Calibration and validation of semi-distributed model of monthly runoff using SUFI-2 algorithm for Shimsha catchment, Karnataka, India

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 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. These predictors, however, need further work to validate reliability.

Keywords: ~~{m~~Model, ~~probability~~Probability, ~~algorithm~~Algorithm, ~~uncertainty~~ Uncertainty, ~~and p~~Parameters~~}~~

Comment [L1]: This word is not suitable for keywords

1. INTRODUCTION

Comment [L2]: The introduction section is very short and concise. It is better to complete.

Hydrological models are essential tools for generating synthetic hydrological data in ungauged watersheds by estimating runoff, a key factor in assessing climate change impacts. Both physically-based and semi-distributed models have shown reliable performance, provided accurate data on topography, land use, land cover, soil properties, and climatic conditions within the catchment area. These models play a crucial role in understanding and predicting the hydrological response of watersheds, thereby supporting effective water resource management and environmental planning [1]. Once the models were executed, it becomes necessary to calibrate the results, as they were initially developed to match the specific conditions of their original design. 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, RMSE, and MAE. SWAT CUP serves as a versatile interface and standalone program designed for the calibration of SWAT models [2]. It offers various techniques, including PSO, SUFI-2, GLUE, Parasol, and MCMC. 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.

Comment [L3]: Not used in the manuscript.

Comment [L4]: It is suggested that this section be moved to the Materials and Methods.
The equations used in materials and methods section should be presented.

The primary objective of this study is to calibrate the SWAT model specifically for the Shimsha catchment in Southern 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. MATERIAL AND METHODS

2.1 Description of the study area:

The Shimsha River, a tributary of the Cauvery River, originates within the Devarayanadurgaforest 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 $77^0 11'$E to $13^0 22'$N and $76^0 51'$E to $12^0 57'$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.

Comment [L5]: - Reference??
- The map of the geographic location of the study area should be added.
- Why are land use, curve numbers (CN), soil and etc. not provided?
- The introduction of the physical characteristics of the Shimsha catchment has not been done correctly.

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.

Comment [L6]: Reference??

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. 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 [3]. 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 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 NeeravariNigama 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 [5]. The index of agreement (d), introduced by [6], 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") [7]. 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, [2] 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.1(calibration) and Fig. 2(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.

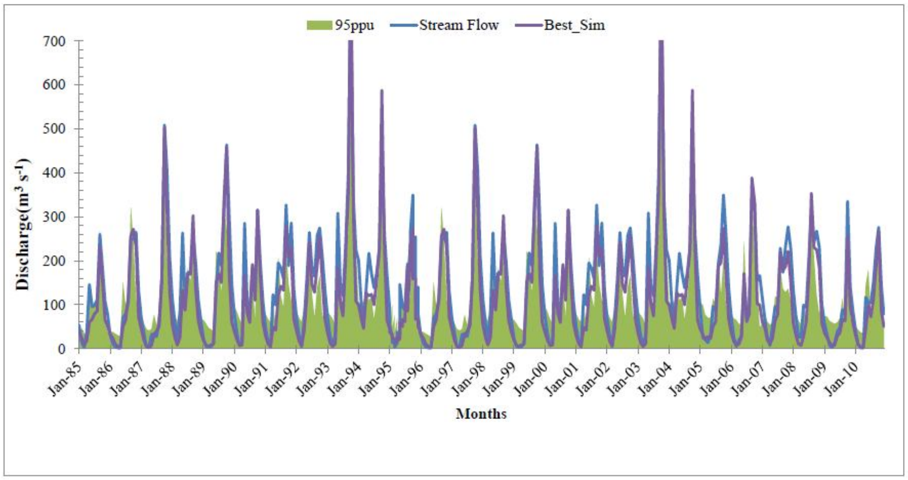

Fig.1: Latin hypercube one factor at a time of stream flow parameters for catchment area for calibration period

