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Streamflow Simulation of Brahmani River Basin using SWAT Model

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ABSTRACT: A popular semi-distributed model for watershed hydrological study is the Soil and Water Assessment Tool (SWAT). The SWAT-CUP model's uncertainty analysis capability now has the ability to integrate ParaSol, Sequential Uncertainty Fitting (SUFI-2), Generalized Likelihood Uncertainty Estimation (GLUE), Particle Swarm Optimisation, and Markov Chain Monte Carlo (MCMC) into a single platform. In the current work, the SWAT model was calibrated for the years 1994 to 2005 while using the first three years as a warm-up phase (1990 to 1993) and validated for monthly streamflow simulation from 2006 to 2015. For Bramhani River Basin the SUFI-2 technique was used for the uncertainty analysis was performance. For sensitivity analysis, ten notable parameters were chosen. Nash-Sutcliffe Efficiency (NSE), the coefficient of determination (R2), and Percentage BIAS (PBIAS) were used to evaluate the model's performance on a monthly time scale streamflow simulation. The P and R variables were utilized to determine how much ambiguity there was. During the calibration period, the values of NSE, R^2, and PBIAS were determined to be 0.80, 0.81, and -0.08; and for the validation period, they were 0.72, 0.76, and -0.17, respectively. During calibration, the P and R factor values were observed to be 0.77 and 0.89, respectively, and 0.86 and 0.82, respectively, during the validation period. During the calibration and validation periods, the simulated streamflow is also well matched within the 95 percent prediction uncertainty (95PPU) range of the SUFI-2 method, suggesting an acceptable performance of the model under parameter uncertainty.

Keywords: SWAT, SUFI-2, Streamflow, uncertainty analysis, sensitivity parameter.

INTRODUCTION

Water is a key component of all living things on the ecosystem and is considered as the most priceless and important natural resource (Chapin *et al.*, 2009). It has gradually become the top national and global problem of the day since the amount of water that is readily accessible is constant and it is being used excessively as a result of population growth and expanding urbanisation. Therefore, effective utilization of water resources is essential to satisfy both the present and future needs of civilization (Cosgrove and Loucks 2015; Panigrahi *et al.*, 1992). To do that, it could be necessary to assess the potential of water resources at the basin scale. For the assessment and management of water resources at the watershed scale, hydrological modelling is a crucial tool. There have been several watershed models created for this purpose, ranging from straightforward empirical models to more intricate physically based distributed models (Schoups *et al.*, 2013). Despite the fact that the physical principles underlying all hydrologic processes are taken into account when creating a model structure, the end product is almost always merely an approximation of the actual system (Beven, 2002). This is due to the modeler's incorporation of both conceptual representations of the unidentified principles underlying the process being modelled and the physical processes already known to exist. As a result, there are several types of uncertainties related to model structure, parameters, input data, and randomness that might arise during the implementation of any sort of model. In the end, these uncertainties cause a sizable simulation inaccuracy. Therefore, it is crucial to determine the level of uncertainty associated with model findings before making any judgements or recommendations. As a result, scientists today favor using combined stochastic and deterministic models with a deterministic core enclosed in a stochastic frame (Regan *et al.*, 2002). The uncertainty in determining the model parameters is the main issue in any hydrological modelling, out of all sorts of uncertainties. The incompatibility between a model's complexity and the data needed to parameterize it leads to further issues (Zhang *et al.*, 2012; Song *et al.*, 2015). One such technique is sensitivity analysis (SA), which identifies the variables that significantly affect a model's outputs and, consequently, its effectiveness (Mario *et al.*, 2008). SA is essentially the change in the output reactions to the change in one or more model inputs or parameters in hydrological modelling (Song *et al.*, 2015). It is also important to note that SA considers the influence of parameters as well as the uncertainty in model forcing (Mooji *et al.*, 2010). The more sensitive parameters in a calibration process are optimized more quickly and precisely than the less sensitive ones (Dubois *et al.*, 1995). According to Power *et al.* (2006), SA based on automatic calibration techniques may be split into two categories: local search strategies and global search strategies. Global techniques analyze the change in output by altering all the parameters concurrently throughout the whole possible range, whereas local approaches assess the influence of parameters on the output by adjusting each parameter, one at a time, around any base case (Jenkinson *et al*., 2002). Although it has only recently become more popular, the use of SA approaches in hydrological modelling (Vrugt *et al*., 2003) has received some attention.

