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Reshma B Kadlag
Ph.D. Scholar, Department of Soil and Water Conservation Engineering, Dr. A. S. College of Agricultural Engineering and Technology, Mahatma Phule Krishi Vidyapeeth, Rahuri, Maharashtra, India

Dr. Virendra N Barai
Professor, Department of Soil and Water Conservation Engineering, Dr. A. S. College of Agricultural Engineering and Technology, Mahatma Phule Krishi Vidyapeeth, Rahuri, Maharashtra, India

Dr. Bhau K Gavit
Associate Professor, Department of Soil and Water Conservation Engineering, Dr. A. S. College of Agricultural Engineering and Technology & Deputy Director of Research, Mahatma Phule Krishi Vidyapeeth, Rahuri, Maharashtra, India

Dr. Suhas K Upadhye
Associate Professor, Department of Agricultural Meteorology, College of Agriculture, Pune, Maharashtra, India

Dr. Anil G Durgude
Ex-Analytical Chemist, Micronutrient Research Scheme, Department of Soil Science & Agricultural Chemistry, Mahatma Phule Krishi Vidyapeeth, Rahuri, Maharashtra, India

Dr. Mahesh R Patil
Professor, Department of Statistics, Post Graduate Institute, Mahatma Phule Krishi Vidyapeeth, Rahuri, Maharashtra, India

Corresponding Author:
Reshma B Kadlag
Ph. D. Scholar, Department of Soil and Water Conservation Engineering, Dr. A. S. College of Agricultural Engineering and Technology, Mahatma Phule Krishi Vidyapeeth, Rahuri, Maharashtra, India

Sensitivity analysis for streamflow parameters using SUFI-2 Algorithm of SWAT-CUP

Reshma B Kadlag, Virendra N Barai, Bhau K Gavit, Suhas K Upadhye, Anil G Durgude and Mahesh R Patil

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Abstract
A watershed is regarded as the fundamental unit for the planning and execution of conservation and resource management initiatives. The first stage in creating efficient watershed management and planning strategies is to evaluate the temporal and spatial variations in runoff and soil erosion. Recent advancements in hydrological research, computational tools, and modelling approaches have facilitated the development of sophisticated simulation models that include GIS for thorough watershed analysis. The Soil and Water Assessment Tool (SWAT) semi-distributed model intended to simulate hydrological and water quality processes over extended durations at the watershed scale. Finding the most sensitive parameters for streamflow aids in lowering uncertainty and increasing model prediction accuracy. This study employed the SUFI-2 (Sequential Uncertainty Fitting-2) algorithm of SWAT-CUP (SWAT-Calibration and Uncertainty Programme) to conduct a sensitivity analysis of streamflow parameters for the Karad sub-basin in Maharashtra, India. The SCS Curve Number for moisture condition II (CN2) identified as the most sensitive parameter affecting streamflow among twenty examined parameters for the study area.

Keywords: Sensitivity analysis, SUFI-2, SWAT-CUP, streamflow, SWAT

1. Introduction

Globally, hydrologic models are commonly employed to simulate several hydrologic phenomena, including the quantity and quality of streamflow within a basin. Maintaining gauging stations to collect water quality and quantity data over an extended duration from multiple locations is highly costly, time-consuming, and labor-intensive. Consequently, hydrologic models are essential for simulating various hydrologic processes, including sediment production, rainfall-runoff conceptualization, and water quantity and quality. Many models are available to model long-term patterns of hydrologic processes at both small and large watershed areas. SWAT is the most widely utilized tool for modeling the management and climate change effects on hydrologic processes at the watershed scale.

