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Hydrological Simulation and Uncertainty Analysis using SWAT Model on Mahan River Basin, Surajpur, Chattisagarh

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ABSTRACT

Soil and Water Assessment Tool (SWAT) and SWAT-CUP are semi-distributed, process-oriented models that accurately replicate the hydrological cycle in large and complex watersheds and calibrate the results. The objective of this study is to assess the effectiveness of the SWAT model and SWAT-CUP software for hydrological analysis, evaluate the uncertainty associated with the SWAT model, and analyse runoff. This model delineates the basin into five sub-basins and 200 hydrological response units. The model calibration and validation were performed with the SUFI-2 algorithm for the periods 2012 to 2017 and 2018 to 2020 respectively, incorporating a two-year warm-up phase. The sensitivity analysis indicates that, ESCO, ALPHA_BF, SOL_BD, SFTMP, CN2, and SOL_AWC are the six parameters affecting the hydrological process. This aspect is essential in assessing output runoff. Among these characteristics, SCS-CN and ALPHA_BF were identified as the most sensitive variables. The calibration results from 2012 to 2017 provide exceptional outcomes, with R^2, PBIAS and NS values of 0.94, 0.89, 14.9 and 0.93, respectively. The validation phase from 2018 to 2020 demonstrates commendable results for the same model, producing values of 0.92, 0.86, 19.4 and 0.91, respectively. Twelve parameters were established during calibration, which are essential for runoff modeling in the designated region. A thorough comprehension of hydrological processes and the identification of pertinent parameters are crucial for developing a simulation model. SWAT and SWAT-CUP were chosen over alternative models primarily due to their superior capability in uncertainty assessment, which enhances the reliability of hydrological simulations and informs future decision-making in the selected watersheds.

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1. INTRODUCTION

Runoff is an essential attribute for understanding the hydrological conditions of any basin. It aids in delineating rainfall-runoff connections and mitigating daily water scarcity challenges, hence promoting optimal water resource management. To address water-related challenges, the application of sophisticated techniques and rainfall runoff modeling simulations is essential in surface hydrology. The hydrological simulation of the model is essential (Khalid 2018) for understanding the hydrological dynamics of a watershed. There are two main categories of hydrological models: distributed and semi-distributed (Khalid 2018; Khayyun et al. 2019). The semi-distributed model is typically the most employed framework for this type of modeling. The calibration and validation phase is essential for finalizing the model outcomes of the chosen watershed in the hydrological simulation process. The aforementioned model comprises various parameters; based on the simulation, the sensitive parameters that would substantially affect the watershed basin must be determined (Kushwaha and Jain 2013; Qi et al. 2016).

The watershed simulation is completed utilizing the Soil and Water Assessment Tool (SWAT) (Malik et al. 2022). SWAT requires extensive data for simulation, including weather and meteorological information. This is the most precise instrument for analysing land-use alterations within the watershed. This model is employed for flow simulation as well as for evaluating sediment, nutrient, and evapotranspiration dynamics (Athira et al. 2018; Bannwarth et al. 2014; Ning et al. 2015). SWAT can precisely replicate all parameters associated with any water body. SWAT utilizes Sequential Uncertainty Fitting version 2 (SUFI-2), Markov Chain Monte Carlo (MCMC), Particle Swarm Optimization (PSO), Parameter Solution (ParaSol), and Generalized Likelihood Uncertainty Estimation (GLUE) for calibration and validation. SUFI-2 is the most dominant and efficient platform owing to its exceptional accuracy and intuitive interface (Malik et al. 2022). In this framework, uncertainty can be characterized by the R^2 and NS types of objective functions. They can clearly define the values that represent the ideal alignment for that specific watershed parameter. The model results indicate that the soil evaporation compensation factor (ESCO), groundwater flow reaction coefficient (ALPHA_BF), moist bulk density (SOL_BD), snowfall temperature (SFTMP), SCS runoff curve number (CN2), and soil available water capacity (SOL_AWC) are important parameters affecting flow. The curve number is the most sensitive statistic for peak discharge in watersheds and for efficiency as well. Prior studies indicate that different regions display diverse climates and changes in input data, which substantially affect the results of the SWAT simulation (Teshager et al. 2016). A multitude of studies concentrate on uncertainty analysis utilizing SWAT and SWAT-CUP, especially in arid and semi-arid areas, which underscores SWAT's superior capabilities in tackling diverse hydrological simulation issues (Lin et al. 2020). The present research

highlights the challenges associated with simulating hydrological parameters and conducting uncertainty analysis using SWAT and SWAT-CUP methodologies. The main goal of the current research was to determine sensitivity and to calibrate and validate the flow, with the intention of resolving challenges in water resource management. The assessment of applicability and the outcomes of the model are critically significant in the chosen study area. Upon the compilation of the necessary data, the model was implemented. By determining the critical parameters, we calibrate and validate the model. Thereafter, the findings are examined in terms of quantity and quality. This model increases the understanding of the complex dynamics of the Mahan basin for effective water resource management (Jaberzadeh et al. 2024; Tufa and Sime 2021). The population growth, coupled with diminishing water availability, presents significant challenges to water resources, resulting in water stress and impactful droughts. Consequently, decision-makers and policymakers are now compelled to pursue sustainable water resource management, addressing the repercussions of human activities and climate variability on streamflow.

Although several studies have applied hydrological models in Indian river basins, limited research has focused on uncertainty analysis of SWAT simulations in the Mahan River basin using satellite-based rainfall data (Dhone et al. 2025). The present study addresses this gap by integrating SWAT and SWAT-CUP to evaluate both model performance and parameter uncertainty under data-scarce conditions, thereby contributing to improved understanding of hydrological processes in semi-arid central India.

2. METHODOLOGY

2.1 Study area

The Mahan is a river that functions as a tributary of the Mahanadi in the Surajpur district of Chhattisgarh, eastern India. The research area is situated in the Mahan River basin at a latitude of 23°29'59" N and a longitude of 82°55'54.8" E, with an elevation of 261 meters and a total area of 2109 km^2. This location experiences an average precipitation of 1292 millimetres. Winters are pleasurable due to low temperatures and less humidity. The temperature varies from 30–47°C in summer and from 5 to 25°C in winter. The Mahanadi is the origin of the research domain. The chosen study region is significantly smaller than the district boundaries depicted in Figure 1. The land use diversity is significant, with aquatic bodies and agricultural areas comprising 68%, characterized by three distinct soil types, the most prevalent being red soil with medium texture.

