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# Assessment of calibration parameters and uncertainty analysis of SWAT model for monthly streamflow simulation in Kantamal catchment of Mahanadi river basin (India)

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**ABSTRACT**

The soil and water assessment tool (SWAT) is a widely accepted semi-distributed agro-hydrological model. In the present study, the SWAT has been calibrated for the agriculture-dominated Kantamal catchment of Mahanadi river basin, Odisha, India, to simulate streamflow at the Kantamal gauging station. The model was run for 19 years from 2000 to 2018 to simulate monthly streamflow. In addition, the model has been calibrated for the period 2004 to 2012, considering the initial 4 years (2000-2003) as a warm-up period and validated for 6 years from 2013 to 2018. Uncertainty analysis was carried out using the SUFI-2 algorithm in SWAT-CUP. The sensitivity of the parameters was determined using the *t-stat* and *p-value*. Fifteen distinguished parameters were selected for sensitivity analysis (SA). The performance of the model was evaluated satisfactorily on monthly time scale streamflow simulation using Nash-Sutcliffe Efficiency (NSE), 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 0.91, 0.94, and -0.07 during the calibration period and 0.82, 0.87, and -0.16 during the validation period, respectively. The P- and R- factors values were 0.77 and 0.98 during calibration and 0.79 and 0.86 during the validation period, respectively. The simulated streamflow is well fitted within the 95% prediction uncertainty (95PPU) band of the SUFI-2 algorithm during the calibration and validation periods, indicating a satisfactory model performance under parameter uncertainty. Overall, it is depicted that the SWAT model can be successfully used for streamflow modeling and water resources assessment in agriculture-dominated catchments.

## 1. INTRODUCTION

Water is the symbol of life, and freshwater, the most precious natural resource, accounts for the sustenance of life on the earth. Out of the vast water resources of the earth, only 0.5% is freshwater, and it is available for meeting the various needs of human beings (Padhiary *et al.,* 2020). The quantity and quality of this finite resource are gradually depleting due to various anthropogenic activities like injudicious use in agriculture, domestic and industrial purposes (Pathan and Sil, 2019). Hence, conservation of the resource with respect to quantity and quality is one of the most important national and international concerns today. Out of total available freshwater, 70-80% is used in Agriculture. Overuse of freshwater for irrigation and blending of agrochemicals and fertilizers in agricultural fields and draining of industrial effluent to the water bodies etc., are creating threats for the scarce resource. So, proper management of water resources is imperative to meet the need of current and future demands (Ahmadi *et al*., 2020; Panigrahi *et al.,* 1992). Assessment of the potential of water resources at basin or sub-basin scale may be a pre-requisite for using the resource in a planned manner. The natural system is very complex, and to overcome this, hydrologists use simulation models that are the simplified representation of a natural hydrologic system for assessing various components of the hydrological cycle on a watershed scale. Hydrological models starting from simple empirical models to more complex physically-based distributed models, have been evolved over the years to understand the different aspects of hydrology (Samadi *et al*., 2017). Although the natural hydrological processes are represented by simplified or complex mathematical equations in hydrological models, the final design is invariably only an approximation of the complex natural system. This is because the modeler combines existing knowledge of the physical processes with some conceptual representations of unknown principles underlying the modeled process. Therefore, applications of any model are associated with several kinds of uncertainties with respect to model structure, parameters, input data, and natural randomness. These uncertainties finally lead to a considerable error in the model simulation. It is necessary to quantify the degree of uncertainty associated with model results before drawing any conclusion and recommending it. Hence, using stochastic hydrological models or deterministic models having a deterministic core within a stochastic frame is becoming popular in hydrology.

Complex hydrological models use several parameters for different water cycle components that increase the possibility of model parameter uncertainty. Further complications arise owing to the mismatch between model complexity and data availability to parameterize a model (Uniyal *et al.*, 2015; Song *et al.,* 2015). Parameters influencing the simulation of a hydrological process are generally selected and optimized using a suitable algorithm during the model calibration process. Also, various automatic calibration algorithms have been developed with respect to the hydrological model development (Guse *et al.,* 2019). Sensitivity analysis (SA) of calibration parameters is one method that helps identify those parameters having a strong impact on the model outputs, thereby influencing the model's efficiency.

The application of SA in hydrological modeling is gaining greater attention nowadays. SA is performed by studying the changes in model responses to the change in one or more model inputs or parameters. It is also worth mentioning that SA considers the effect of parameters and the uncertainties in model forcing (Padhiary *et al.,* 2019). In a calibration process, higher sensitivity parameters are quickly and closely optimized than less sensitive ones. SA based on automatic calibration procedures is generally divided into two types, i.e., local and global search strategies (Uniyal *et al.*, 2015; Yesuf *et al.,* 2016). The local approaches deal with assessing the effect of change in parameter value on model output by selecting one parameter at a time. In contrast, the global approaches assess the change in model output by varying all the parameter values simultaneously over the entire feasible range.