The USDA-ARS created SWAT, a physically based, continuous, deterministic simulation model for watershed-scale analysis (Arnold *et al.*, 1998; Neitsch *et al.*, 2005) [7, 15]. The model replicates the quantity and quality of surface and groundwater across small watersheds to large river basins. The SWAT model has been extensively utilized globally to assess the impacts of land use, climate change, and long-term management of water in watersheds. Improving model calibration to more accurately simulate water quantity and quality has become an important priority for hydrologists. However, due to the large regional variability and wide range of input parameters, working with hydrologic models involves a significant amount of uncertainty. These uncertainties may lead to decisions that overestimate or underestimate hydrologic processes. To improve simulations, it is crucial to accurately conduct the sensitivity, calibration and uncertainty analysis of hydrologic models.

SWAT was developed to help water resource managers in forecasting the effects of land management practices on water, sediment, and agricultural chemical outputs. The model has been effectively employed by researchers globally for watershed modeling and the management of water resources in watersheds with diverse climatic and topographical attributes. A comprehensive research of SWAT model applications, calibration, and validation has been conducted by numerous researchers (Moriasi *et al.*, 2007; Arnold *et al.*,

2012) [14, 6]. SWAT-CUP is a program designed to assess the prediction uncertainties associated with the calibration and validation outcomes of the SWAT model. The software supports various procedures, including SUFI-2 (Abbaspour *et al.,* 2007) [4], Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992) [8], Parameter Solution (ParaSol) (Griensven and Meixner, 2006) [11], Particle Swarm Optimization (PSO) and Markov Chain Monte Carlo (MCMC) (Kuczera and Parent, 1998) [13].

The SWAT model categorizes watershed hydrology into two primary components: i) the land phase of the hydrologic cycle, which quantifies water, sediment, nutrient, and pesticide loadings to the main channel in each sub-watershed, and ii) the routing phase, which simulates the transport of water, sediments, and other materials to the watershed outlet via the channel network.

The hydrologic cycle, as modeled by SWAT, is predicated on the subsequent water balance equation:

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

where, SW_t is the final soil water content, SW_0 is the initial soil water content, t is the time in days, R_{day} is the daily precipitation, Q_{surf} is the daily surface runoff, E_a is the daily evapotranspiration (ET), W_{seep} is the daily water entering the vadose zone from the soil profile and Q_{gw} is the daily return flow, all units in mm.

The SWAT model requires calibration of numerous input parameters related to streamflow, sediment, and various environmental objectives. The sensitivity analysis of the Karad sub-basin employed 20 SWAT input parameters associated with streamflow. The parameters were derived from various previous investigations (Arnold *et al.*, 2012; Shi *et al.*, 2013; Khalid *et al.*, 2015; Ali *et al.*, 2014) [6, 16, 12, 5]. The analysis included a global sensitivity analysis. This paper provides a fundamental explanation of the SUFI-2 Algorithm, along with details on model setup and simulation. Additionally, it addresses the output of the sensitivity analysis, concentrating on the parameters that exhibit significant sensitivity.

2. SUFI-2 algorithm

In this study, SUFI-2 algorithm, a multisite and semi-automated global search procedure developed by Abbaspour *et al.* (2004) [2] and Yang *et al.* (2007) [18], was employed for sensitivity analysis. Sensitivity analysis is the process of determining the model's most significant influencing factors. There are two reasons why sensitivity analysis is crucial: first, processes are represented by parameters, and sensitivity analysis offers details on the most significant processes in the study area. Second, by removing the parameters that have been determined to be insensitive, sensitivity analysis aids in reducing the total number of parameters in the calibration process. Local sensitivity analysis and global sensitivity analysis are the two primary forms of sensitivity analysis that are typically carried out. In local sensitivity analysis, all parameters are kept constant while one is changed to see how it affects an objective function or model output. Since every parameter in the global sensitivity analysis is changing, more runs (500-1000 or more), depending on the process and number of parameters are required to observe how each parameter affects the objective function. To measure the sensitivity of each parameter, global sensitivity analysis employs a multiple regression technique:

$$g = \alpha + \sum_{i=1}^{n} \beta_i b_i \quad \ldots(1)$$

where, g is value of objective function, α is regression constant, and β is coefficient of parameters. Each parameter's significance level is then determined using the t-test. The sensitivities are estimates of the average changes in the objective function that occur when each parameter is changed while all other parameters remain constant. This only offers a limited understanding of the objective function's sensitivity to model parameters because it provides relative sensitivities based on linear approximations. In this study, the more sensitive the parameter, the higher the absolute value of the t-statistic and the lower the p-value.