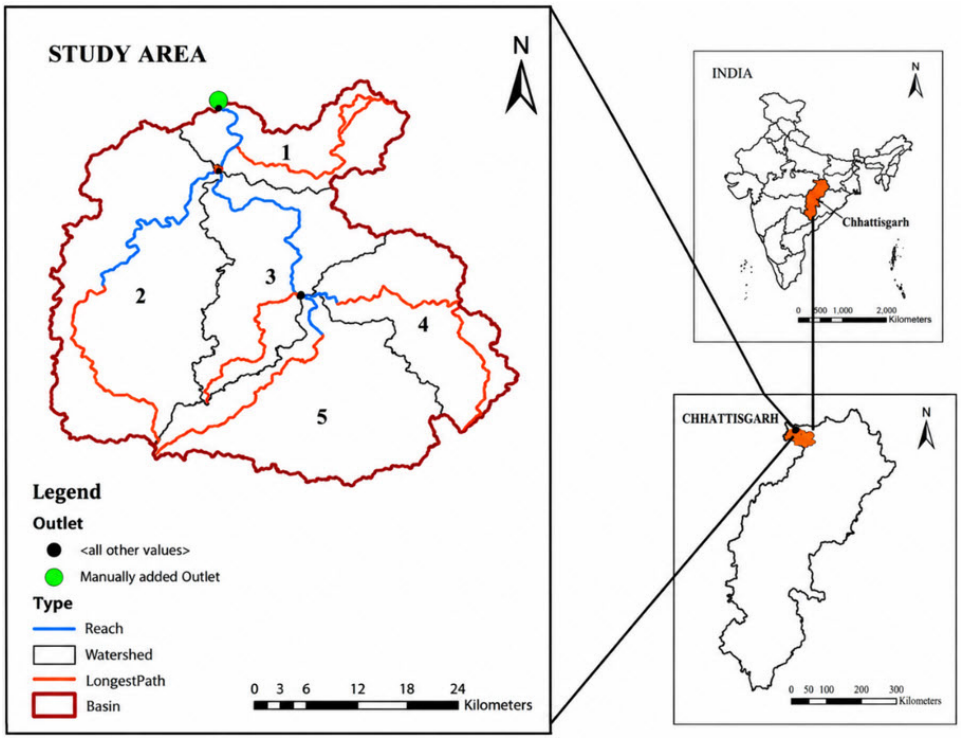

Figure 1 Location map of the study area.

2.2 Description of SWAT model

The Soil and Water Assessment Tool (SWAT) is a semi-distributed model developed for the improved daily simulation of runoff volume, sediment, nutrients, and pesticides at the catchment level. SWAT is proficient at forecasting alterations in land use and land cover across diverse climatic scenarios.

The principal aim of the SWAT model is to evaluate the effects of climatic conditions on water resources, sediments, and nutrients (Aawar and Khare 2020).

The water balance equation is essential for the functioning of the SWAT model in the soil profile, simulating surface runoff, rainfall, evapotranspiration, infiltration, and percolation, as demonstrated in Equation 1.

$$SW_t = SW_0 + \sum_{i=0}^{t} \left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw} \right) \quad (1)$$

Where:

SW_t = final soil water content (mm),

SW_0 = initial soil water content (mm),

R_{day} = precipitation amount on day *i* (mm),

Q_{surf} = surface runoff on day i (mm),
E_a = evapotranspiration amount on day i (mm),
W_{seep} = seepage amount on day i (mm),
Q_{gw} = return flow on day i, and
t = time in days.

This study employed the SCS-CN methodology to predict surface runoff within the watershed. The SCS-CN equation is a pivotal formula for estimating runoff volume based on precipitation data (Choudhary and Athira 2021). The curve number varies from 0 to 100, where lower values indicate minimal runoff potential and high infiltration, whereas higher values denote maximum runoff potential with reduced infiltration.

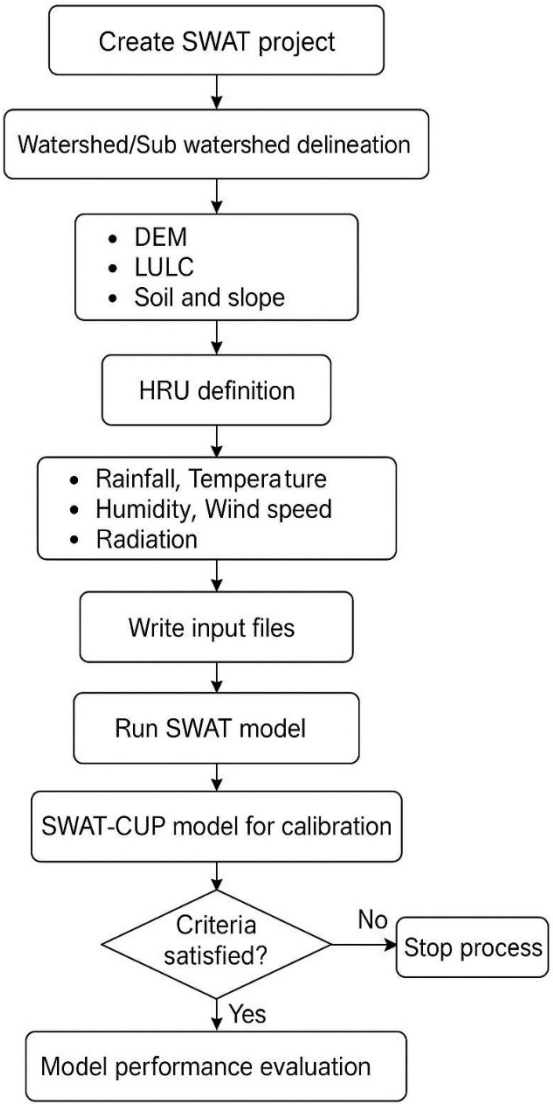

Figure 2 Research methodology using SWAT.