As SWAT-CUP (SWAT Calibration and Uncertainty Procedures) model is a technique for sensitivity and uncertainty analysis, the Soil and Water Assessment Tool (SWAT) model is now becoming more and more well-known as a combined stochastic and deterministic model (Gado, 2016). In essence, SWAT is a semi-distributed hydrologic model with a physical foundation that was first created to mimic streamflow in an ungauged basin (Arnold *et al.*, 1998). Today, it is often used to model a variety of watershed-scale processes, including streamflow, sediment production, crop yield, etc. (Yesuf *et al*., 2016; Raneesh and Thampi 2011; Mukundan *et al*., 2013). This model may also be used to analyze the effects of climate change on streamflow (Jha *et al*., 2004; Chien *et al*., 2013) and the assessment of blue and green water resources combined (Faramarzi *et al*., 2009). Thus, it demonstrates the SWAT model's broad usefulness in the management and modelling of land, water, and agricultural systems.

Because it is challenging to remove erroneous data gathered from many sources, there is always uncertainty associated with model outputs. However, this may be reduced by doing thorough field research, having a sufficient and effective monitoring network, using effective parameter estimate tools and procedures (better data collecting), treating data carefully, and conducting efficient manufacture and maintenance (Yan *et al*., 2015). In order to make science-based decisions and to focus research on model structural advancements and uncertainty reduction, it is crucial to make a realistic evaluation of the many causes of inaccuracy (Gregory *et al*., 2012). It is well knowledge that hydrological model simulations need to incorporate an explicit assessment of the related uncertainty.

To decrease the uncertainties created by modifications in the model's parameters and structure, sensitivity analysis and uncertainty analysis are both crucial techniques. SUFI-2 (Sequential Uncertainty Fitting) method (Abbaspour *et al*., 2004), GLUE (Generalised Likelihood Uncertainty Estimation) method (Beven and Binley 1992), ParaSol (Parameter Solution) method (Yang *et al*., 2008), and MCMC (Markov Chain Monte Carlo) method) are recently developed calibration and uncertainty analysis techniques for watershed models. These methods (GLUE, Parasol, SUFI-2, and MCMC) provide sensitivity and uncertainty analysis of model parameters as well as the structure (Narsimlu *et al*., 2015) and have been integrated to the SWAT model using SWAT-CUP (Abbaspour *et al*., 2007). With further research in diverse agro-climatic scenarios, SWAT model calibration and uncertainty analysis using these methodologies have been highlighted and proven by several studies throughout the world. This will increase the degree of confidence. The SUFI-2 approach was used by (Abbaspour *et al*., 2004) to evaluate the SWAT model. In comparison to previous strategies, the SUFI-2 methodology requires a less number of model simulations to get a high-quality calibration and uncertainty findings (Wu *et al*., 2021; Yang *et al*., 2008). In this study, streamflow simulation of Brahmani River Basin, India was carried out using the SWAT model. SUFI-2 algorithm was used to evaluate the Sensitivity and uncertainty in streamflow of SWAT-CUP model.

MATERIALS AND METHODS

Study Area. Brahmani River Basin is situated in eastern India mostly belonging to the state of Odisha. It is Odisha's second-largest river. Land use is generally agricultural and forestry. In the basin, agriculture makes up about 52% of the total area. In the rest of the basin, forests are the major land use. The south koel and sankh river combines to form Brahmani river basin. Its latitude extends from 20°28′ to 23°35′ N and longitude extends from 83°52′ to 87°03′E. The total catchment area is found to be 39,313 km^2 and receives almost about 1305.2 mm of normal annual rainfall. The basin has a tropical climate. The maximum temperature reaches as high as 47° during summer and drops to a minimum temperature of 4° in winter. Around 70% of the basin has a gentle slope. The maximum elevation of the basin is nearly 1181 m from MSL. Fig. 1 depicts the location of the study area.