The SWAT model is gaining popularity as a joint stochastic and deterministic model due to the development of the SWAT Calibration and Uncertainty Procedures (SWAT-CUP) model for sensitivity and uncertainty analysis (Agrawal *et al.,* 2011). SWAT is a physically-based semi-distributed hydrologic model initially developed to simulate streamflow in an un-gauged basin (Arnold *et al*., 1998; Samadi *et al.*, 2017). Nowadays, it is widely used for simulating streamflow, sediment yield, evapotranspiration, soil moisture, crop yield, etc., on the watershed scale (Yesuf *et al.,* 2016; Bhatt *et al*., 2016; Zhang *et al.*, 2019; Panda *et al.*, 2021). Furthermore, the impact of climate change on streamflow (Ahmadi *et al*., 2020; Padhiary *et al.,* 2020) 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 potential of the SWAT model and its wide applicability in the land, water, and agricultural system simulation and management.

Uncertainty is always associated with model outputs because of the difficulty of eliminating spurious data collected from several sources (Warusavitharana, 2020). However, this can be minimized through intensive field investigation, adequate and efficient monitoring network, efficient parameter estimation tools and techniques, careful data handling, and efficient manufacturing and maintenance (Afshar *et al.,* 2020). A realistic assessment of various sources of error is essential for science-based decision-making and directs the research towards model structural improvements and uncertainty minimization. Therefore, it is accepted that hydrological model simulations should explicitly include an estimate of their associated uncertainty.

Generally, distributed hydrologic models comprise many unknown parameters, and the model's efficacy in simulating the hydrological processes depends heavily on the accurate estimation of these parameters through calibration (Choudhari *et al.,* 2014; Vema and Sudheer, 2020). Both sensitivity and uncertainty analysis are essential processes to reduce the uncertainties developed by the model parameters and structure variations. Recently developed calibration and uncertainty analysis techniques for watershed models include Markov Chain Monte Carlo (MCMC) method, Generalized Likelihood Uncertainty Estimation (GLUE) method, Parameter Solution (ParaSol) method, and Sequential Uncertainty Fitting (SUFI-2) method (Abbaspour *et al*., 2004; Wu and Chen, 2015). These techniques (GLUE, Parasol, SUFI-2, and MCMC) have been linked to the SWAT model through SWAT-CUP and enable sensitivity and uncertainty analysis of model parameters and structure (Abbaspour *et al.,* 2007). The calibration of the SWAT model and uncertainty analysis through these techniques is emphasized and confirmed by various studies worldwide and suggests more investigation in different agro-climatic situations to enhance confidence levels. Abbaspour *et al*. (2004) applied the SUFI-2 technique to evaluate the SWAT model. The SUFI-2 technique needs a minimum number of model simulations to attain high-quality calibration and uncertainty results compared to other techniques (Thavhana *et al*., 2018). In this study, the streamflow simulation in the middle reach of Mahanadi river basin, India, was carried out at Kantamal gauging station using the SWAT model. Sensitivity and uncertainty in streamflow were evaluated using the SUFI-2 algorithm of the SWAT-CUP model.

## 2. MATERIALS AND METHODS

### Study Area

The study was undertaken in the Kantamal catchment located at the middle reach of the Mahanadi river basin. The catchment extends over 20,024 km$^2$, which is nearly 12.85% of the state's total geographical area. The catchment area lies between 82°02′11″ to 84°18′56″ East longitudes and 19°16′ 7″ to 20°44′12″ North latitudes. The middle reach of the Mahanadi basin drained by two tributaries of Mahanadi *viz.,* Tel and Ong river is the major rainfed area of the basin in the state of Odisha. It covers eight districts of Odisha, namely, Kalahandi, Bolangir, Nuapada, Kandhamal, Nabarangpur, Rayagada, Boudh, and Sonepur, comprising 49 revenue blocks and one district of the adjacent state Chhatisgarh, namely, Gariabandh. About 95% of the basin is in the state of Odisha, and the rest 5% area is in the Gariabandh district of Chhattisgarh (Fig. 1). Cultivable land is the predominant land use of the basin among various land uses. Major crops grown in this catchment are rice, pulses, cotton, millet, groundnut, sugarcane, and vegetables. The normal annual rainfall of the catchment is 1360 mm, out of which 1170 mm occurs during the monsoon season (June to September). The maximum temperature of the catchment ranges from 31-48°C, whereas the minimum temperature ranges from 6-23°C. Average relative humidity of the study area varies from 39% during summer to about 87% during the monsoon season. The temporal variability of the meteorological parameters is presented in Fig. 2.

