Calibration and Validation of Semi-distributed Model of Monthly Stream Discharge Using SUFI-2 Algorithm for Shimsha Catchment, Karnataka, India

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

The Shimsha Catchment employed the Semi-distributed SWAT model for runoff prediction, which considered geographical features, surface vegetation, and soil characteristics. The catchment was subdivided into six sub-watersheds based on geography, natural drainage patterns, and designated discharge points. In the Hydrological Response Unit (HRU) analysis, 136 HRUs were created in

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SWAT model by incorporating land use and soil maps and defining HRUs with specific threshold percentages. To calibrate and validate the model, simulated values were compared with observed data from stream gauge discharge records. The calibration process utilized the SUFI-2 algorithm integrated into the SWAT-CUP model. The results demonstrated the model's strong predictive capabilities across the entire catchment, achieving calibration values of 0.87, 0.92 and 0.78 for the Nash-Sutcliffe Efficiency (NSE), coefficient of determination (R^2) and index of agreement(d) respectively. Parameter selection and ranges were determined by considering the unique characteristics of the study area, recommendations from the model for new parameter ranges, and examination of a 95% probability plot. The analysis of uncertainty highlighted 14 sensitive parameters, with the curve number emerging as the most influential factor, followed by groundwater parameters. Capturing the dynamics of water flow, sediment transport and nutrient cycles to ensure reliable predictions to show the model reliability need to be assessed.

1. INTRODUCTION

"Nowadays, many hydrological models along with the application of GIS can enumerate water discharge more easily and correctly rather than traditional methods. Water resources assessment involves developing a comprehensive understanding of water inflows, storage, outflows, sediment yield and their inter-relationship over time. Hydrological models along with the application of GIS can enumerate water discharge more easily and correctly rather than traditional methods. Water resources assessment involves developing a comprehensive understanding of water inflows, storage, outflows, sediment yield and their inter-relationship over time" [1]. "These models play a crucial role in understanding and predicting the hydrological response of watersheds, thereby supporting effective water resource management and environmental planning. SWAT has been extensively used for a variety of purposes and its applications have expanded worldwide in the last decade demonstrating its use in various areas. Calibration and validation of hydrological model can help to evaluate the ability of the model to sufficiently predict stream-flow" [2]. "To adapt the model for use in a different area of interest, calibration is imperative, ensuring that the simulated values align with observed data. Calibration can be achieved through manual adjustment or by employing automated calibration tools that utilize statistical measures such as d, R^2, NSE and RMSE. SWAT CUP serves as a versatile interface and standalone program designed for the calibration of SWAT models" [3]. "While SUFI-2 is a user-friendly option, it requires a solid understanding of model parameters and their effects on model outputs. The Sequential Uncertainty Fitting Algorithm (SUFI-2) holds the advantage of combining optimization with uncertainty analysis and can effectively handle a large number of parameters. The goodness of calibration and prediction uncertainty can be measured on the basis of the closeness of the p-factor to 100% (i.e., all observations bracketed by the prediction uncertainty) and the r-factor to 1 (i.e., achievement of rather small uncertainty band). Most uncertainties in the concept and data are reflected in the measurements (e.g., discharge), bracketing most of the measured data in the prediction 95PPU ensures that all uncertainties are depicted by the parameter uncertainties" [4]. The primary objective of this study is to calibrate the SWAT model specifically for the Shimsha catchment in Karnataka using the SUFI-2 algorithm. Subsequently, the study aims to validate the model using the calibrated parameters, ensuring its accuracy and reliability for future hydrological assessments in the region.