2.3 Data input

Digital Elevation Map

One of the most critical parameters for SWAT is the Digital Elevation Model (DEM). The digital elevation data was sourced from the USGS Earth Explorer (https://earthexplorer.usgs.gov/) with a resolution of 30 m by 30 m. The data was acquired for watershed delineation in ARC-SWAT. The elevation map shown in Figure 3a, which has an elevation of 390 m, was produced using Arc-GIS 10.4.

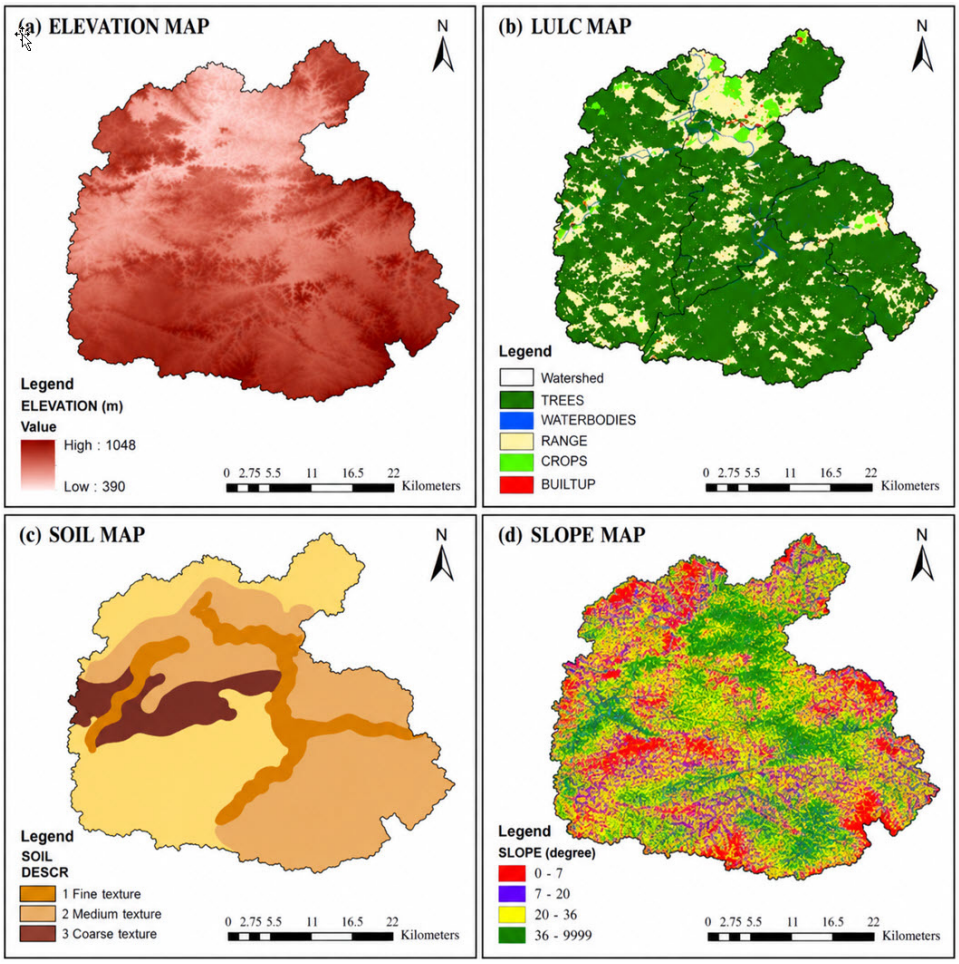

Figure 3 a) Digital Elevation Map, b) Land Use Land Cover Map, c) Soil map, and d) Slope map.

LULC map

The formulation of Land Use and Land Cover (LULC) is crucial for forecasting hydrological processes. The land use and land cover data was acquired from the Esri-LandUse website (https://livingatlas.arcgis.com/landcover/). Google Earth and ARC GIS 10.4 were employed for the Land Use/Land Cover map (Luo et al. 2011). The categorization was performed utilizing both supervised and unsupervised classification methodologies. The accuracy assessment resulted in 75.50%, with a kappa coefficient of 0.82 for the Mahan basin LULC map, as depicted in Figure 3b.

Soil map

The soil data is crucial in determining the SCS-CN number. The soil data was sourced from the IWRIS website (https://indiawris.gov.in/wris/) for India and extracted from the comprehensive file utilizing ARC GIS 10.4. The study site has three unique soil types, as depicted in Figure 3c.

Slope map

The topographic slope map is essential for categorizing different Hydrological Response Units (HRUs) and assessing flow dynamics throughout the terrain. The slope map is divided into four categories: 0–7%, 7–20%, 20–36%, and over 36%, as depicted in Figure 3d.

Meteorological data

Rainfall data

Various sources are available for collecting rainfall data; however, gridded data is necessary for model analysis. For this study, the NASA POWER platform was selected, which is easily accessible and ensures accuracy. Daily precipitation data were obtained from the NASA POWER database (https://power.larc.nasa.gov/) for the years 2010 to 2020, which provides spatially continuous meteorological variables derived from satellite observations and global atmospheric models. The dataset was used due to the limited availability and spatial inconsistency of long-term ground-based rainfall observations within the study basin (Dhone and Ahmad 2026a). The use of satellite-derived rainfall data has been widely adopted in hydrological modeling studies conducted in data-scarce regions, where consistent and long-term gauge records are unavailable. The specific locations of the stations for the data are delineated in Table 1.

Table 1 Meteorological data of the stations.

Sr.No.	Station Number	Latitude	Longitude	Elevation (m)
1	Station 1	23° 52' 48"	82° 18' 48"	390
2	Station 2	23° 42' 36"	82° 6' 00"	404
3	Station 3	23° 43' 48"	82° 16' 12"	402
4	Station 4	23° 40' 12"	82° 28' 12"	520
5	Station 5	23° 34' 12"	82° 19' 48"	516

Maximum and minimum temperature

Temperature data is a crucial resource for predicting rainfall runoff modeling as a component of meteorological data. This temperature data was sourced from the NASA POWER platform (https://power.larc.nasa.gov/) for the years 2010 to 2020.