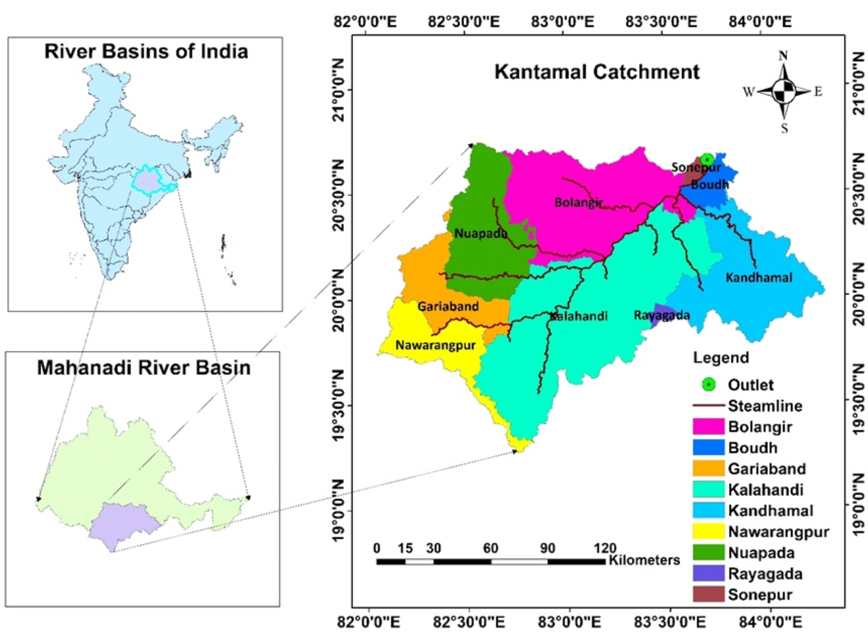


**Fig. 1. Location map of Kantamal catchment**

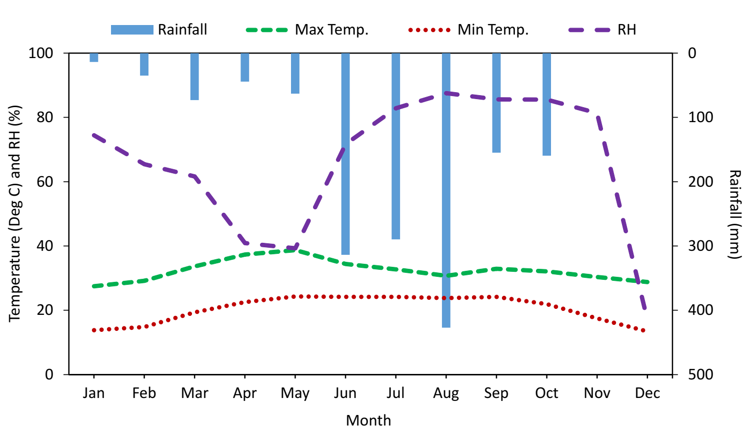


**Fig. 2. Temporal variability of meteorological parameters in the catchment**

**Data Requirement**

SWAT needs various field data to set up the model for simulating streamflow. Therefore, soil, land use, weather, discharge, and elevation databases were collected from different sources / agencies as listed in Table 1. The detailed soil and LU maps are illustrated in Fig's 3 and 4, respectively.

**Land Use and Soil Type**

Land use / land cover (LU/LC) mainly affects the runoff and infiltration processes of the hydrological cycle (Tegegne *et al.,* 2019). LU/LC map at 1:50000 scale used in this study was obtained from National Remote Sensing Centre (NRSC), Hyderabad, India, developed for 2011-12. The study area is divided into five LU/LC classes: water bodies, wasteland, forest, build-up, and agricultural land, as illustrated in Fig. 3. Water bodies are found to cover only 1.96% area of the catchment. On the other hand, the agricultural land is the dominant land use of the catchment, and it covers half of the study area (50.11%) and is mostly spread in the central and northern parts of the catchment.

The forest land covers 37.52% of the catchment and spreads mostly in the eastern, south-eastern, and western regions. The built-up areas (1.2% of catchment area) and wastelands (9.21% of catchment area) are scattered sporadically throughout the catchment. Soil type also plays a prominent role in governing the hydrological response. The soil map of the study area was collected from the NBSS& LUP, Kolkata. The soil texture for the study area is represented by seven classes: clay, silty clay, clay loam, silty clay loam, sandy clay loam, loam, and sandy loam, as illustrated in Fig. 4. Clay loam soil covers about half of the catchment area (49.88%), followed by sandy loam soil spreading over 26.52% area of the catchment. Sandy clay loam and sandy clay types of soil spread over 21.11% and 2.49% area of the catchment, respectively. The details of the soil characteristics of the study area are presented in Table 2.

**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). The SWAT model has been built and developed in a semi-distributed way, where the catchment is sub-divided into sub-catchments and further into hydrological response units (HRUs), and the land use, soil, and slope can be accounted for by the model (Uniyal *et al.*, 2015). Hence, the input requirements consist of climatic parameters, soil properties, topography, vegetation, and land management practices (Neitsch *et al.*, 2011; Padhiary *et al*., 2019). The SWAT model uses a daily, monthly, and annual time step and can conduct continuous simulations over a long period (Arnold *et al*., 1998; Neitsch *et al.*, 2011). It can reasonably simulate a large un-gauged basin's streamflow, sediment, and nutrients load (Neitsch *et al.,* 2011; Panda *et*