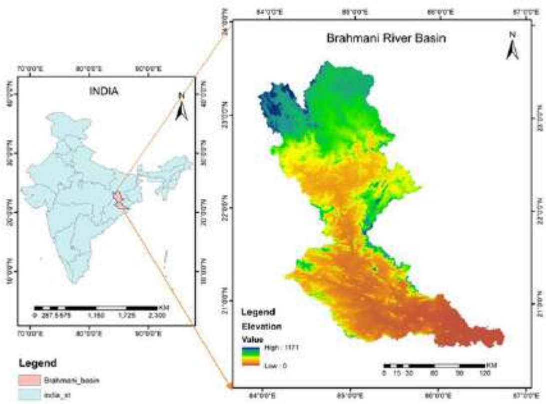

Fig. 1. Location map of Brahmani River Basin.

Data used. SWAT needs various field data to set-up the model for simulating streamflow. Spatial maps of Digital Elevation Model (DEM), soil map, and land use land cover were taken as input data. Daily weather data (precipitation, and minimum and maximum air temperature) were also used for simulation. The input data and their sources were shown in Table 1. The detailed soil and land use maps are shown in Fig. 2 and 3, respectively.

Table 1: The sources of input data.

Data	Source
Soil	Harmonized World Soil Database (HWSD) developed by the Food and Agriculture Organization of the United Nations (http://www.fao.org)
Land use	National Remote Sensing Centre (https://www.nrsc.gov.in/).
Rainfall and Temperature	Daily rainfall and temperature data collected from the India Meteorological Department (IMD), (1990-2020) gridded data (1°*1°)
Discharge	Daily discharge data from (1990-2020) was collected from CWC, Bhubaneswar
DEM	Shuttle Radar Topography Mission (SRTM 90) of USGS (http://srtm.csi.cgiar.org/).

Land Use and Soil. According to Dadhwal *et al*. (2010), the hydrological cycle's runoff and infiltration processes are primarily impacted by land use and land cover (LULC). The National Remote Sensing Centre (NRSC), in Hyderabad, India, provided the LULC map at 1:250000 scale for this study. According to Fig. 2, the land use is primarily divided into seven types. The hydrological response of a watershed is also significantly influenced by the kind of soil present. The research area's soil map was taken from the FAO-developed Harmonised World Soil Database (HWSD). The two most prevalent soil types in the catchment area are sandy loam and loam. Additionally, sandy clay-loam and clay soils may be found in a few other areas of the watershed (Fig. 3).

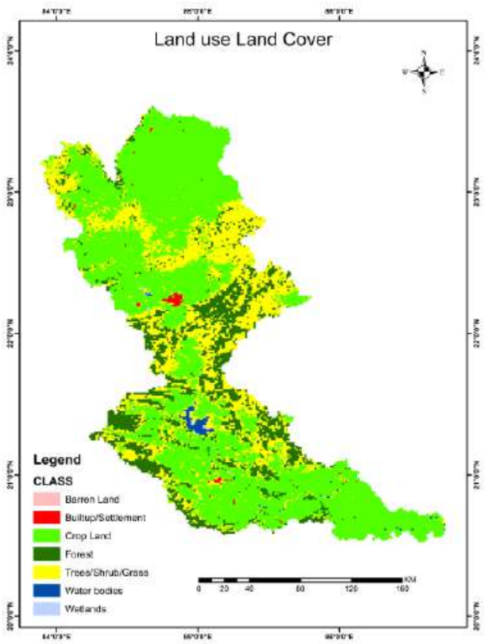

Fig. 2. Land use map of the study area.