Discharge data

Observed daily discharge data used for model calibration and validation were obtained from the Central Water Commission (CWC) gauging station. The Ramgarh Gauge station is located at the outlet of the Mahan River basin (23°40'56.63"N, 82°24'44.56"E). The dataset covered the period from 2010 to 2020 and was examined for continuity and missing values prior to analysis (Dhone and Ahmad 2026b). Only quality-checked and continuous discharge records were used to ensure the reliability of model calibration and validation.

2.4 Model evolution

The model output and performance in flow simulation were evaluated using the coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE), and percent bias (PBIAS) metrics (Ferraz et al. 2024). The three parameters are ascertained with Equations 2–4.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Qobs,i - Qsim,i)^2}{\sum_{i=1}^{n}(Qobs,i - Qobs(mean))^2} \quad (2)$$

$$PBAIS = 100 \times \frac{\sum_{i=1}^{n}(Qobs,i - Qsim,i)}{\sum_{i=1}^{n}(Qobs,i)} \quad (3)$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}(Qobs,i - Qobs(mean))(Qsim,i - Qsim(mean))}{\sqrt{\sum_{i=1}^{n}(Qobs,i - Qobs(mean))^2}\ \sqrt{\sum_{i=1}^{n}(Qsim,i - Qsim(mean))^2}}\right)^2 \quad (4)$$

Where:

R^2 = coefficient of determination,
NSE = Nash Sutcliffe efficiency,
PBAIS = current bias,
n = time,
Qobs,i and *Qsim,i* = observed and simulated streamflow, respectively, and
Qobs (mean) and *Qs(mean)* = mean values of observed and simulated discharge, respectively.

2.5 Uncertainty analysis, calibration and validation of SWAT model

An uncertainty analysis is essential for forecasting the accuracy of the simulation outcome. The use of SWAT-CUP enables the calibration and validation of data derived from SWAT (Khaleghi and Hosseini 2024; Zhang 2018). The present study employed the Sequential Uncertainty Fitting 2 method for calibration, validation, and uncertainty assessment. This methodology assesses uncertainty utilizing the *R*-factor and *P*-factor, with the *P*-factor denoting the proportion of observed data, and the *R*-factor representing the ratio of the mean band employed to estimate the standard deviation of the observed data.

3. RESULTS

3.1 Morphological trait of study area

In compliance with the SWAT model specifications, we converted our data into the required format and sent it to SWAT. SWAT replicates spatial data by incorporating the input data.

Table 2 Area and HRUs of the sub basin from the SWAT results.

Sr. No	Sub-basin No.	Area (km^2)	HRUs
1	1	234.70	36
2	2	689.16	56
3	3	369.81	46
4	4	320.71	32
5	5	497.98	30

Hydrological Response Units (HRUs) were delineated by overlaying land use, soil, and slope maps within each sub-basin using the ArcSWAT interface. Threshold values of 25% for land use, 10% for soil, and 15% for slope were applied to exclude minor spatial classes and control the number of HRUs generated. This approach reduced model complexity while preserving the dominant watershed characteristics. The current model is segmented

into various basins, each comprising multiple Hydrological Response Units (HRUs) as indicated in Table 2. The present study includes five sub-basins and 200 HRUs, spanning an area of 2112.36 km^2. This level of spatial discretization was considered appropriate to capture land surface heterogeneity without excessively increasing model parameterization. Although higher HRU numbers may increase the number of calibration parameters, sensitivity analysis was used to identify the most influential parameters and reduce the risk of over-parameterization.

3.2 Analysis of sensitivity about elements influencing runoff

The SUFI-2 program is crucial to sensitivity analysis. Twelve parameters affected the runoff in the present study. The model uses twelve parameters and their corresponding ranges, having performed one hundred simulations to yield the results. The SUFI-2 program calculates the *t*-statistic for all parameters and selects the most sensitive (Sisay et al. 2017; Yadav and Singh 2024). A higher *t*-statistic denotes strong sensitivity of the parameter, whereas a lower *t*-statistic implies poor sensitivity. In the present study, ALPHA_BF and CN2 demonstrate high sensitivity, whilst ESCO and SOL_BD indicate intermediate sensitivity, and SFTMP and SOL_K have the lowest sensitivity parameters. The parameter range is explicitly stated in Table 4. The high sensitivity of CN2 indicates that surface runoff generation plays a dominant role in the hydrological response of the basin, which is consistent with the presence of extensive agricultural land and moderate slopes. The sensitivity of ALPHA_BF reflects the importance of groundwater contribution to streamflow, particularly during the non-monsoon season when baseflow sustains river discharge. The parameter GW_DELAY further influences the timing of groundwater recharge and discharge processes, highlighting the role of subsurface storage in regulating streamflow variability. Parameter sensitivity was evaluated based on the *t*-statistic and corresponding *p*-values generated by the SUFI-2 algorithm, where higher absolute *t*-stat values and lower *p*-values indicate greater sensitivity.

Table 3 Sensitivity ranking of selected SWAT Parameter obtained from SUFI-2 Analysis

Parameter	*t*-statistic	*p*-value	Rank	Hydrological meaning
CN2	2.4	<0.01	1	Surface runoff generation
ALPHA_BF (day^{-1})	2.1	<0.05	2	Base flow recession
GW_DELAY (days)	-1.2	<0.05	3	Groundwater lag

The dominance of CN2 as the most sensitive parameter reflects the semi-arid characteristics of the basin, where runoff generation is highly dependent on soil infiltration capacity and land use patterns. Areas with agricultural land and moderately permeable soils contribute to rapid runoff response, making the model highly responsive to variations

in curve number values. Similarly, ALPHA_BF was identified as the second most sensitive parameter which is shown in Table 3, indicating the importance of groundwater contribution to streamflow.

Table 4 Parameters input to the model, including their lowest and maximum values.

