DELAY.gw	Groundwater delay (day)	0	500
4	a_GWQMN.gw	Threshold water depth in the shallow aquifer required for return flow to occur (mm)	0	5000
5	v_ESCO.hru	Soil evaporation compensation factor	0.01	0.3
6	r_SOL_AWC(1).sol	Available water capacity of 1st soil layer (mm mm^{-1})	0.06	0.24
7	v_CH_K2.rte	Effective alluvium (mm hr^{-1})	18.00	103.00
8	r_SOL_K (1).sol	Saturated hydraulic conductivity (mm hr^{-1}) of 1st layer	-0.25	0.25
9	v_SURLAG.bsn	Surface runoff lag coefficient (day)	0.5	5

N.B. (i) a_ means the given value is added to the existing parameter value; (ii) r_ means the existing parameter value is multiplied by (1+a given value); (iii) v_ means the existing parameter value is to be replaced by the given value.

(R^2), NSE, Percentage BIAS (PBIAS), P-factor and R-factor. The coefficient of determination (R^2), NSE and Percentage BIAS (PBIAS), are expressed mathematically in the following eqs. 2, 3 and 4, respectively.

$$R^2 = \frac{[\Sigma_{i=1}^{t} (S_i - \bar{S})(O_i - \bar{O})]^2}{\Sigma_{i=1}^{t} (S_i - \bar{S})^2 \, \Sigma_{i=1}^{t} (O_i - \bar{O})^2} \quad ...(2)$$

$$NSE = 1 - \frac{\Sigma_{i=1}^{N} (O_i - S_i)^2}{\Sigma_{i=1}^{N} (O_i - \bar{O})^2} \quad ...(3)$$

$$PBIAS = \frac{\Sigma_{i=1}^{N} (O_i - S_i)}{\Sigma_{i=1}^{N} O_i} \times 100 \quad ...(4)$$

Where, O_i is the i^{th} observed data; S_i the i^{th} predicted / simulated value; $\bar{O}$ the mean of measured / observed data; S_i the mean of predicted data and N the total number of simulation period.

The P-factor (percentage of measured data bracketed by the 95% prediction boundary) was used to quantify all the uncertainties associated with the SWAT model. The range of the P-factor varies from 0 to 1 with values close to 1 indicating a very high model performance and efficiency, while the R-factor is the average width of the 95PPU band divided by the standard deviation of the observed variable and varies in the range 0-∞ (Abbaspour *et al.,* 2007; Yang *et al.,* 2008). The P-factor and the R-factor are expressed mathematically in the following way (Abbaspour *et al.,* 2007; Yang *et al.,* 2008):

$$P\text{-}factor = \frac{ny_{ti}}{N} \quad ...(5)$$

Where, ny_{ti} the number of measured values bracketed by the 95PPU and N the total number of measured values.

$$R\text{-}factor = \frac{\frac{1}{n}\Sigma_{t_i=1}^{n} (y^m_{t_i,97.5\%} - y^m_{t_i,2.5\%})}{\sigma_{obs}} \quad ...(6)$$

Where, $y^m_{t_i,97.5\%}$ and $y^m_{t_i,2.5\%}$ are the upper and lower boundaries of the 95 Uncertainty Band (UB), respectively and σ_{obs} is the standard deviation of the observed data.

3. RESULTS AND DISCUSSION

Model Calibration and Sensitivity Analysis (SA)

In this study, a rigorous calibration based on SA of model parameters was made following the SWAT-CUP documentation (Neitsch *et al.,* 2005). A total number of 9 SWAT parameters presented in Table 3, were selected for model calibration and uncertainty analysis based on previous studies and SWAT documentation (Neitsch *et al.,* 2002). In the early stage of calibration, global SA was conducted at the monthly time-step using Latin hypercube sampling. The first step in the calibration process is to adjust the input parameter values for matching the simulated results closely with the observed variables and to find out the most sensitive parameters influencing the observed variable more than other parameters. SA was performed with 1000 times run of the model and the results were examined. Dotty plots are the result of the model run with NSE as an objective function during calibration and are used to depict the distribution of sampling points as well as parameter sensitivity. The dotty plots conditioned in this study by SUFI-2 algorithm (Fig. 4) show that most of the sensitive parameters have NSE values more than the threshold value (0.5), during the monthly streamflow simulation.