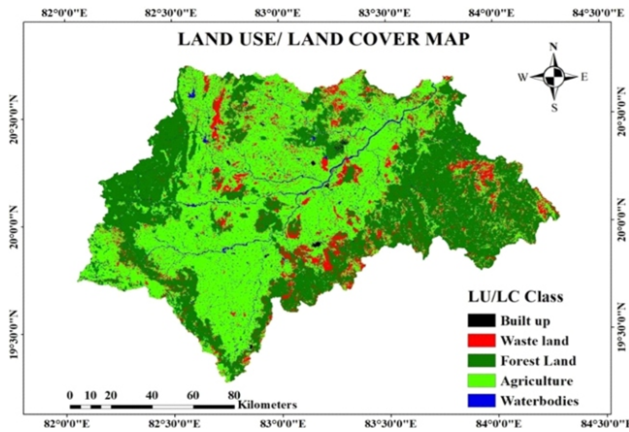


**Fig. 3. Land use / Land cover map of the study area**

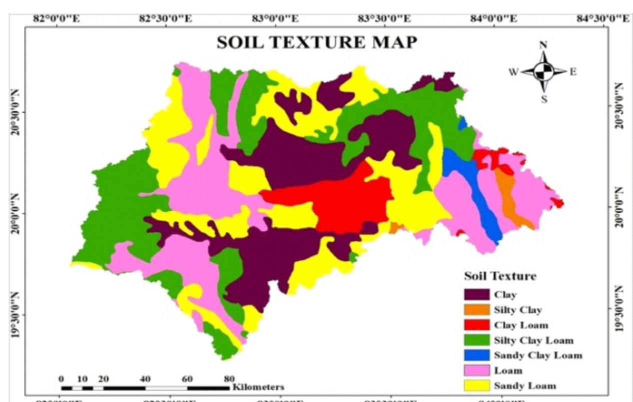


**Fig. 4. Soil map of the study area**

**Table: 1**
**Sources of input data**

| Data | Source |
|---|---|
| Soil | NBSS&LUP (1:50000) (https://www.nbsslup.in/) |
| Land use | National Remote Sensing Centre (1:50000) (https://www.nrsc.gov.in/) |
| Rainfall | Recorded block-wise rainfall data from Special Relief Commissioner, Odisha (https://srcodisha.nic.in/) |
| Temperature | 0.25× 0.25 Gridded maximum and minimum temperature data from India Meteorological Department (IMD), Pune |
| Discharge | Daily discharge data (2000-2018) from Water Resources Information System of India (India-WRIS), CWC (https://indiawris.gov.in/wris) |
| DEM | Digital Elevation Model (DEM) from Shuttle Radar Topography Mission (SRTM 30) of USGS (http://srtm.csi.cgiar.org/) |

**Table: 2**
**Soil characteristics of the Kantamal catchment**

| S.No. | Soil taxonomy class | Texture | Bulk density (g cm$^{-3}$) | Available water content (mm mm$^{-1}$) | EC (dS m$^{-1}$) |
|---|---|---|---|---|---|
| 1 | *Aeric Endoaquepts* | Clay loam | 1.40 | 0.14 | 0.28 |
| 2 | *Aeric Epiaqualfs* | Clay loam | 1.40 | 0.14 | 0.28 |
| 3 | *Arenic Haplustalfs* | Silty clay | 1.34 | 0.16 | 0.31 |
| 4 | *Chromic Haplusterts* | Clay | 1.32 | 0.13 | 0.42 |
| 5 | *Entic Haplusterts* | Clay | 1.32 | 0.13 | 0.42 |
| 6 | *Kandic Paleustalfs* | Sandy loam | 1.49 | 0.1 | 0.26 |
| 7 | *Lithic Haplustepts* | Sandy loam | 1.49 | 0.08 | 0.09 |
| 8 | *Lithic Ustorthents* | Loam | 1.42 | 0.15 | 0.09 |
| 9 | *Rhodic Paleustalfs* | Sandy loam | 1.49 | 0.09 | 0.07 |
| 10 | *Typic Epiaquepts* | Clay | 1.32 | 0.13 | 0.42 |
| 11 | *Typic Haplustalfs* | Silty clay | 1.34 | 0.16 | 0.31 |
| 12 | *Typic Rhodustalfs* | Loam | 1.44 | 0.13 | 0.07 |
| 13 | *Ultic Haplustalfs* | Sandy loam | 1.48 | 0.09 | 0.11 |
| 14 | *Ultic Paleustalfs* | Sandy clay loam | 1.51 | 0.10 | 0.13 |
| 15 | *Vertic Endoaquepts* | Silty clay | 1.27 | 0.15 | 0.23 |

*al.*, 2021). It simulates runoff based on the United States Department of Agriculture, Natural Resources Conservation Services-Curve Number Method, 1972 (USDA, NRCS-CN). The water balance equation (Neitsch *et al.,* 2011) shown in eq. 1 has been used for simulating the hydrological components.

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

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

In the SWAT model, Muskingum or variable storage method is built therein for streamflow routing (Arnold *et al.,* 1998). The lateral flow is estimated using the kinetic reservoir routing method based on the degree and length of slope and saturated hydraulic conductivity (Sloan *et al.,* 1983). Green and Ampt infiltration methods (Green and Ampt, 1911) are used for quantifying the rate of infiltration, whereas return flow is simulated by creating a shallow aquifer (Arnold *et al.,* 1998). Percolated water from the unsaturated zone is divided into shallow and deep aquifer recharges. A simplified volumetric water balance equation is used for groundwater recharge. SWAT can simulate groundwater height in the shallow aquifer in each HRU without any physical datum (Neitsch *et al.,* 2011). Also, it does not simulate groundwater flow between adjacent HRUs. There are two methods for calculating the surface retention coefficient in the SWAT model. In the first method, the surface retention coefficient changes with moisture content in the soil profile, and in the second method, the surface retention coefficient changes with the cumulative evapotranspiration. The model calculates evaporation from soil and plant separately. Any of the three methods can calculate potential evapotranspiration, *i.e.,* Penman-Monteith equation (Monteith, 1965), Priestley-Taylor method (Priestley and Taylor, 1972), and Hargreaves method (Hargreaves and Samani, 1985) based on climatic data availability.