~~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.~~

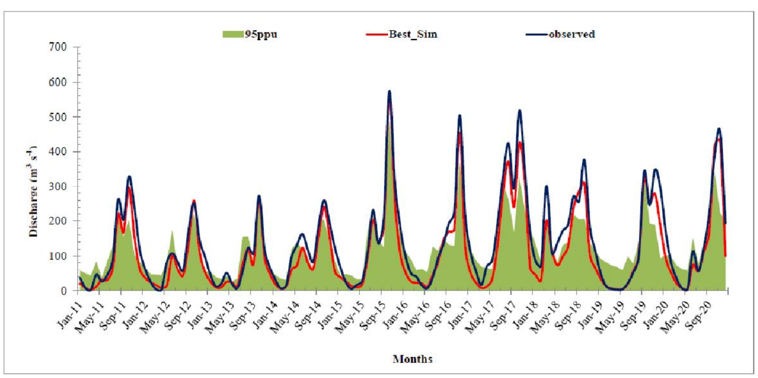

Fig. 2. Latin hypercube one factor at a time of stream flow parameters for catchment area for validation period

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.

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	5.00	130.00	73.125	Channel

		main channel (mm hrs^{-1})				
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

[8]

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 [9].

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 0.78and 0.048 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 [10]

Comment [L7]: Unit??

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 respectively, reaffirming the calibrated model's robustness in making predictions beyond the calibration period (Table 3).

Comment [L8]: Unit?

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	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.~~13.~~ 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 effectivewatershedmanagement[11].

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, R^2 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 R^2, 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.

REFERENCES

1. Sandra G and Sathian KK, Assessment of water balance of a watershed using SWAT model for water resources management. *Int. J. of Engg. Sci and Res.Tech.,* 2016,5(4): 177-184.
2. Abbaspour KC,Rouholahnejad E, Vaghefi S, Srinivasan R, Yang H. and Klove B, A continental-scale hydrology and water quality model for Europe: calibration and uncertainty of a high resolution large scale-swat model. *J of Hydrology*, 2015524: 733-752.
3. Schoul J, Abbaspour KC, Srinivasan R. and Yang H, Estimation of fresh water availability in the West African sub-continent using the SWAT hydrologic model. J of Hydrology, 2008, 352: 30-49.
4. Abbaspour, KC, SWAT-CUP: SWAT Calibration and Uncertainty Programs-A user manual. Eawag, Swiss Federal Institute of Aquatic Science and Technology, Duebendorf, Switzerland. 2015.
5. Santhi C, Muttiah RS., Arnold JG. and Srinivasan R, A GIS-based regional planning tool for irrigation demand assessment and savings using SWAT. *Trans. of ASAE,* 2005, 48(1): 137-147.
6. Willmott, C. J., 1981, On the validation of models. Physical Geography 2: 184-194.
7. Nash JE. and Sutcliffe J, River flow forecasting through conceptual models: part I-a discussion of principles. J. Hydrology, 1970,10: 282-290.
8. Pandi D, Kothandaraman S. and KuppusamyM, Simulation of Water Balance Components Using SWAT Model at Sub Catchment Level. *Sustainability* 2023,15(1438):1-20.
9. Abbaspour KC, Yang J, Maximov I, Siber R, Bogner K, Miel EJ, Zobrist J. and Srinivasan R, Modelling hydrology and water quality in the Pre-alpine/alpine Thur watershed using SWAT. *J. of Hydrol*., 2007, ,333(9): 413-430.
10. Tejaswini V. and Sathian, KK, Calibration and Validation of Swat Model for Kunthipuzha Basin Using SUFI-2 Algorithm. *Int.J.Curr.Microbiol.App.Sci.,*2018,7(1):2162-2172.
11. Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., Santhi, C., Harmel, R. D., Van Griensven, A., Van Liew, M., Kannan, N. and Jha, M.K., 2012, SWAT: Model use, calibration and validation. Trans. Of ASABE, 55(4): 1491-1508.

Comment [L9]: Remove extra spaces between words.