2. MATERIALS AND METHODS

2.1 Description of the Study Area

The Shimsha River, a tributary of the Cauvery River, originates within the Devarayanadurga forest range in Tumkur district. It is impounded by the Markonahalli Dam, facilitating the irrigation of a vast agricultural expanse spanning 5600 hectares. The portion of its catchment area extending to the Markonahalli Reservoir falls within coordinates 77°11' E to 13°22'N and 76°51'E to 12°57'N, covering an area of 4100 square kilometers and featuring an elevation differential of 151 meters. The region experiences an average annual rainfall of 780 millimeters [5]. Fig. 1 shows the catchment details of study area with streams.
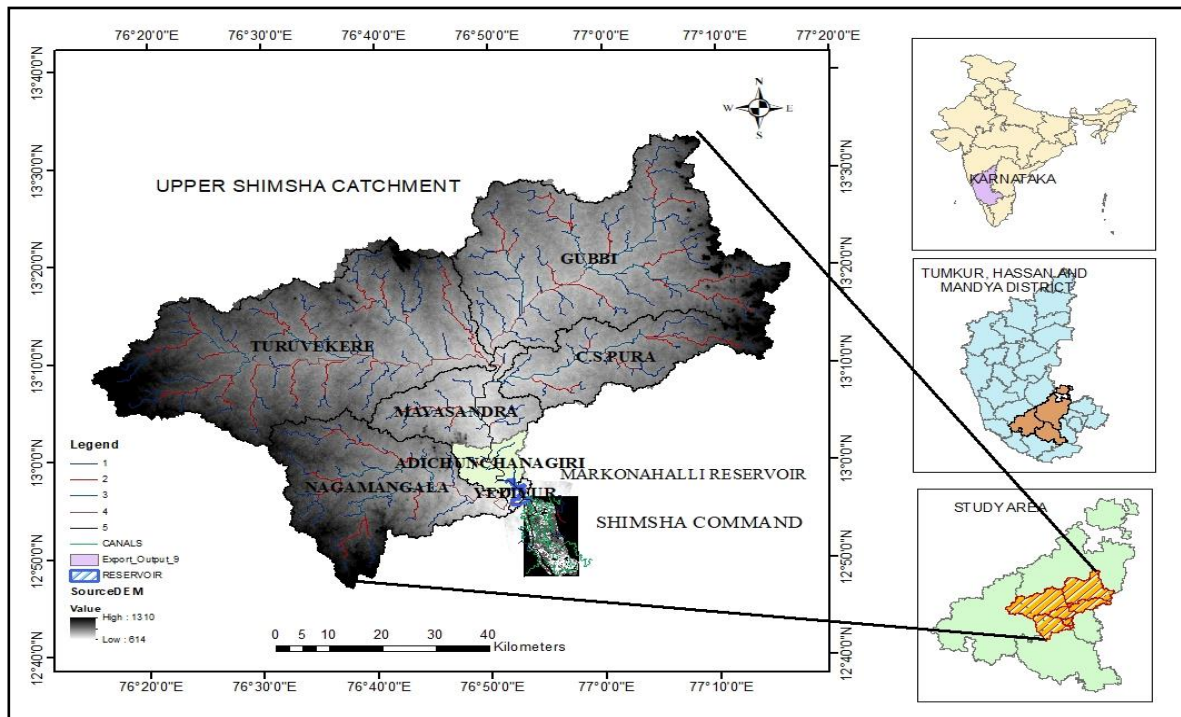
Fig. 1. Catchment area with streams and subwatersheds generated by ArcGIS-SWAT

An ESRI land use land cover image of 10 m resolution was downloaded through their online platform. The imagery was explored to understand the coverage area, temporal extent and thematic content. Metadata associated with the imagery was used to learn more about its acquisition and processing to know the predefined classification of study area. The land use maps for our study area were sourced from NRSC, ISRO Hyderabad, corresponding to the year 2020-21. These maps were mosaic together to form a consolidated map, which was subsequently clipped using a specific shape file. Subsequently, the soil map for the study region was extracted from imagery sourced from the ISRIC-World Soil Information website and the NBSS and LUP (National Bureau of Soil Survey and Land Use Planning) Regional office, Bengaluru.