**SWAT-CUP**

SWAT calibration and uncertainty procedure (SWAT-CUP) is a freeware model developed and coupled with the SWAT model by Abbaspour *et al.* (2007). It allows for SA, calibration, validation, and uncertainty analysis of various hydrological parameters. The SUFI-2 algorithm in SWAT-CUP was used to study the sensitivity and uncertainty in streamflow simulation. This technique is based on a Bayesian framework, which 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). In addition, several objective functions are used in the SUFI-2 technique to reduce the non-uniqueness problem in the model parameterization (Warusavitharana, 2020).

Further, a *t-test* was used 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 the *t-test* indicates a parameter to be more sensitive, and lower *p-values* close to zero show more significance (Narsimlu *et al.,* 2015). The SUFI-2 algorithm accounts for different types of uncertainties arising from model conceptualization, parameters, and observed data (Abbaspour *et al.*, 2015, Kumarasamy and Belmont, 2018). The input parameter uncertainty is represented by uniform distribution, while the output uncertainty is computed at 95% prediction uncertainty (95PPU) (Khoi and Thom, 2015). The cumulative

**Table: 3**
**Minimum-maximum and fitted value of calibration parameters by SUFI-2**

| S.No. | Parameter | Description | Minimum | Maximum | Fitted value |
|---|---|---|---|---|---|
| 1 | v__OV_N.hru | Manning's "n" value for overland flow | 0.01 | 30.0 | 18.49 |
| 2 | v__LAT_TIME.hru | Lateral flow travel time | 0 | 180.0 | 48.99 |
| 3 | v__ ESCO.hru | Soil evaporation compensation factor | 0 | 1.0 | 0.02 |
| 4 | v__EPCO.hru | Plant uptake compensation factor | 0 | 1.0 | 0.35 |
| 5 | v_SURLAG.hru | Surface runoff lag coefficient (day) | 0.05 | 24.0 | 15.83 |
| 6 | v__CANMX.hru | Maximum canopy storage | 1.0 | 100.0 | -17.55 |
| 7 | v__RCHRG_DP.gw | Deep aquifer percolation fraction | 0 | 1.0 | 0.95 |
| 8 | r_SOL_K (1).sol | Saturated hydraulic conductivity (mm hr$^{-1}$) | 0 | 2000.0 | 899.96 |
| 9 | r_SOL_AWC(1).sol | Available water capacity of the soil layer r (mm mm$^{-1}$) | 0.23 | 1.06 | 0.35 |
| 10 | r__CH_N2.rte | Manning's "n" value for the main channel | 0.11 | 0.45 | 0.29 |
| 11 | r_CH_K2.rte | Effective hydraulic conductivity in main channel alluvium (mm hr$^{-1}$) | 0.01 | 500.0 | 74.20 |
| 12 | r_CN2.mgt | SCS runoff curve number | -0.20 | 0.20 | -0.10 |
| 13 | v_ALPHA_BF.gw | Base flow alpha factor (days) | 0.00 | 1.00 | 0.46 |
| 14 | v_GW_DELAY.gw | Groundwater delay (days) | 0 | 500.0 | 242.00 |
| 15 | v_GWQMN.gw | Threshold depth of water in the shallow aquifer required for return flow to occur (mm) | 0.00 | 5000.0 | 0.51 |

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

distribution of an output variable is obtained through the Latin hypercube sampling method calculated at 2.5 and 97.5% prediction limit (Abbaspour *et al.*, 2015). The calibration and uncertainty analysis strength is quantified by two additional statistics known as P and R-factor. The P-factor represents the percentage of measured data bracketed by 95% prediction uncertainty (95PPU), while the R-factor represents the average width of the 95PPU band divided by the standard deviation of the observed variable.

**Calibration and Validation**

SWAT has been calibrated and validated for monthly streamflow by comparing the observed streamflow at the Kantamal outlet. The model was run for 19 years (2000-2018) by considering the first 4 years as the warm-up period. Streamflow data from 2004 to 2012 were used for calibration, whereas the remaining 6 years of the datasets, *i.e.,* 2013-2018, were used for validating the model. After completing the simulation, the SWAT-CUP was used for model sensitivity, calibration, and uncertainty analysis. Global SA was performed to identify the most sensitive parameters. The objective of the calibration is to optimize the model parameters. Almost 15 parameters were selected for model calibration, sensitivity, and uncertainty analysis of streamflow simulation. Recommended ranges of these fifteen parameters in terms of maximum and minimum values are shown in Table 3.

**Performance Indicators**

Five parameters such as coefficient of determination ($R^2$), Nash-Sutcliffe Efficiency (NSE), Percentage BIAS (PBIAS), P-factor, and R-factor have been used for the evaluation of model performance. These parameters are expressed mathematically through eqs. 2, 3, and 4.

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

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

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

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

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 varies in the range of 0 to ⊤ (Abbaspour *et al.,* 2007; Zhao *et al*., 2018). A P-factor value equal to 1.0 and an R-factor value of 0 are obtained when there is no uncertainty in the modeling study. The P and R-factor are expressed mathematically as presented in eq. 5 and 6, respectively (Abbaspour *et al.,* 2007; Verma and Verma, 2019).

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

Where, $ny_{ti}$ is the number of measured values bracketed by the 95PPU, and $N$ is 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 boundaries of the 95UB (Uncertainty Band), respectively and $\sigma_{obs}$ is the standard deviation of the observed data.