In SUFI-2, the degree to which all uncertainties are considered is quantified by a measure known as the p-factor, representing the percentage of measured data bracketed by the 95% prediction uncertainty (95 PPU). The r-factor serves as an additional metric for assessing the reliability of calibration and uncertainty analysis, defined as the average thickness of the 95 PPU band divided by the standard deviation of the measured data. SUFI-2 aims to include the majority of the measured data within the narrowest feasible uncertainty band. The 95 PPU is derived from the 2.5% and 97.5% thresholds of the cumulative distribution of an output variable, which is generated via Latin hypercube sampling, excluding the worst 5% of simulations. The p-factor theoretically ranges from 0 to 100%, whereas the r-factor ranges from 0 to infinity. A p-factor of 1 and an r-factor of zero represent a simulation that precisely corresponds with the measured data.

3. Study area description

The second-largest river system in Peninsular India that drains eastward is the Krishna river basin. It encompasses large areas of Maharashtra, Karnataka, and Andhra Pradesh as well as the Deccan Plateau. The research region, the Karad sub-basin, is located in the Satara district of Maharashtra and spans 5,425.62 km². It is part of the upper Krishna basin. It spans the geographic latitudes of $17^0$07'24.71"N to $18^0$02'58.55"N and the longitudes of $73^0$33'10.93"E to $74^0$18'42.20"E. Near Karad, the sub-basin drains into the Krishna River. This area's elevation varies from 535 to 1,435 meters above mean sea level (MSL). The study area's location map is shown in Fig. 1. The average annual rainfall in the basin is 1,783 mm, according to an analysis of 30 years of rainfall data (1989-2018). The lower section receives as little as 800 mm of rainfall annually, while the upper watershed recorded the greatest average of about 5,000 mm. The tropical climate zone encompasses the study region.