Two indicators, t-stat and p-value (Abbaspour *et al.*, 2015) were used to measure the sensitivity and relative significance of each parameter. The relative ranking of the nine parameters according to their response to streamflow is presented in Table 3. The most sensitive parameter was found to be SCS-CN value for AMC II followed by base flow recession ALPHA factor and groundwater delay. SCS-CN basically depends on catchment characteristics like land use, hydrological soil group and crop management practices. CN2 ranks first among the sensitive parameters which means that the catchment characteristics have more influence on runoff generation. The second sensitive parameter, base flow recession ALPHA factor represents groundwater flow response to change in recharge. Its value varies from 0.1-0.3 and 0.9-1.0 for catchment having a slow

Table: 3
Best fitted, t-stat and p-value of sensitive calibration parameters by SUFI-2

S.No.	Parameter	Description	Fitted Value	t-stat	p-value
1	r_CN2.mgt	Soil Conservation Service curve number for AMC II	0.025	2.86	0
2	v_ALPHA_BF.gw	Base flow recession alpha factor (days)	0.40	1.29	0.12
3	a_GW_DELAY.gw	Groundwater delay (day)	280	1.05	0.21
4	a_GWQMN.gw	Threshold water depth in the shallow aquifer required for return flow to occur (mm)	2600	-0.32	0.52
5	v_ESCO.hru	Soil evaporation compensation factor	0.15	-0.17	0.59
6	r_SOL_AWC(1).sol	Available water capacity of 1st soil layer (mm mm^{-1})	0.13	1.50	0.11
7	v_CH_K2.rte	Effective alluvium (mm hr^{-1})	18.29	-1.476	0.142
8	r_SOL_K (1).sol	Saturated hydraulic conductivity (mm hr^{-1}) 1st soil layer	0.15	0.028	0.98
9	v_SURLAG.bsn	Surface runoff lag coefficient (day)	3	0.182	0.855