## 3. RESULTS AND DISCUSSION

### Model Calibration and Parameterization

In the present study, a rigorous calibration based on SA of model parameters has been made using the SWAT-CUP model (Neitsch *et al.,* 2011). A total number of 15 SWAT parameters, as presented in Table 3, were selected for model calibration and uncertainty analysis based on previous studies and SWAT literature (Neitsch *et al.,* 2002). Global SA was conducted at a monthly time-step using latin hyper cube sampling in the early calibration stage. The first step in the calibration process is to adjust the input parameter values to closely match the simulated results with the observed variables and, thus, screen out the most sensitive parameters influencing the variable compared to the other parameters. The SUFI-2 algorithm performed a SA in SWAT-CUP with five iterations and all iterations having 1000 simulations to obtain the optimal values of model parameters. Dotty plots so developed were the outputs of the model run with an objective function of maximizing Nash Sutcliffe Efficiency (NSE) during calibration and used to depict the distribution of sampling points and parameter sensitivity. The dotty plots conditioned in this study using the SUFI-2 algorithm (Fig. 5) represent most of the sensitive parameters with NSE values greater than the threshold value (0.5) during the monthly streamflow simulation.

Two indicators, such as *t-stat* and *p-value,* were used to measure each parameter's sensitivity and relative significance (Abbaspour *et al.*, 2015). The relative ranking of these fifteen parameters according to their response to

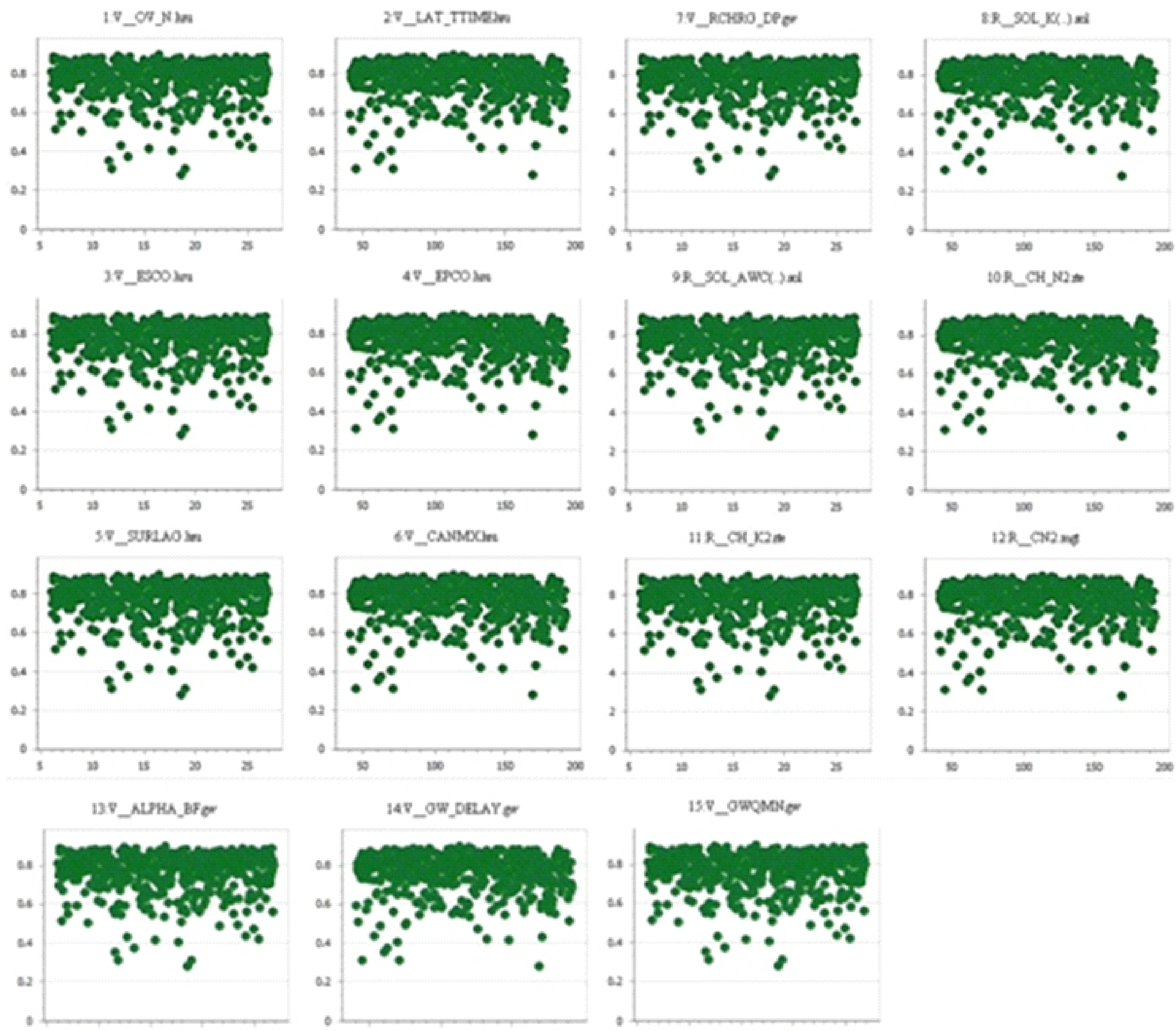

**Fig. 5. Dotty plots with the objective function of NSE against each aggregate SWAT parameter during the calibration period**