"The model takes input data on soil water characteristics, including soil texture (Percentage of sand, silt and clay), along with the percentage of organic carbon content. Using this input, the model calculates various soil characteristics such as texture class, wilting point, field capacity (expressed in percent by volume), available soil water, saturated hydraulic conductivity, and bulk density" [6]. Additionally, the model determines the soil erodibility factor (K factor) by utilizing the erodibility equation developed by [7], which considers both soil texture and organic carbon content as input variables.

$$K = f_{c_{sand}} \times f_{ci-six} \times f_{org} \times f_{hi_{sand}} \qquad \text{---(1)}$$

$$f_{c_{sand}} = 0.2 + 0.3e^{(-0.0256\,ms)(1-M_{silt/100})} \qquad \text{---(2)}$$

$$f_{cl-si} = \left(\frac{m_{silt}}{m_c + m_{silt}} \right)^{0.3} \qquad \text{---(3)}$$

$$f_{org} = 1 - \frac{0.25orgC}{orgC + e^{(3.72-2.95orgC)}} \qquad \text{---(4)}$$

$$f_{hi_{sand}} = \left(1 - \frac{0.7\left(1 - \frac{m_s}{100}\right)}{\left(1 - \frac{m_s}{100}\right) + e^{\left(-5.51 + 22.9\left(1 - \frac{m_s}{100_s}\right)\right)}}\right)$$

---(5)

Where, $f_{c_{sand}}$ is a factor that gives low soil erodibility factor for soils with high coarse-sand contents and high values for soils with little sand; f_{cl-si} = is a factor that gives low soil erodibility factors for soils with high clay to silt ratios; f_{org} is a factor that reduces soil erodibility for soils with high organic carbon content and $f_{hi_{sand}}$ = is a factor that reduces soilerodibility for soils with extremely high sand contents; m_s is the percentage of fine sand (0.05-0.10mm), m_{silt} is the percentage of silt (0.002-0.05mm), mc is the percentage of clay (< 0.002 mm), and orgC is the percentage of organic carbon

2.2 Tools Used for Modeling and Calibration

2.2.1 ArcGIS10.4

ArcGIS is a licensed Geographic Information System software used to display the geographic information on a map and provides a common frame to work with different spatial data obtained from various sources.

2.2.2 SWAT model

The SWAT (Soil and Water Assessment Tool) is a physically-based, semi-distributed hydrological model capable of operating on daily, monthly, and annual time intervals. This tool facilitates the assessment of the impact of land management practices on water quality, sediment transport, and the release of agricultural chemicals in watersheds characterized by varying soil types, land use patterns, and management approaches.

"The watershed hydrology in SWAT consists of two major components: the land phase and the routing phase. The land phase governs the quantity of water, sediment, nutrients, and pesticides that are transported to the main stream within each sub-basin. Meanwhile, the routing phase controls the movement of water, sediments, and other materials through the channel network to the catchment outlet" [8].

2.2.3 SWAT-CUP

"The calibration, uncertainty, or sensitivity program was integrated with SWAT using a versatile interface known as SWATCUP, which stands for SWAT Calibration Uncertainty Procedures. SWATCUP offers sensitivity analysis, calibration, and validation capabilities for SWAT models. It offers various techniques, including PSO, SUFI-2, GLUE, Parasol, and MCMC. For this study, we employed the latest version, SWATCUP 2012 version 5.2.1, to carry out calibration and uncertainty analysis. In this specific research, we utilized SUFI-2 for parameter sensitivity analysis, calibration, and validation. The Sequential Uncertainty Fitting Algorithm (SUFI-2) is highly efficient, not only in terms of pinpointing an optimal parameter range but also in minimizing the number of simulations required" [4]. Although SUFI-2 is user-friendly, it is semi-automated, requiring interaction from the modeler to validate a set of suggested posterior parameters. This necessitates a sound understanding of parameters and their effects on model outputs.

"Calibrating a model with a large number of parameters can be challenging. To streamline the calibration effort, sensitivity analysis was conducted. Parameter selection for sensitivity analysis was based on the characteristics of the study area and existing literature. Parameter identifiers were applied based on changes that had physical significance and reflected factors such as land use, soil, elevation, etc". [4].