Sr.No	Parameter	Abbreviation	Max	Min
1	Soil Evaporation Compensation factor	V_ESCO	1.0	0.8
2	Manning coefficient in the main channel (s/m^(1/3))	V_CH_N2	0.3	0.0
3	Soil Available Water Capacity (mm/mm)	R_SOL_AWC	0.4	-0.2
4	Soil hydraulic conductivity (mm/h)	R_SOL_K	0.8	-0.8
5	Hydraulic steering in the main channel (mm/h)	V_CH_K2	130	5.0
6	Conservation service runoff curve number	R_CN2	0.2	-0.2
7	Groundwater flow reaction coefficient (day^{-1})	V_ALPHA_BF	1	0.0
8	Groundwater recharge and lag time (days)	V_GW_DELAY	450	30
9	Threshold depth of water in the shallow aquifer for return flow to occur (mm)	V_GWQMN	2	0.0
10	Groundwater "Revap" Coefficient	V_GW_REVAP	0.2	0.0
11	Moist bulk density (g/cm^3)	R_SOL_BD	0.2	-0.2
12	Snowfall temperature (°C)	V_SFTMP	5.0	-5.0

The presence of shallow aquifers and delayed subsurface flow in the basin influences base flow recession behavior, which is directly controlled by this parameter. GW_DELAY was identified as the third most sensitive parameter, indicating the role of groundwater travel time in influencing streamflow response. This suggests that the timing of subsurface flow contribution is an important factor in the hydrological behavior of the basin.

3.3 Model calibration and validation

The SWAT model was calibrated and validated to improve runoff simulation (Bressiani et al. 2015; Nyeko 2015). The calibration employed six years of daily data analysed in SWAT-CUP from 2012 to 2017 and included a two-year warm-up period. Validation was performed on the same platform throughout a three-year span from 2018 to 2020. The runoff statistic is presented in Table 5.

Table 5 Efficient parameters and their corresponding fitted values.

Sr.No	Parameter	Abbreviation	Max	Min	Fitted Value
1	Soil Evaporation Compensation factor	V__ESCO	1.0	0.8	0.849
2	Manning Coefficient in the main channel (s/m^(1/3))	V_CH_N2	0.3	0.0	0.163
3	Soil Available Water Capacity (mm/mm)	R__SOL_AWC	0.4	-0.2	0.343
4	Soil hydraulic conductivity (mm/h)	R__SOL_K	0.8	-0.8	0.584
5	Hydraulic steering in the main channel (mm/h)	V_CH_K2	130	5.0	24.375
6	Conservation service runoff curve number	R_CN2	0.2	-0.2	0.01
7	Groundwater flow reaction coefficient (day^{-1})	V__ALPHA_BF	1	0.0	0.515
8	Groundwater recharge and lag time (days)	V__GW_DELAY	450	30	36.299
9	Threshold depth of water in the shallow aquifer for return flow to occur (mm)	V__GWQMN	2	0.0	1.53
10	Groundwater "Revap" Coefficient	V__GW_REVAP	0.2	0.0	0.033
11	Moist bulk density (g/cm^3)	R__SOL_BD	-0.5	-0.6	0.088
12	Snowfall temperature (°C)	V__SFTMP	-5.0	5.0	0.950

3.4 Calibration and validation of runoff

The model's efficacy was determined through the evaluation of the R^2, PBIAS, and NS metrics. This model confirms that all three designated parameters are employed to assess its efficiency. Figure 4 depicts the relationship between the simulation and empirical results during the calibration phase, together with the calibrated and validated outcomes of the model assessment shown in Table 6. The statistical performance metrics presented in Table 6 were computed using monthly aggregated streamflow values, whereas the scatter plot in Figure 4 represents daily flow comparisons. This difference in temporal resolution explains the variation in R^2 values observed between the figure and the table. The model demonstrated satisfactory overall performance, with certain deviations observed during peak and low-flow conditions.

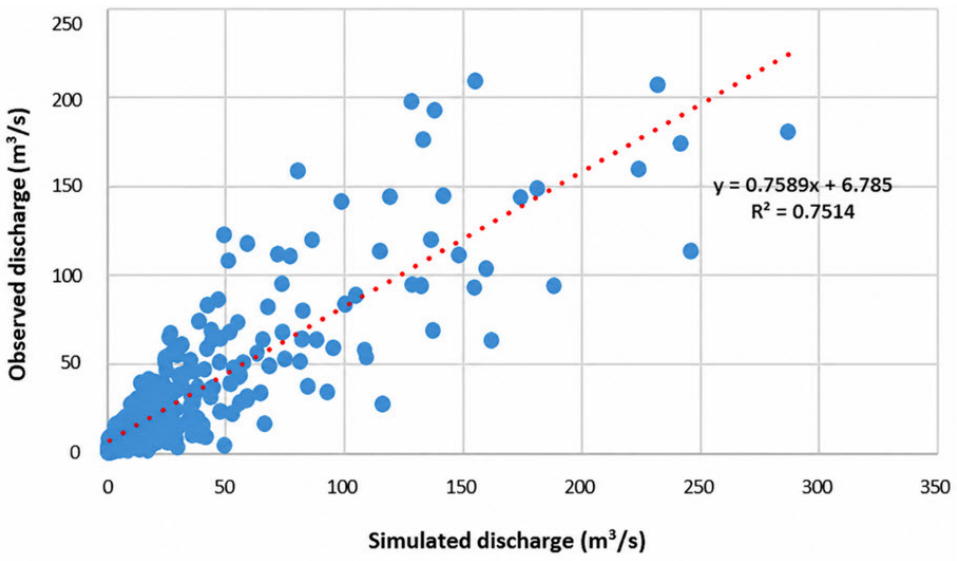

Figure 4 Interrelation diagram between simulated and observed data in the calibration phase.

Table 6 Overview of model efficacy during calibration and validation phases.

Year	Period	Assessment of statistical parameters				
		P-factor	*R*-factor	R^2	PBIAS	NS
2012–2017	Calibration	0.86	0.68	0.94	14.9	0.93
2018–2020	Validation	0.56	0.27	0.92	19.4	0.91

The uncertainty analysis using SUFI-2 indicated a *P*-factor of 0.86 during calibration and 0.56 during validation, suggesting that only 56% of observed streamflow data were enclosed within the 95% prediction uncertainty (95PPU) band in the validation period. This indicates moderate model predictive capability and highlights the presence of residual uncertainty in the simulation of peak and low flows.