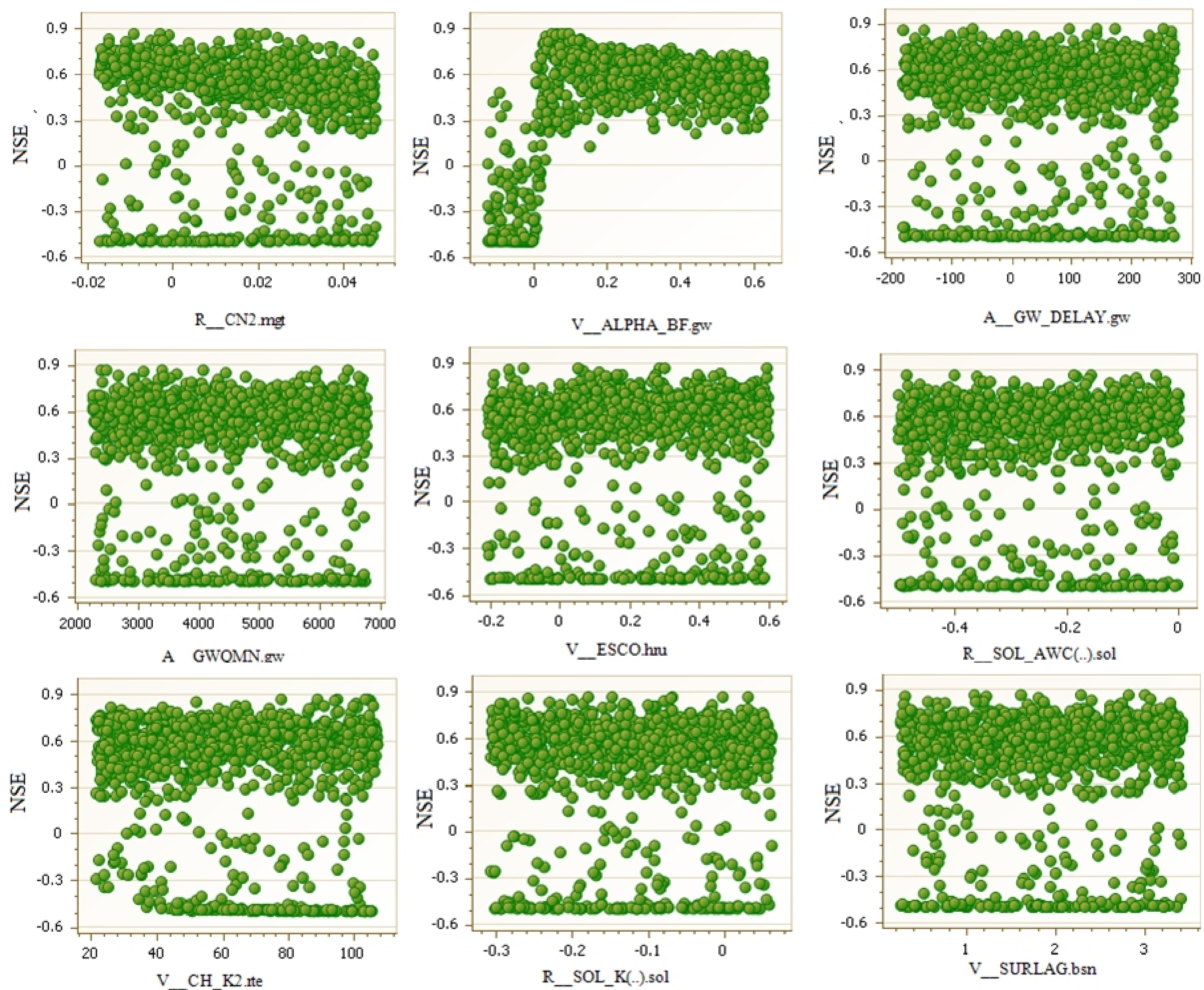

Fig. 4. Dotty plots with objective function of NSE against each aggregate SWAT parameters during calibration period

and high response to recharge, respectively (Arnold *et al.,* 2001). In this case, the fitted value is 0.4, which indicates the Jaraikela catchment has a medium response to groundwater flow with respect to recharge.

Model Performance and Uncertainty Analysis (UA)

In the present study, the simulated discharges were compared with the observed ones at the outlet of Jaraikela catchment during the calibration period from 1990 to 2000 and validation period from 2001 to 2010 as presented in Fig's 5 and 6, respectively. The performance indices obtained during the calibration and validation periods are listed in Table 4. The NSE, R^2, and PBIAS values were observed as 0.84, 0.85 and -0.08, respectively during calibration and 0.71, 0.73 and -0.17, respectively during validation. This indicates that model simulation results are quite satisfactory.

Further, the simulated streamflow was compared with observed flow using scatter plots. Scatter plot of simulated versus observed streamflow (Fig's 7 and 8) illustrates that the simulated streamflow maintains a balance around the 1:1 line during both calibration and validation periods. This indicates that the streamflow simulated by the model is at proximity of the observed values. However, Fig's 7 and 8 also depict an over prediction of streamflow by the model during the low flow periods. This shows the limitation of SWAT model in simulating the base flow component of the catchment.

Parameter uncertainty in streamflow simulation is quantified by P- and R-factors during calibration and validation periods. The values of P- and R-factors were obtained to be 0.79 and 0.92 during calibration and 0.89 and 0.96 during validation period, respectively (Table 4). The P-factor and the R-factor values are within the desired range during both calibration and validation period which suggests that the parameter uncertainties are acceptable during the entire simulation period.

Further, the simulated streamflow values in a monthly time step were plotted with the observed values with 95PPU band as shown in Fig's 5 and 6. The results indicate that most of the observations are bracketed within the 95PPU band. However, some irregularities were observed during the peak flow simulation. The calibration results (Fig. 5) revealed that the observed peak values in years 1996, 1997 and 1998, and during validation in 2001, 2007 and 2008 were not falling under 95PPU band. The model is under predicting the peak flow in these periods, which indicates the drawback of SWAT model to simulate extreme events of the catchment. Otherwise, the overall performance of the model is satisfactory under parameter uncertainty.