The simulated discharges/outflow(m^3/sec) obtained for calibration and validation period were compared with the observed discharges/ water release data for the respective period. The observed data was collected from the office of Cauvery Neeravari Nigama Ltd, Karnataka for periods of October 1982 to May 2022. The datasets used for various processes in SWAT model are:

i) Total Simulation period: 38years (1984-2022)

ii) Number of years to skip (NYSKIP) i.e. Warm-up period = 4 years (1980- 1984)
iii) Calibration period: 16 years (1985-2010) and
iv) Validation period: 13 years (2010-2022)

2.2.4 Evaluation of model performance

"Assessing model performance can be accomplished through both subjective and objective comparisons of simulated results to observed data. Pearson's correlation coefficient (r) and coefficient of determination (R^2) describe the degree of co linearity between simulated and measured data. Coefficient of determination (R^2) value depicts how well a data fits into a statistical model. The range of coefficient of determination lies between 0 and 1, with higher values indicating less error variance, and typically values greater than 0.5 are considered acceptable" [9]. The index of agreement (d), introduced by [10], serves as a standardized measure for assessing the extent of model prediction error and ranges from 0 to 1. It quantifies the ratio between the mean square error and what is termed the "potential error". "A value of 1 signifies a perfect alignment between the measured and predicted values, while 0 indicates no agreement whatsoever. Nash-Sutcliffe efficiency (NSE) is a normalized statistic that determines relative magnitude of the residual variance ("noise") compared to the measured data variance ("information")" [11]. NSE ranges between ∞ and 1.0 (inclusive 1), with NSE = 1 being the optimal value. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values < 0.0 indicates that the mean observed value is a better predictor than the simulated value, which indicates unacceptable performance.

2.2.5 p-factor and r-factor

The above statistical indices only apply to the comparison of two signals and are not adequate when outputs are expressed as uncertainty bands. In this case, as the simulation results are usually expressed by the 95per cent prediction uncertainties (95PPU), they cannot be compared with the observation signals using the traditional R^2 and NSE statistics. For this reason, [3] suggest "using two measures, referred to as the p-factor and the r-factor. The p-factor is the percentage of the measured data bracketed by the 95PPU. This index provides a measure of the model's ability to capture uncertainties. As all the "true" processes are reflected in the measurements, the degree to which the 95PPU does not bracket the measured data indicates the prediction error. Ideally, the p-factor should have a value of 1, indicating 100per cent bracketing of the measured data, hence capturing or accounting for all the correct processes. The r-factor, on the other hand, is a measure of the quality of the calibration and indicates the thickness of the 95PPU. Its value should ideally be near zero, hence coinciding with the measured data".

3. RESULTS AND DISCUSSION

The initial step in the calibration and validation process of SWAT involves determining the most influential parameters on stream flow for the Markonahalli reservoir catchment area. This determination is accomplished through a sensitivity analysis, which aims to assess the impact of changes in model input parameters on model outputs.

3.1 Sensitivity Analysis

This process expedites optimization by focusing on determining optimal values for a limited number of influential parameters governing the model. The analysis, illustrated graphically in Fig. 2 (calibration) and Fig. 3(validation) using the Latin hypercube one factor at a time (LH-OAT) technique, focuses on FLOW_OUT_6, representing stream flow at the outlet of sub-basin 6. In both the figures results for a hydrological model, showcasing the comparison between observed and simulated data. This comparison is crucial to assess the model's performance and accuracy in predicting hydrological responses.

Table 1 highlights the importance of various hydrological processes and soil properties in the SWAT model and provides guidance on the ranges and relative sensitivities of key parameters used for model calibration. The model is sensitive to parameters related to runoff processes, such as the initial SCS runoff curve number (R__CN2.mgt) and the surface runoff lag coefficient (V__SURLAG.bsn). These parameters influence the amount and timing of surface runoff generated in the model. Several parameters in the Table 1 are associated with groundwater processes, including base flow alpha factor (V__ALPHA_BF.gw), groundwater delay time (V__GW_DELAY.gw), threshold depth for return flow (V__GWQMN.gw) and groundwater revap coefficient