streamflow is presented in Fig. 6. The most sensitive parameter was the SCS-CN value for AMC II, followed by the soil evaporation compensation factor. SCS-CN depends on catchment characteristics like land use, hydrological soil group, crop management practices, and antecedent soil moisture conditions. CN2 ranks first among the sensitive parameters, reflecting a more significant influence of catchment characteristics on runoff generation (Padhiary *et al.,* 2019; Verma and Verma, 2019). CN2 is the primary source of uncertainty for streamflow modeling in SWAT (Gassman *et al.,* 2007, Tegegne and Kim, 2018; Tegegne *et al.,* 2019; Zhang *et al.*, 2019). As SWAT is programmed with a curve number method to estimate the direct runoff, the curve number of any hydrologic response unit (HRU) is directly proportional to the runoff generation. Higher the curve number represents high runoff potential and *vice-versa*. The soil evaporation compensation factor that represents the range of the soil depth used to meet the evaporative soil demands appears to be the second sensitive parameter for influencing runoff generation. Its value varies from 0.01 to 1, and in the present scenario, the fitted value is 0.02. It indicates that the model is capable of extracting moisture from the lower depths of soil due to capillary action and the development of cracks and fissures, as in the case of clay soil.

## Model performance and Uncertainty Analysis (UA)

In the present study, the simulated discharges were compared with the corresponding observed ones at the outlet of Kantamal catchment during the calibration period from 2004 to 2012 and the validation period from 2013 to 2018, as portrayed in Fig's 7 and 8, 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 0.91, 0.94, and -0.07, respectively, during calibration and 0.82, 0.87, and -0.16, respectively, during validation. It indicates that model simulation results are quite satisfactory. Similar results have been reported by Uniyal *et al*., 2015; Padhiary *et al*., 2019; Verma and Verma, 2019; Vema and Sudheer, 2020.

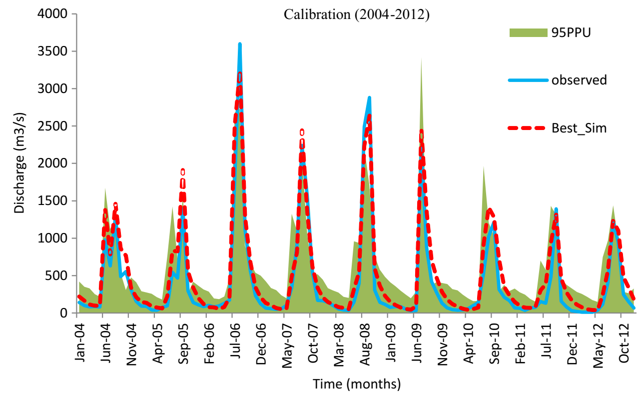


**Fig. 7. Location map of Kantamal catchment time series plot of simulated *vs.* observed streamflow with 95PPU band during the calibration period**

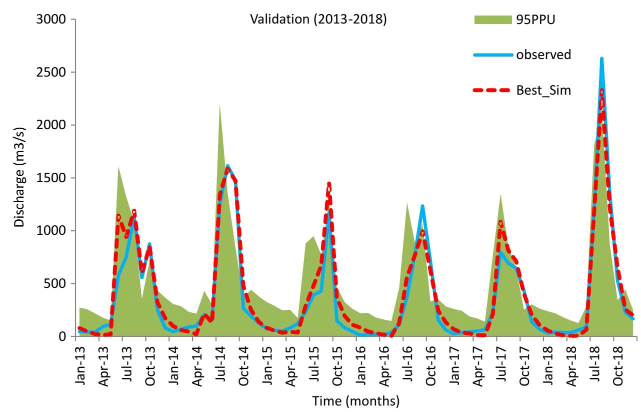


**Fig. 8. Time series plot of simulated *vs.* observed streamflow with 95PPU band during the validation period**

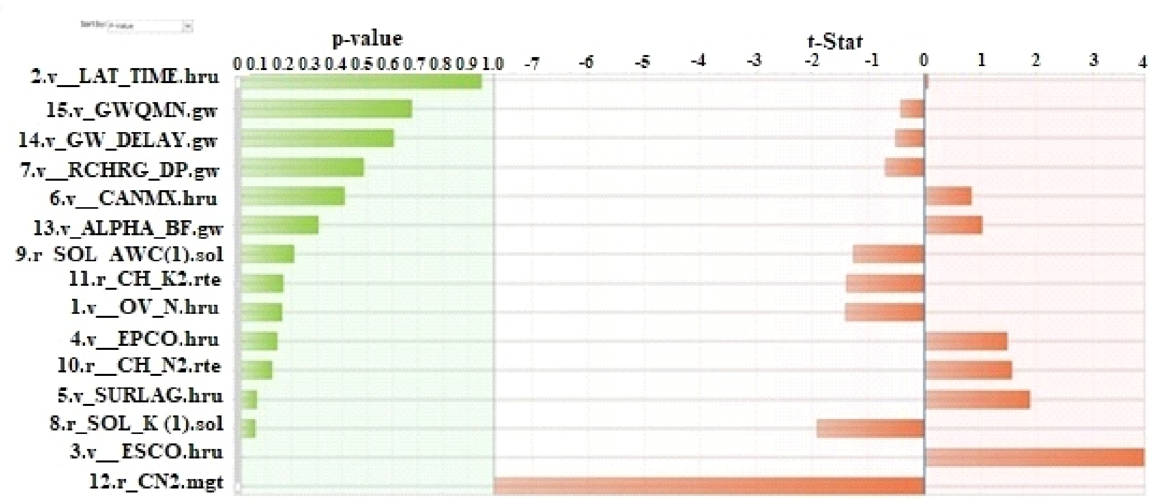


**Fig. 6. Best fitted, t-stat and p-value of calibration parameters by SUFI-2**

**Table: 4**
**Summary statistics of model performance**

| Indices | Calibration | Validation |
|---|---|---|
| $R^2$ | 0.94 | 0.87 |
| NSE | 0.91 | 0.82 |
| PBIAS | -0.07 | -0.16 |
| P-factor | 0.77 | 0.79 |
| R-factor | 0.98 | 0.86 |