SWAT Model. A semi-distributed hydrological model called the SWAT model was created by the Agricultural Research Service (USDA-ARS) of the United States Department of Agriculture (Arnold *et al*., 1998). According to Neitsch *et al*. (2011), it can accurately replicate the streamflow, sediment, and nutrient load from a sizable un-gauged basin. The water balance equation has been utilised to simulate various hydrological components, as illustrated in Eq. 1 (Neitsch *et al*., 2011; Nasiri *et al*., 2020).

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

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.

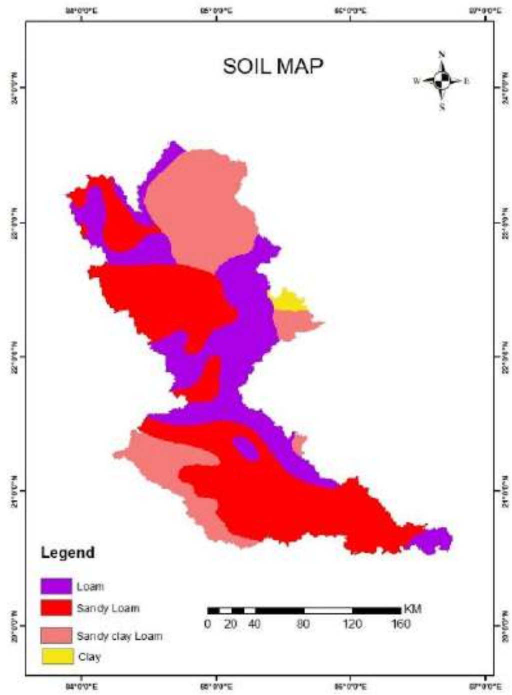

Fig. 3. Soil map of the study area.

SUFI-2 Algorithm. For calibration, sensitivity, and uncertainty analysis, Abbaspour *et al*. (2015) SWAT model is specifically created and integrated with SWAT-CUP. Using this universal interface, the SWAT model may be simply connected to any calibration/uncertainty or sensitivity programme (Tejaswini and Sathian 2018). SWAT-CUP includes the methods ParaSol, SUFI-2, GLUE, and MCMC on a single platform. This study examined the sensitivity and uncertainty in streamflow simulation using the SUFI-2 method.The SUFI-2 method is based on a Bayesian framework that generates the posterior parameters from priors and uses them to construct new values (posterior parameters) for the relative likelihood of occurrences of interest (Uniyal *et al*., 2015; Haan, 1977).

The SUFI-2 approach makes use of a number of objective functions to address the non-uniqueness issue in model parameterization (Schuol and Abbaspour 2006). According to Rockenfeller *et al*. (2015), the relative sensitivities are described as the average change in the objective functions with respect to the ensuing changes in each parameter. It provides some details on the sensitivity of the target function and is based on a linear approximation of the model's parameters.

All sources of uncertainty are considered in SUFI-2 in terms of "parameter uncertainty," which takes into account uncertainties in driving factors (such rainfall), model conceptualization, parameterization, and observed data. Parameter uncertainty is quantified and expressed as a percentage of the 95 percent prediction uncertainty band (95PPU) (Shen *et al*., 2015). To determine the 95PPU the cumulative distribution of output variables' levels 2.5% and 97.5% are used. To create separate parameter sets, a "Latin hypercube" sampling approach has been utilised (Lee *et al*., 2006). The P-factor and R-factor, two additional statistics, are used to measure the robustness of a calibration and uncertainty study (Kumar *et al*., 2017).

Calibration and Validation. For the analysed catchment's daily flow, information from the Indian Water Resources Data System was collected from January 1990 through December 2015. This information gathering has been utilised to contrast, further calibrate, and validate the simulated data gathered by the SWAT model. In this study, twenty-fiveyears' data were considered. You have to depart (NYSKIP) for a certain amount of time (1990–1993). Numerous studies have shown that good outcomes require a warm-up phase of about 3 years. 12 years (1994–2005) and 10 years (2006–2015) were used for calibration and validation respectively. According to the SWAT CUP programme, the Arc SWAT model's calibration and validation were carried out using a (Sequential Uncertainty Fitting Version 2) SUFI2 method. The first step in the inquiry is to develop very sensitive criteria for both the watershed and SWAT calibration. Ten parameters were selected for model calibration, sensitivity and uncertainty analysis of streamflow simulation and their maximum and minimum recommended values are shown in Table 2.