3.5 Seasonal and flow-based evaluation of model performance

To further evaluate the reliability of the SWAT model beyond aggregate statistical metrics, model performance was assessed under different hydrological conditions. The simulated and observed streamflow series were analysed separately for monsoon (June–September) and non-monsoon periods, as well as for high-flow and low-flow conditions.

Seasonal performance

To evaluate model reliability under varying climatic conditions, the simulated and observed streamflow series were analysed separately for monsoon (June–September) and non-monsoon periods. The model exhibited better agreement during the monsoon season due

to the strong rainfall–runoff relationship and higher discharge magnitudes. During the non-monsoon period, relatively larger deviations were observed, which may be attributed to groundwater-dominated flow and lower precipitation inputs.

High-flow and Low-flow simulation

The ability of the model to reproduce extreme hydrological conditions was also examined. The SWAT model captured the general timing of peak discharge events; however, certain peak flows were slightly underestimated. This underestimation contributed to the moderate PBIAS values observed during calibration and validation. Low-flow conditions showed greater variability between simulated and observed values, reflecting uncertainties in base flow parameterization and spatial variability in rainfall inputs.

4. DISCUSSION

This study aimed to evaluate the effectiveness of the SWAT model and the SWAT-CUP software in simulating hydrological processes and quantifying uncertainty in runoff potential estimation within the specified watershed. The model outcomes were calibrated and validated via the SUFI-2 methodology. The outcomes from the calibration and validation phases were evaluated using the R^2, PBIAS, and NS coefficient values. In this study, the values at the calibration stage were 0.94, 0.89, 14.9, and 0.93, respectively. In the validation phase, the values recorded were 0.92, 0.86, 19.4, and 0.91, respectively. The findings indicate that the model exhibits outstanding performance in both the calibration and validation phases. The slightly lower performance during the validation period may be attributed to variability in rainfall patterns and the presence of extreme flow events, which are more difficult for the model to accurately simulate. Similar behavior has been reported in other monsoon-dominated basins where high seasonal rainfall variability introduces additional uncertainty in runoff simulation.

The statistical performance of the SWAT model used in this study is comparable to results reported in previous SWAT applications in Indian river basins. For instance, studies conducted in the Godavari River and Narmada River basins reported NSE values ranging between 0.65 and 0.82 during calibration and validation. The performance metrics achieved in the present study fall within this range, indicating that the model simulation is consistent with other monsoon-dominated catchments in India.

The relatively low *P*-factor obtained during the validation phase indicates that the model was not able to fully capture the variability of observed runoff, particularly during high-flow events. This may be attributed to uncertainties in rainfall input data, parameter equifinality, and simplifications inherent in the SWAT model structure. The simulated and field data exhibit good accuracy, as evidenced by the results of the validation optimization

coefficient. Both results indicate that further simulations and enhancements to the evaluation are unnecessary. Although the NASA POWER dataset provides complete spatial coverage, satellite-derived rainfall may introduce biases, particularly during high-intensity monsoon events. The absence of bias correction or direct comparison with ground-based observations represents a potential source of uncertainty in runoff simulation and may contribute to discrepancies observed during peak flow periods. The graph illustrates that the daily runoff simulation exhibits enhanced performance during both the calibration and validation phases, as depicted in Figure 5 and Figure 6. Indices and precision of the result values. Conduct further simulations without the necessity to enhance the evaluation indices and the correctness of the result values.

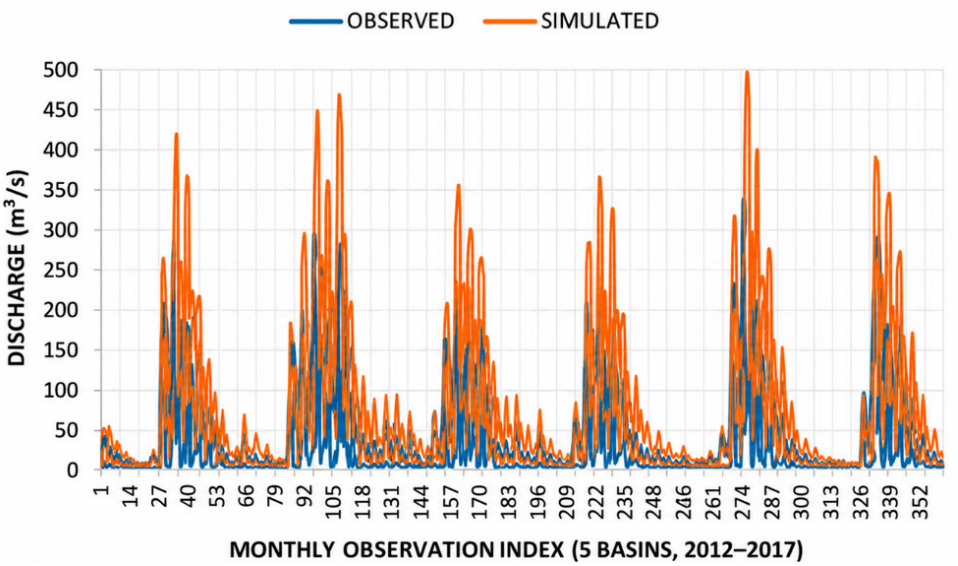

Figure 5 Comparison of calibrated, observed, and simulated monthly runoff values for five basins from 2012 to 2017.

For the calibration stage, the monthly observation index represents the combined monthly observations from five basins. The calibration period covers 2012–2017, corresponding to 72 months for each basin, and for the validation stage, the monthly observation index represents the combined monthly observations from five basins. The validation period covers 2018–2020, corresponding to 36 months for each basin.

The observed and simulated daily runoff series, together with the uncertainty band shown in Figure 7, further demonstrate the model's ability to reproduce the temporal variability and peak-flow characteristics of the watershed.