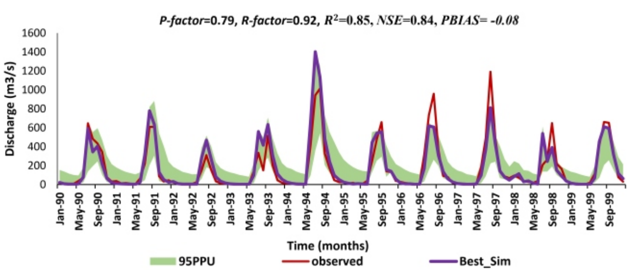

Fig. 5. Time series plot of simulated vs observed streamflow with 95PPU band during calibration

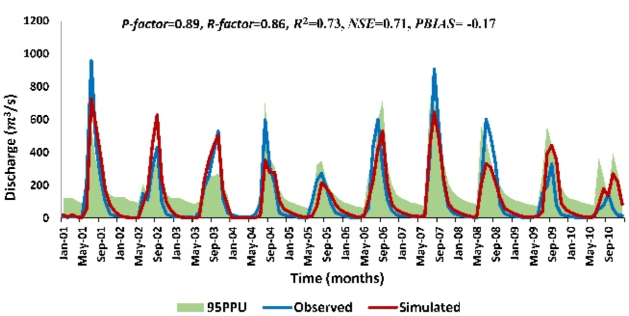

Fig. 6. Time series plot of simulated vs observed streamflow with 95PPU band during validation

Table: 4
Summary statistics of model performance

Indices	Calibration	Validation
R^2	0.85	0.73
NSE	0.84	0.71
PBIAS	-0.08	-0.17
P-factor	0.79	0.89
R-factor	0.92	0.86

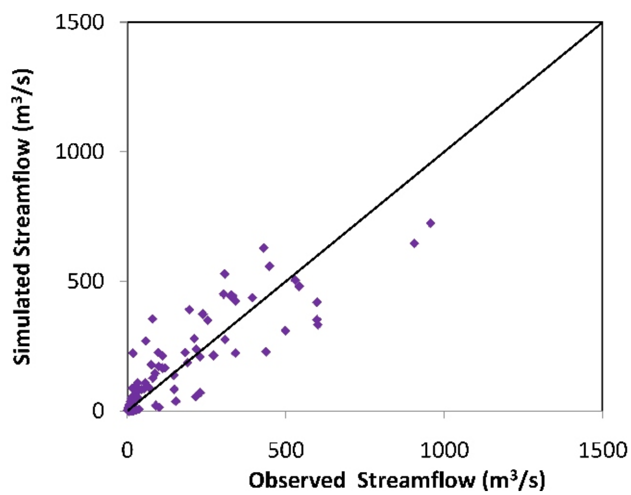

Fig. 7. Scatter plots of observed vs simulated streamflow by SUFI-2 during calibration

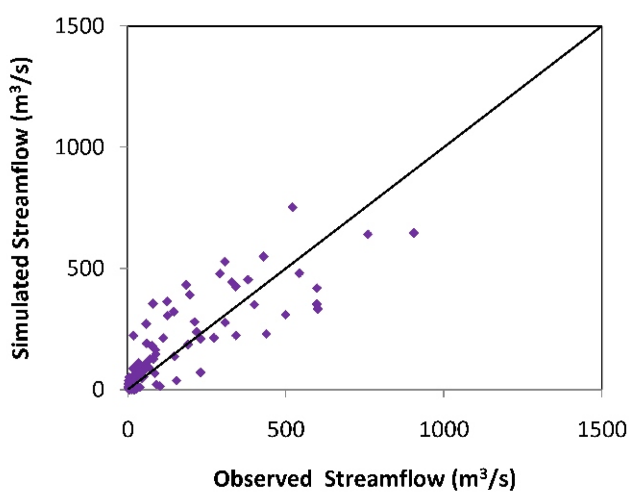

Fig. 8. Scatter plots of observed vs simulated streamflows by SUFI-2 during validation