(V__GW_REVAP.gw). These parameters control the contribution of groundwater to streamflow, the timing of groundwater discharge, and the potential for groundwater evaporation. The table includes parameters related to soil properties, such as available water capacity (R__SOL_AWC), saturated hydraulic conductivity (R__SOL_K) and bulk density (R__SOL_BD). These parameters influence the movement and storage of water in the soil profile, which can impact various hydrological processes, including runoff, evaporation and groundwater recharge. The parameters V__CH_N2.rte (Manning's coefficient for the main channel) and V__CH_K2.rte (hydraulic conductivity in the main channel) are related to channel routing processes, which determine the movement and timing of water through the channel network.
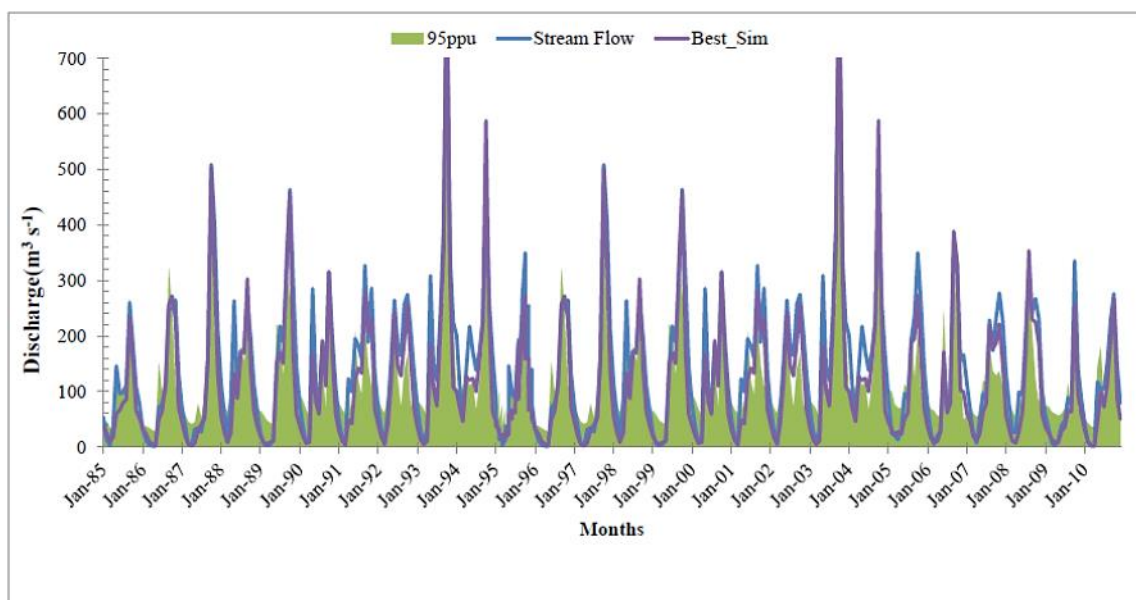

Fig. 2. Latin hypercube one factor at a time of stream flow parameters for catchment area for calibration period
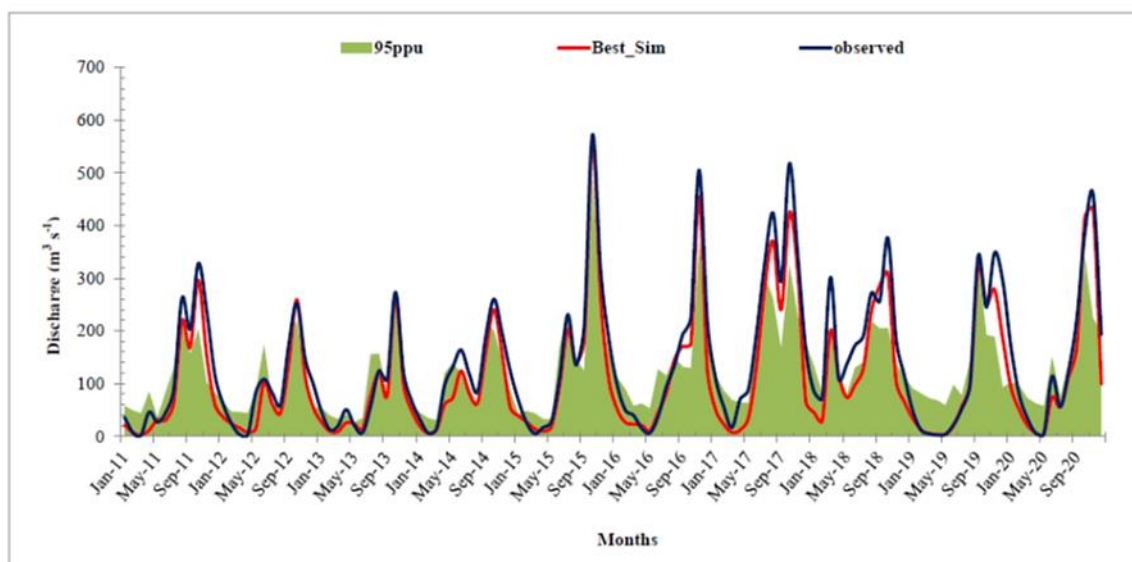