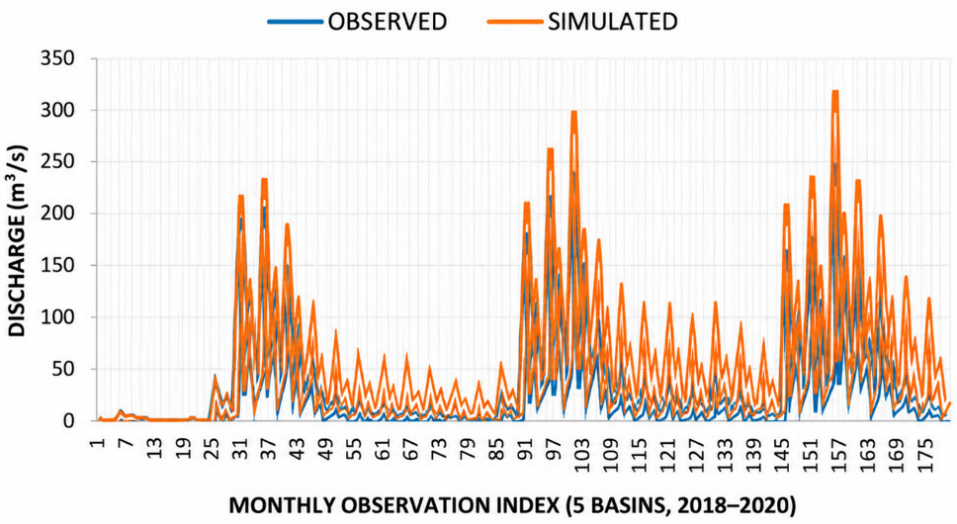

Figure 6 Comparison of validated, observed, and simulated monthly runoff values for five basins from 2018 to 2020.

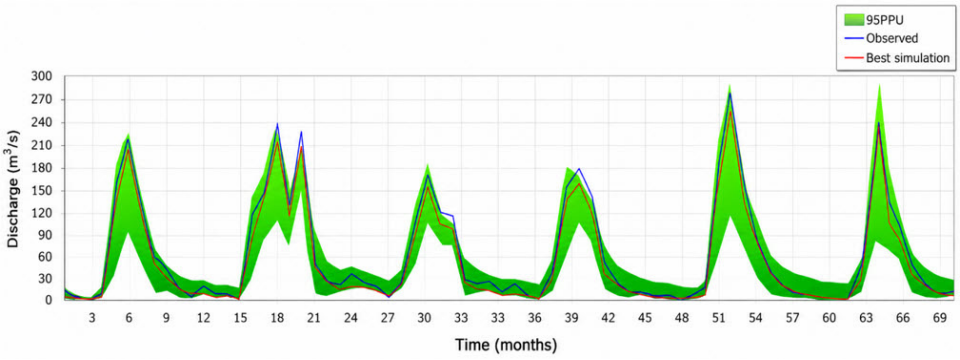

Figure 7 Uncertainty band for Mahan basin runoff after calibration.

The SWAT model is the most successful for monthly runoff simulations, producing accurate results because of dependable input data gathered from several government entities across multiple seasons. The calibration and validation datasets are allocated 70% and 30%, respectively, for the SWAT-CUP model. The results demonstrate that the model exhibited outstanding performance during the calibration and validation phases. The results indicate that twelve parameters affect runoff simulation; however, two parameters, specifically ALPHA_BF and CN2, are the most sensitive and have a direct impact on runoff. The curve number is the most critical metric for runoff. The SWAT model exhibits the greatest accuracy in predicting the Mahan Basin, with the Curve Number (CN) recognized as the most sensitive variable affecting runoff.

5. CONCLUSION

Assessing parameter uncertainty in the SWAT model is essential for improving the reliability of hydrological simulations and supporting effective water resource management. In this study, the calibration and validation processes were challenging due to the large number of model parameters and the requirement for technical expertise. Nevertheless, the model demonstrated satisfactory performance in simulating streamflow, as reflected by acceptable statistical and graphical agreement between observed and simulated data. The uncertainty analysis indicated that only a moderate proportion of observed streamflow fell within the 95% prediction uncertainty band, suggesting the presence of residual uncertainty and highlighting the need for further refinement of input data and parameter calibration. Despite these limitations, the model provided reasonably consistent results during both the calibration and validation phases, indicating its suitability for watershed-scale hydrological assessment.

The results of this study demonstrate that the SWAT model can be effectively applied for simulating hydrological processes in the Mahan River basin, although model performance remains influenced by data quality and structural assumptions. Future studies may improve simulation reliability by incorporating bias-corrected satellite rainfall products and integrating ground-based gauge observations. The findings of this study provide a useful basis for further hydrological investigations and water resource planning in the basin.

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REFERENCES

Aawar, T. and D. Khare. 2020. “Assessment of climate change impacts on streamflow through hydrological model using SWAT model: a case study of Afghanistan.” *Modeling Earth Systems and Environment* 6, 1427–1437. https://doi.org/10.1007/s40808-020-00759-0

Athira, P., C. Nanda, and K.P. Sudheer. 2018. “A computationally efficient method for uncertainty analysis of SWAT model simulations.” *Stochastic Environmental Research and Risk Assessment* 32, 1479–1492. https://doi.org/10.1007/s00477-018-1538-9

Bannwarth, M.A., W. Sangchan, C. Hugenschmidt, M. Lamers, J. Ingwersen, A.D. Ziegler, and T. Streck. 2014. “Pesticide transport simulation in a tropical catchment by SWAT.” *Environmental Pollution* 191, 70–79. https://doi.org/10.1016/j.envpol.2014.04.011

Bressiani, D. de A., P.W. Gassman, J.G. Fernandes, L.H.P. Garbossa, R. Srinivasan, N.B. Bonumá, E.M. Mendiondo. 2015. “Review of soil and water assessment tool (SWAT) applications in Brazil: Challenges and prospects.” *International Journal of Agricultural and Biological Engineering* 8 (3): 1–27. https://doi.org/10.3965/j.ijabe.20150803.1765