4. CONCLUSIONS

The present study demonstrates the application of SWAT model in Jaraikela catchment of Brahmani river basin, India for simulating streamflow, identification of the most sensitive parameters and estimation of model parameters uncertainty using SUFI-2 algorithm. Identification of sensitive parameters and their ranking was done during the pre-calibration uncertainty analysis process. The results indicate that nine parameters were most sensitive and had a great impact on streamflow. Soil conservation service curve number for AMC II factor was identified as the most sensitive parameter among all other streamflow parameters. The model performance during streamflow calibration by SUFI-2 was found to be excellent with NSE, R^2 and PBIAS values of 0.84, 0.85 and -0.08, respectively for the monthly streamflow simulation. During validation, the model performance was reasonably acceptable as indicated by the NSE, R^2 and PBIAS values of 0.71, 0.73 and -0.17, respectively. The P and R factor values to the tune of 0.79 and 0.92 during calibration, and 0.89 and 0.86 during the validation period, respectively indicate that the model performance was quite satisfactory under the parameter uncertainty. Basing upon the model simulation results, it may be inferred that the SWAT model can be successfully used for streamflow simulation under parameter uncertainty in an un-gauged watershed.

REFERENCES

Abbaspour, K.C., Johnson, A. and Van-Genuchten, M.T. 2004. Estimating uncertain low and transport parameters using a sequential uncertainty fitting procedure. *Vadose Zone J*., 3(4): 1340–1352.

Abbaspour, K.C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H. and Klove, B. 2015. A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high resolution large-scale SWAT model. *J. Hydrol*., 5(24): 733–752.

Abbaspour, K.C., Vejdani, M. and Haghighat, S. 2007. SWAT-CUP calibration and uncertainty programs for SWAT. In: MODSIM 2007 International Congress on Modelling and Simulation, Modelling and Simulation Society of Australia and New Zealand.

Agrawal, N., Verma, M. and Tripathi, M. 2011. Hydrological modelling of Chhokranala watershed using weather generator with the SWAT model. *Indian J. Soil Cons*., 39(2): 89-94.

Arnold, J.G., Allen, P.M. and Morgan, D. 2001. Hydrologic model for design of constructed wetlands. *Wetlands*, 21(2):167–178.

Arnold, J.G., Srinivasan, R., Muttiah, R.S. and Williams, J.R. 1998. Large area hydrologic modeling and assessment. Part I: Model development1. *J. Am. Water Resour. Assoc*., 34(1), 73–89.

Beven, K. and Binley, A. 1992. The future of distributed models: model calibration and uncertainty prediction. *Hydrol. Proc.,* 6(3): 279–298.

Bhatt, V., Tiwari, A. and Sena, D. 2016. Application of SWAT model for simulation of runoff in micro-watersheds of the lower Himalayan region of India. *Indian J. Soil Cons.*, 44(2): 133-140.

Blasone, R.S., Madsen, H. and Rosbjerg, D. 2007. Parameter estimation in distributed hydrological modelling: comparison of global and local optimisation techniques. *Nord. Hydrol.*, 38: 451.

D'Agnese, F.A., Faunt, C.C., Hill, M.C. and Keith Turner, A. 1999. Death Valley regional ground-water flow model calibration using optimal parameter estimation methods and geoscientific information systems. *Adv. Water Resour.*, 22: 777–790.

Dahal, V., Shakya, N.M. and Bhattarai, R. 2016. Estimating the impact of climate change on water availability in Bagmati Basin. *Nepal. Env. Proc.*, 3(1): 1-17.

Duan, Q., Schaake, J., Andreassian, V., Franks, S., Goteti, G., Gupta, H.V., Gusev, Y.M., Habets, F., Hall, A., Hay, L., Hogue, T., Huang, M., Leavesley, G., Liang, X., Nasonova, O.N., Noilhan, J., Oudin, L., Sorooshian, S., Wagener, T. and Wood, E.F. 2006. Model parameter estimation experiment (MOPEX): An overview of science strategy and major results from the second and third workshops. *J. Hydrol.*, 320: 3–17.

Faramarzi, M., Abbaspour, K.C., Schulin, R. and Yang, H. 2009. Modelling blue and green water resources availability in Iran. *Hydrol. Proc.*, 23: 486–501.