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

Sr. No.	Parameter	Minimum	Maximum
1.	RCHRG_DP	0.03	0.5
2.	SOL_K	0.30	0.7
3.	CH_N2	0.03	0.3
4.	SOL_AWC	-0.15	0.15
5.	ALPHA_BF	0.4	1.2
6.	SLSUBBSN	0.1	0.2
7.	ALPHA_BNK	0.32	0.61
8.	GW_SPYLD	0.20	0.34
9.	GW_DELAY	0.90	2.20
10.	GWQMN	2900	4700

Performance Indices. Five parameters have been used for evaluation of model performance, namely coefficient of determination (*R^2*), Nash–Sutcliffe Efficiency (*NSE*), Percentage BIAS (*PBIAS*), *P-factor* and *R-factor*. The coefficient of determination (*R^2*), Nash–Sutcliffe Efficiency (*NSE*) and Percentage BIAS (*PBIAS*), are expressed mathematically in the following Eqn. 2, 3 and 4, respectively.

$$R^2 = \frac{\left[\sum_{i=1}^{n} (s_i - \underline{s})(o_i - \underline{o})\right]^2}{\sum_{i=1}^{n}(s_i-\underline{s})^2 \sum_{i=1}^{n}(o_i-\underline{o})^2} \quad (2)$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}(o_i - s_i)^2}{\sum_{i=1}^{N}(o_i-\underline{o})^2} \quad (3)$$

$$PBIAS = \frac{\sum_{i=1}^{n}(o_i - s_i)}{\sum_{i=1}^{n} o_i} \times 100 \quad (4)$$

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

All of the SWAT model's uncertainties were quantified using the P-factor (the percentage of observed data included inside the 95% prediction boundary).

The P-factor's range is 0 to 1, with values close to 1 indicating very high model performance and efficiency, whereas the R-factor's range is 0 to ∞, and it is calculated by dividing the average width of the 95PPU band by the standard deviation of the observed variable. The mathematical expressions of the P-factor and the R-factor are as follows (Abbaspour *et al*., 2007; Yang *et al*., 2008):

$$P - factor = \frac{ny_{t_i}}{N} \quad (5)$$

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

$$R - factor = \frac{\frac{1}{n}\sum_{t_i=1}^{n}\left(y_{t_{i,97.5\%}}^{M} - y_{t_{i,2.5\%}}^{M}\right)}{\sigma_{obs}} \quad (6)$$

where, $y_{t_{i,97.5\%}}^{M}$ and $y_{t_{i,2.5\%}}^{M}$ are the upper and lower limits of the 95UB (Uncertainty Band), respectively and σ_{obs} is the standard deviation of the observed data.

RESULTS AND DISCUSSION

Model Calibration and Sensitivity Analysis (SA). According to the SWAT-CUP documentation (Neitsch *et al*., 2005), a thorough calibration based on sensitivity analysis of model parameters has been done in this work. Based on research and SWAT documentation, a total of 10 SWAT parameters, shown in Table 3, were chosen for model calibration and uncertainty analysis (White and Chaubey 2005; Neitsch *et al*., 2002). Latin hypercube sampling was used in the initial stages of calibration to conduct a global sensitivity analysis at the monthly time-step (Tang *et al*., 2007). The input parameter values are adjusted as part of the calibration process in order to closely match the simulated results with the observed variables and to identify the most sensitive factors that have a greater impact on the variable than other parameters. The model ran 500 times in sensitivity analysis, and the outcomes were looked at. They are produced when the model is run with Nash and Sutcliffe efficiency (NSE) as an objective function during calibration.