Choudhary, R. and P. Athira. 2021. “Effect of root zone soil moisture on the SWAT model simulation of surface and subsurface hydrological fluxes.” *Environmental Earth Sciences* 80*,* 620. https://doi.org/10.1007/s12665-021-09912-z

Dhone, P. and I. Ahmad. 2026a. “Development of Composite Drought Index Using Remotely Sensed Data: A Case Study on Sambhaji Nagar District, Maharashtra, India.” *Journal of Environmental Informatics Letters* 15 (1): 23–33. https://doi.org/10.3808/jeil.202600173

Dhone, P. and I. Ahmad. 2026b. “Identification of the most suitable meteorological drought index for Sambhaji Nagar district, Maharashtra, India.” *Water Practice & Technology* 21 (8): 3774–3787. https://doi.org/10.2166/wpt.2026.382

Dhone, P., M. Ghongade, and P. Lambole. 2025. “GIS Based Approach for Assessing the Surface Runoff Harvesting Potential: A Case Study.” *Studies in Science of Science* 43, 2. https://sciencejournal.eu/index.php/studies-in-science-of-science/article/view/810

Ferraz, L.L., G.M. Santana, L.F. de Sousa, J. da Silva Amorim, C.A. Silva Santos, and R.M. de Jesus. 2024. “Databases and Applications of the Soil and Water Assessment Tool (SWAT) Model in Brazilian River Basins: A Review.” *Environmental Modeling and Assessment* 30, 349–367. https://doi.org/10.1007/s10666-024-10002-0

Jaberzadeh, M., A. Saremi, H. Ghorbanizadeh Kharazi, and H. Babazadeh. 2024. “SWAT and IHACRES models for the simulation of rainfall-runoff of Dez watershed.” *Climate Dynamics* 62, 2823–2835. https://doi.org/10.1007/s00382-022-06215-2

Khaleghi, M.R. and S.H. Hosseini. 2024. “Using SWAT and SWAT-CUP for hydrological simulation and uncertainty analysis of the arid and semiarid watersheds (Case study: Zoshk Watershed, Shandiz, Iran).” *Applied Water Science* 14, 266. https://doi.org/10.1007/s13201-024-02327-8

Khalid, C. 2018. “Hydrological modeling of the Mikkés watershed (Morocco) using ARCSWAT model.” *Sustainable Water Resources Management* 4, 105–115. https://doi.org/10.1007/s40899-017-0145-0

Khayyun, T.S., I.A. Alwan, and A.M. Hayder. 2019. “Hydrological model for Hemren dam reservoir catchment area at the middle River Diyala reach in Iraq using ArcSWAT model.” *Applied Water Science* 9, 133. https://doi.org/10.1007/s13201-019-1010-0

Kushwaha, A. and M.K. Jain. 2013. “Hydrological Simulation in a Forest Dominated Watershed in Himalayan Region using SWAT Model.” *Water Resources Management* 27, 3005–3023. https://doi.org/10.1007/s11269-013-0329-9

Lin, B., X. Chen, and H. Yao. 2020. “Threshold of sub-watersheds for SWAT to simulate hillslope sediment generation and its spatial variations.” *Ecological Indicators* 111, 106040. https://doi.org/10.1016/j.ecolind.2019.106040

Luo, Y., B. Su, J. Yuan, H. Li, and Q. Zhang. 2011. “GIS Techniques for Watershed Delineation of SWAT Model in Plain Polders.” *Procedia Environmental Sciences* 10 (C): 2050–2057. https://doi.org/10.1016/j.proenv.2011.09.321

Malik, M.A., A.Q. Dar, and M.K. Jain. 2022. “Modelling streamflow using the SWAT model and multi-site calibration utilizing SUFI-2 of SWAT-CUP model for high altitude catchments, NW Himalaya’s.” *Modeling Earth Systems and Environment* 8, 1203–1213. https://doi.org/10.1007/s40808-021-01145-0

Ning, J., Z. Gao, and Q. Lu. 2015. “Runoff simulation using a modified SWAT model with spatially continuous HRUs.” *Environmental Earth Sciences* 74, 5895–5905. https://doi.org/10.1007/s12665-015-4613-2

Nyeko, M. 2015. “Hydrologic Modelling of Data Scarce Basin with SWAT Model: Capabilities and Limitations.” *Water Resources Management* 29, 81–94. https://doi.org/10.1007/s11269-014-0828-3

Qi, J., S. Li, Q. Li, Z. Xing, C.P.A. Bourque, and F.R. Meng. 2016. “Assessing an Enhanced Version of SWAT on Water Quantity and Quality Simulation in Regions with Seasonal Snow Cover.” *Water Resources Management* 30, 5021–5037. https://doi.org/10.1007/s11269-016-1466-8

Sisay, E., A. Halefom, D. Khare, L. Singh, and T. Worku. 2017. “Hydrological modelling of ungauged urban watershed using SWAT model.” *Modeling Earth Systems and Environment* 3, 693–702. https://doi.org/10.1007/s40808-017-0328-6

Teshager, A.D., P.W. Gassman, S. Secchi, J.T. Schoof, and G. Misgna. 2016. “Modeling Agricultural Watersheds with the Soil and Water Assessment Tool (SWAT):

Calibration and Validation with a Novel Procedure for Spatially Explicit HRUs." *Environmental Management* 57, 894–911. https://doi.org/10.1007/s00267-015-0636-4

Tufa, F.G. and C.H. Sime. 2021. "Stream flow modeling using SWAT model and the model performance evaluation in Toba sub-watershed, Ethiopia." *Modeling Earth Systems and Environment* 7, 2653–2665. https://doi.org/10.1007/s40808-020-01039-7

Yadav, A. and R.M. Singh. 2024. "Spatio-temporal Estimation of Evapotranspiration and Runoff in Sub-Watersheds of a Basin Using ArcSWAT." *National Academy Science Letters* 47, 649–653. https://doi.org/10.1007/s40009-024-01395-3

Zhang, X. 2018. "Simulating eroded soil organic carbon with the SWAT-C model." *Environmental Modelling and Software* 102, 39–48. https://doi.org/10.1016/j.envsoft.2018.01.005