Further, the simulated streamflow was compared with the observed flow using scatter plots. The scatter plots of simulated versus observed streamflow during calibration and validation, as illustrated in Fig's 9 and 10, respectively, indicate a very close match between the two. Further, both the figures also depict almost efficient predictions of streamflow by the model during high and low flow periods. It shows the potentiality of the SWAT model with respect to the precise estimation of the streamflow in an agriculture dominant catchment.

Parameter uncertainty in streamflow simulation has been quantified by P and R-factors during calibration and validation periods. The values of P and R-factors are 0.77 and 0.98 during calibration and 0.79 and 0.86 during the validation period, respectively (Table 4). The P- and R-factor values within the desired range during both calibration and validation periods suggest that the uncertainty of the parameters is well acceptable during the entire simulation period.

Further, the simulated streamflow values in a monthly time step were plotted with the observed values at the 95PPU band, as shown in Fig's 7 and 8. The derived results indicate that most of the observations are bracketed within the 95PPU band. However, some irregularities are also observed during the peak flow simulation. The slight deviation of the observed peak values from the 95PPU boundary in 2005, 2009, and 2010 during calibration (Fig. 7), and 2013, 2014, and 2016 during validation (Fig. 8) is evidence. Thus, it may be inferred that the model's overall performance under parameter uncertainty is satisfactory.

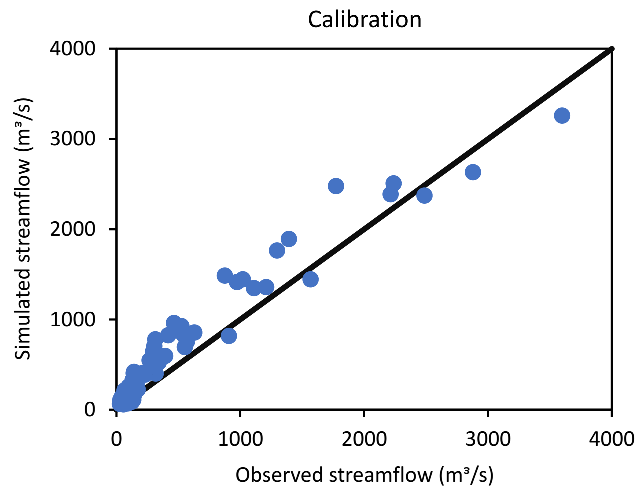


**Fig. 9. Scatter plots of observed *vs.* simulated streamflow by SUFI-2 during calibration (2004-2012)**

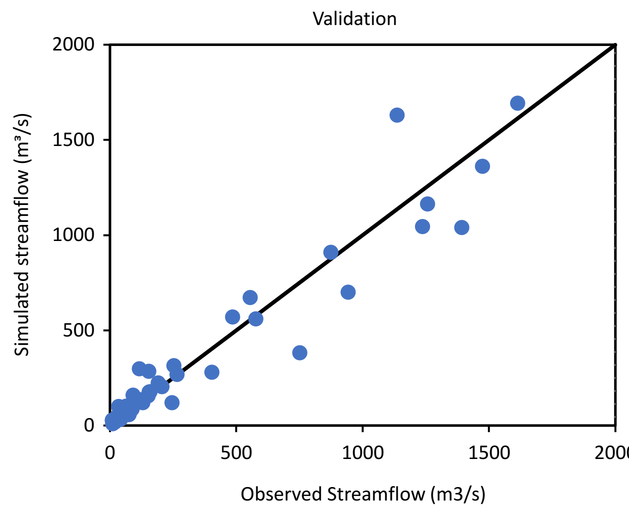


**Fig. 10. Scatter plots of observed *vs.* simulated streamflow by SUFI-2 during validation (2013-2018)**

## 4. CONCLUSIONS

The natural hydrologic system is very complex and not easily understood; therefore, hydrological models are used to simulate the flows. The present study demonstrates the application of the SWAT model in the Kantamal catchment of Mahanadi 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 reveal that fifteen parameters are most sensitive and greatly influence the streamflow. Soil conservation service curve number for AMC II factor has been identified as the most sensitive parameter among all the parameters for Kantamal catchment. The model performance during calibration of monthly streamflow by SUFI-2 was excellent with NSE, $R^2$, and PBIAS values of 0.91, 0.94, and -0.07, respectively. The model performance is reasonably acceptable during validation as indicated by the NSE, $R^2$, and PBIAS values of 0.82, 0.87, and -0.16, respectively. The P and R factor values of 0.77 and 0.98 during calibration and 0.79 and 0.86 during the validation period, respectively, indicate that the model performance is satisfactory under the parameter uncertainty. Based on the model simulation results, it may be inferred that the SWAT model can simulate hydrological fluxes under parameter uncertainty successfully in the agriculture-dominated catchment.

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