To evaluate the sensitivity and relative relevance of all possible parameter, T-stat and p-value were used as two indicators (Abbaspour *et al*., 2015). Baseflow alpha factor (ALPHA_BF) is the most significant baseflow calibration parameter, followed by groundwater recession constant. The groundwater flow's role in the fluctuation in recharge is explained by the alpha factor (ALPHA_BF). These two factors' values should be greater if the basin responds quickly to groundwater replenishment. Another sensitive component that has a significant impact on the flow characteristics is the sub-basin slope parameter (SLSUBBSN). Additionally, a key metric was the SOL_K, which measures how easily water can travel through subsurface soil layers. A moderate value of the river-bank flow recession constant (ALPHA_BNK) suggests that water moves between bank storage areas and neighboring unsaturated zones. which is caused by extreme water stress. The greater surface runoff is a direct outcome of the longer water's resting time over the soil surface, as shown by a larger GW_DELAY value. The larger value of streamflow would also have been applied to the lower GW_SPYLD value.

Model performance and Uncertainty Analysis (UA). In the present study, the simulated discharges were compared with the observed ones at the outlet of Jenapur catchment during the calibration period from 1994 to 2005 and validation period from 2006 to 2015 as presented in Fig. 4 and 5, respectively. Table 4 contains a list of the performance indices attained throughout the calibration and validation periods. During calibration, the NSE, R2, and PBIAS values were 0.80, 0.81, and -0.08 respectively; during validation, they were 0.72, 0.76, and -0.17. This shows that the outcomes of the model simulation are quite good.

Table 3: Best fitted value of sensitive calibration parameters by SUFI-2.

Sr. No.	Parameter	Minimum	Maximum	Fitting Value
1.	RCHRG_DP	0.03	0.5	0.2
2.	SOL_K	0.30	0.7	0.6
3.	CH_N2	0.03	0.3	0,04
4.	SOL_AWC	-0.15	0.15	-0.035
5.	ALPHA_BF	0.4	1.2	1
6.	SLSUBBSN	0.1	0.2	0.1
7.	ALPHA_BNK	0.32	0.61	0.4
8.	GW_SPYLD	0.20	0.34	0.3
9.	GW_DELAY	0.90	2.20	1.5
10.	GWQMN	2900	4700	4423

Table 4: Summary statistics of model performance.

Indices	Calibration	Validation
R^2	0.81	0.76
NSE	0.80	0.72
PBIAS	-0.08	-0.17
P-factor	0.77	0.86
R-factor	0.89	0.82

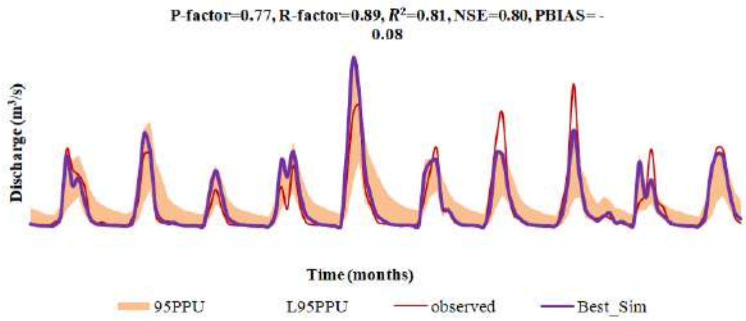

Fig. 4. Time series plot of simulated vs. observed streamflow with 95PPU band during calibration period.

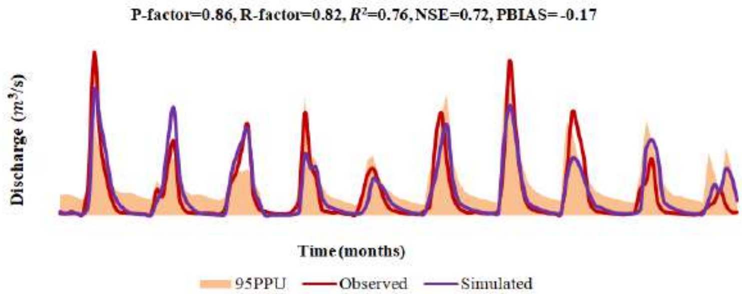

Fig. 5. Time series plot of simulated vs. observed streamflow with 95PPU band during validation.