Fig. 3. Latin hypercube one factor at a time of stream flow parameters for catchment area for validation period

Table 1. Parameters and their ranges used in sensitivity analysis in SWAT-CUP

Sl. No.	Name	Description	Min	Max	Relative sensitivity	Process
1	R__CN2.mgt	Initial SCS runoff CN for moisture condition II (relative change, or absolute values between 35-98))	-0.2	0.20	0.106	Runoff
2	V__SURLAG.bsn	Surface runoff lag coefficient	0.05	24	7.49	Runoff
3	V__ALPHA_BF.gw	Base flow alpha factor (days)	0.0002	1.00	0.80	Groundwater
4	V__GW_DELAY.gw	Groundwater delay time (days)	30	450	357.17	Groundwater
5	V__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0.00	2.00	1.782	Groundwater
6	V__GW_REVAP.gw	Groundwater „revap" coefficient	0.00	0.20	0.185	Groundwater
7	V__ESCO.hru	Soil evaporation compensation factor	0.80	1.00	0.957	Evaporation
8	V__CH_N2.rte	Manning coefficient for main channel	0.00	0.30	0.025	Channel
9	V__CH_K2.rte	Hydraulic conductivity in main channel (mm hrs^{-1})	5.00	130.00	73.125	Channel
10	V__ALPHA_BNK.rte	Base flow alpha factor (days	0.00	1.00	0.065	Groundwater
11	R__SOL_AWC(.).sol	Available water capacity of the soil layer (mm/mm soil)	-0.20	0.40	0.022	Soil
12	R__SOL_K(..).sol	Saturated Hydraulic conductivity of soil (mm hrs^{-1})	-0.8	0.80	-0.523	Soil
13	R__SOL_BD(.)sol	Bulk density of the soil	-0.5	0.60	0.145	Soil
14	V__SFTMP.bsn	V_SFTMP.bsn	-5	5	-3.85	Basin

[12]

Among these parameters, CN2 is identified as the most sensitive, followed byALPHA, BF, GW_DELAY, GWQMN, GW_REVAP and ESCO were presented in Table 2. It is noteworthy that for the Shimsha catchment, base flow plays a predominant role in determining river flow. Therefore, the inclusion of the base flow alpha factor as the second most sensitive parameter is justifiable.

Similarly, the primary factor influencing surface runoff, CN2, also ranks first in sensitivity, aligning with logical expectations. A high channel hydraulic conductivity suggests that drainage channels can facilitate both groundwater discharge and recharge, depending on the relative elevation between the water table and the channel bottom [13].

Table 2. Sensitive parameters with their default range and fitted values

Sensitive parameter	Default parameter range	Fitted values after calibration
r_CN2_mgt	-0.2 to 0.2	0.10
v_ALPHA_BF.gw	0 to 1	0.8
v_GW_DELAY.gw	30 to 450	357
v_GWQMN.gw	0 to 2	1.78
v_GW_REVAP.gw	0 to 0.2	0.18
v_ESCO.hru	0.8 to 1	0.96

3.2 Model Evaluation Using Performance Indices

Evaluation of the model's performance involved comparing observed and simulated flow using statistical criteria. To achieve this, metrics like Nash-Sutcliffe Efficiency (NSE), Coefficient of Determination (R^2) and Index of Agreement (d) were utilized. The performance indices during calibration and validation period is represented in Table 3, which revealed the model's overall capability to predict outcomes across the catchment.