Faramarzi, M., Abbaspour, K.C., Vaghefib, S.A., Farzaneha, M.R., Zehnder, A.J.B., Srinivasan, R. and Yang, H. 2013. Modeling impacts of climate change on freshwater availability in Africa. *J. Hydrol.*, 480: 85–101.

Haan, C.T. 1977. Statistical Methods in Hydrology. 1st Edition, Iowa State University, Press, Iowa.

Hill, M. and Tiedeman, C. 2006. Effective Groundwater Model Calibration: With Analysis of Data, Sensitivities, Predictions, and Uncertainty. John Wiley and Sons, Hoboken, NJ, USA.

Kumar, N., Singh, S.K., Srivastava, P.K. and Narsimlu, B. 2017. SWAT Model calibration and uncertainty analysis for streamflow prediction of the Tons River Basin, India, using Sequential Uncertainty Fitting (SUFI-2) algorithm Model. *Earth Syst. Environ*., 3: 30-38.

Mckay, M.D., Beckman, R.J. and Conover, W.J. 1979. A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technomt.*, 21: 239–245.

Neitsch, S.L., Arnold, J., Kiniry, J., Williams, J. and King, K. 2005. Soil and water assessment tool theoretical documentation. Texas, USA.

Neitsch, S.L., Arnold, J.G., Kiniry, J., Srinivasan, R. and Williams, J.R. 2002. Soil and water assessment tool user manual. Texas Water Resources Institute, College Station, TWRI Report TR-192.

Neitsch, S.L., Arnold, J.G., Kiniry, J.R. and William, J.R. 2011. Soil and Water Assessment Tool theoretical documentation version 2009. Texas Water Resources Institute, Technical Report No. 406. Texas A&M University, System College Station, Texas.

Panigrahi, B., Sharma, S.D. and Behera, B.P. 1992. Irrigation water requirement models of some major crops. *Water Resour. Mang*., 6(1): 69-77.

Rostamian, R., Jaleh, A., Afyuni, M., Mousavi, S.F., Heidarpour, M., Jalalian, A. and Abbaspour, K.C. 2008. Application of a SWAT model for estimating runoff and sediment in two mountainous basins in central Iran. *Hydrol Sci. J.*, 53: 977–988.

Singh, S., Srivastava, P., Gupta, M., Thakur, J. and Mukherjee, S. 2014. Appraisal of land use/land cover of mangrove forest ecosystem using support vector machine. *Environ. Earth Sci.*, 71: 2245–2255.

Song, X., Zhang, J., Zhan, C., Xuan, Y., Ye, M. and Xu, C. 2015. Global sensitivity analysis in hydrological modeling: review of concepts, methods, theoretical framework, and applications. *J. Hydrol*., 523: 739–757.

Sorooshian, S. and Gupta, V. 1995. Model calibration. In: Computer Models of Watershed Hydrology (ed. V.P. Singh). *Water Resources Publications*. Fort Collins, CO, USA, pp 23–68.

Vrugt, J.A., Gupta, H.V., Bouten, W. and Sorooshian, S. 2003. A shuffled complex evolution metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters. *Water Resour. Res*., 39(8): 1201-1029.

Yang, J., Reichert, P., Abbaspour, K., Xia, J. and Yang, H. 2008. Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China. *J. Hydrol*., 358: 1–23.

Yesuf, H.M., Melesse, A.M., Zeleke, G. and Alamirew, T. 2016. Streamflow prediction uncertainty analysis and verification of SWAT model in a tropical watershed. *Environ. Earth. Sci.*, 75: 806-815.

Zhang, D., Zhang, L. and Guan, Y. 2012. Sensitivity analysis of Xinanjiang rainfall–runoff model parameters: a case study in Lianghui, Zhejiang province, China. *Hydrol. Res.*, 43: 123–134.

Zhang, X., Srinivasan, R. and Liew, M.V. 2010. On the use of multialgorithm, genetically adaptive multi-objective method for multi-site calibration of the SWAT model. *Hydrol. Proc*., 24: 955–969.