Additionally, scatter plots were used to compare the simulated streamflow to the actual flow. The scatter plot of the calculated streamflow against the observed streamflow (Figs. 6 and 7) shows that the simulated streamflow consistently maintains equilibrium near the 1:1 line during both the calibration and validation phases. This shows that the streamflow generated by the model is close to the values that were observed. However, Fig. 6 and 7 clearly show that the model overestimates streamflow at times of low flow. This demonstrates the SWAT model's limitations in simulating the catchment's base flow component.

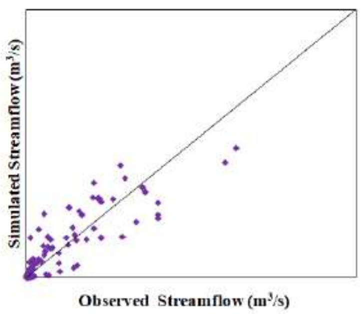

Fig. 6. Scatter plots of observed versus simulated streamflow by SUFI-2 during calibration.

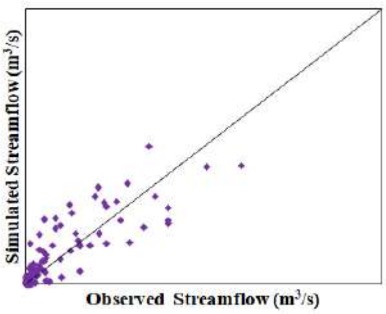

Fig. 7. Scatter plots of observed versus simulated streamflow by SUFI-2 during validation.

P and R factors are used throughout the calibration and validation phases to quantify parameter uncertainty in streamflow modelling. In the calibration period and the validation period, the values of the P and R factors are determined to be 0.77 and 0.89 and 0.86 and 0.82 respectively (Table 4). The P-factor and R-factor values fall within the intended range for both the calibration and validation periods, indicating that the uncertainties of the parameters are tolerable for the duration of the simulation period.

CONCLUSIONS

The current study demonstrates how to utilise the SWAT model to simulate streamflow catchment of the Indian Brahmani River Basin, identify the parameters that are most sensitive, and quantify model parameter uncertainty using the SUFI-2 method. The pre-calibration uncertainty analysis resulted in the identification and ranking of sensitive parameters. The statistics show that nine variables are very sensitive and significantly affect streamflow. The soil conservation service curve number for AMC II factor has been shown to be the most sensitive parameter for the Brahmani river basin. The model's monthly streamflow simulation during the streamflow calibration by SUFI-2 was found to have excellent NSE, R2, and PBIAS values. These numbers were, respectively, 0.80, 0.81, and -0.08. The model performance is reassuringly sufficient, as evidenced by the validation's NSE, R2, and PBIAS values of 0.72, 0.76, and -0.17, respectively. Given the parameter uncertainty, the model performance is rather good, as indicated by P and R factor values of 0.77 and 0.89 during calibration and 0.86 and 0.82 throughout the validation period, respectively. The results of the model simulation indicate that the SWAT model may be successfully applied for streamflow simulation under parameter uncertainty in an ungauged watershed.

FUTURE SCOPE

The SWAT model is suitable for streamflow prediction in the Brahmani river basin, according to the results of sensitivity and uncertainty analysis using SWAT and SUFI-2. The model may be calibrated and validated for nutrients and sediments in addition to flow, making it more effective for predicting the effects of changing land use and land cover on water quality in the Brahmani river basin. The model may be used to study future climatic scenarios, aiding in the risk assessment of floods and droughts. Watershed managers may utilize the study's findings to help them make better judgements and manage their watersheds more effectively.

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Conflicts of Interest. None.

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