Following calibration, the NSE, R^2, d and RMSE values stood at 0.78, 0.84 0.78 and 0.048(m^3/s) respectively, indicating strong predictive accuracy. Nevertheless, even post-calibration, some peak flows were underestimated by the SWAT model. Furthermore, the reliance of the SWAT model on the empirical SCS Curve Number method for runoff calculations, which does not account for precipitation duration and intensity, could also contribute to these discrepancies [14].

For model validation, an independent dataset spanning from January 1, 2010, to December 31, 2022, was employed. Evaluation statistics, including NSE, R^2, d and RMSE values for this validation period yielded values of 0.82, 0.87, 0.81 and 1.31(m^3/s) respectively, reaffirming the calibrated model's robustness in making predictions beyond the calibration period (Table 3).

Table 3. Performance indices during calibration and validation periods

Statistical Criteria	Calibration	Validation
NSE	0.87	0.82
R^2	0.92	0.87
d	0.78	0.81
RMSE(m^3/s)	0.05	1.31
P-factor	0.84	0.79
R-factor	1.30	0.93

The validation results reinforced the model's robustness, with 82 percent of the observed data falling within the 95PPU band. The d-factor during validation was 0.81, slightly higher than during calibration, indicating consistent model performance in predicting discharge under different conditions. These results demonstrate that the model maintains its predictive capability beyond the calibration period, thereby confirming its reliability and accuracy for practical applications in hydrological forecasting and water resource management.

Parameter selection and their respective ranges were determined based on the study area's characteristics, suggested parameter ranges from the model, and observations from the 95th percentile prediction uncertainty (PPU) plot. Since SUFI-2 is an iterative process, a higher number of simulations were conducted. Despite the calibration efforts, some peak flows remained poorly simulated by the model, indicating the need for further enhancements in the SWAT model's capacity to simulate peak flows.

SWAT assigns different CN values for rainy and non-rainy seasons, with a larger CN value expected for the rainy period due to distinct runoff generation processes. The model adjusts CN values accordingly for dry and wet periods. For the calibration and validation periods, the P-values for CN are 0.21 and 0.0, with corresponding t-stat values of -1.42 and -4.85, respectively. Another key parameter is ALPHA_BF, representing a base flow recession constant that directly reflects groundwater flow response to changes in shallow aquifer recharge. The P-values for ALPHA_BF during calibration and validation are 0.66 and 0.44, and the t-stat values are -0.47 and -0.84, respectively as presented in Table 4. The ultimate goal of calibrating a watershed model is to accurately represent the watershed's hydrological behavior and characteristics. This includes capturing the dynamics of water flow, sediment transport and nutrient cycles to ensure reliable model predictions and effective watershed management [15].

Table 4. Sensitive parameters and their ranking identified by SUFI-2 algorithm after calibration and validation

Sensitivity Rank	Parameter	Description	Calibration		Validation	
			t-value	p-value	t-value	p-value
1	CN2_mgt	Curve Number	-1.42	0.21	-4.85	0.00
2	ALPHA_BF.gw	Base flow alpha factor	-0.47	0.66	-0.84	0.44
3	GW_DELAY.gw	Groundwater delay	-4.27	0.00	-2.82	0.00
4	GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur	0.66	0.50	0.34	0.21
5	GW_REVAP.gw	Groundwater "revap" coefficient	-0.55	0.57	-0.23	0.21
6	ESCO.hru	Soil evaporation compensation factor	2.97	0.01	1.34	0.01

4. CONCLUSION

Following calibration, the NSE, R² and d values stood at 0.87,0.92 and 0.78 respectively, indicating strong predictive accuracy. Nevertheless, even post-calibration, some peak flows were underestimated by the SWAT model. These discrepancies may stem from inaccuracies in meteorological data, errors within input datasets like land use and soil maps, as well as issues during data preparation and processing. For model validation, an independent dataset spanning from January 1, 2010, to December 31, 2022, was employed. Evaluation statistics, including NSE and R², for this validation period yielded values of 0.82 and 0.87, respectively, reaffirming the calibrated model's robustness in making predictions beyond the calibration period.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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