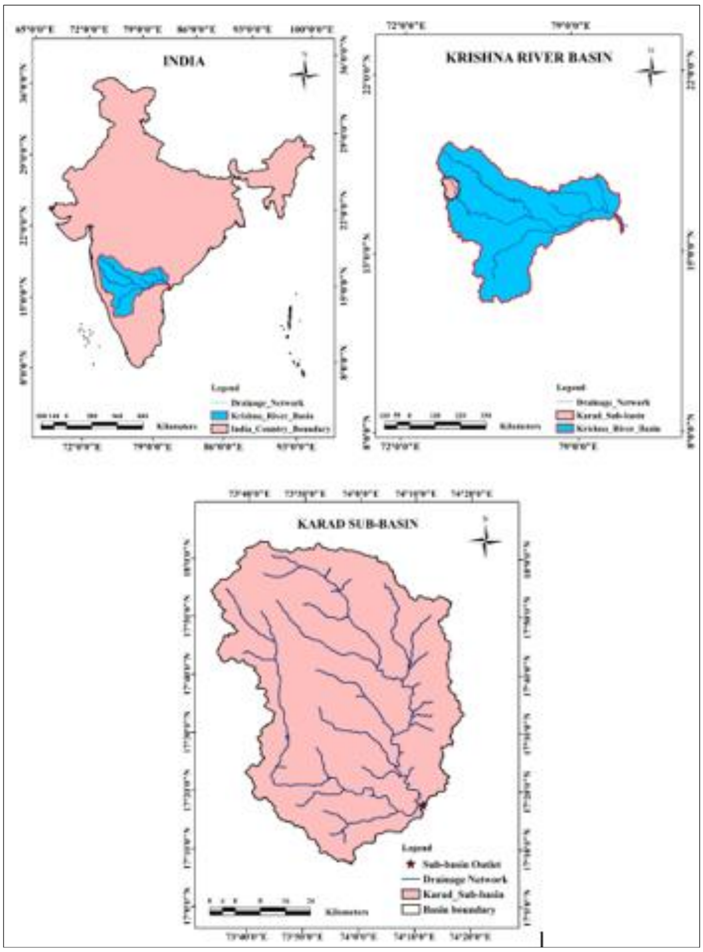

Fig 1: Location map of study area

4. Model setup and simulation

The model setup involved several key steps *viz*., initializing the project, automatically delineating the watershed, generating land use and land cover (LULC), soil and topographic maps, analyzing Hydrologic Response Units (HRUs), defining meteorological inputs, preparing input tables, modifying input data executing the SWAT simulation and finally, interpreting the output results.

The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) provided the DEM for this research. The hydrological modeling procedure used this 30-meter resolution DEM as a starting point for topography analysis, watershed delineation, slope computation, and drainage network extraction. Fig. 2 displays the study basin's processed DEM map. The DEM used for watershed delineation provided the slope data needed for the SWAT model. The slopes were divided into five groups based on the FAO's recommendations for conservation soil and water: 0-3%, 3-8%, 8-15%, 15-30%, and >30%. According to the findings, the 3-8% slope class constitutes up the majority of the watershed, accounting for 28.03% (1520.65 km^2) of its entire size. Slopes between 8 and 15 percent and more than 30 percent cover 21.35% (1158.50 km^2) and 19.74% (1071.04 km^2) of the area, respectively. The 0-3% slope range has the lowest percentage at 12.39% (671.99 km^2), while the 15-30% slope group comprises 18.49% (1003.44 km^2). Fig. 3 shows the slope class's spatial distribution within the watershed.

The National Bureau of Soil Survey and Land Use Planning (NBSS&LUP), Nagpur, provided the digital soil layer used in this study (Fig. 4). Important details on a number of soil properties were derived from the digital soil map. An attribute table was used to connect the watershed's comprehensive soil information to the soil map. At 41.01% (2225.14 km^2) of the entire watershed, the Lithic Ustorthents soil taxonomy is the largest. Type Ustorthents occupy 23.60 km^2 (0.44%), Typic Chromusterts occupy 1083.13 km^2 (19.96%), Typic Ustropepts occupy 1062.21 km^2 (19.58%), and Udic Rhodustalfs occupy 1031.54 km^2 (19.01%).

The LULC maps of the research area were created using Google Earth Engine (GEE), a cloud-based platform (Fig. 5). In this study, a supervised image classification method was used. Agricultural land accounts to 61.58% of the watershed's total area. Other important land use classes are water bodies (3.47%), forest (12.36%), built-up areas (1.44%), and barren land (21.15%). The majority of the land is agriculture, accounting to 3340.70 km^2 of the watershed's total area of 5425.62 km^2. Following that are barren land (1147.44 km^2), and forest land (670.87 km^2), water bodies (188.23 km^2). The built-up area is the smallest category, comprising 78.38 km^2.

Meteorological information was gathered from the Hydrology Data Users Group (HDUG), Nasik. The study's meteorological data is divided into categories such as maximum and minimum temperature, wind speed, sunlight hours, relative humidity, and rainfall. The Central Water Commission (CWC), Hyderabad, provided stream discharge for the Karad sub-basin. Table 1 shows the data source for the study.

Table 1: Data source for the study

Sr. No.	Data	Source	Description
1	DEM	https://earthexplorer.usgs.gov	ASTER GDEM (30 m resolution)
2	Soil map	National Bureau of Soil Survey and Land Use Planning, Nagpur	Soil texture and organic carbon
3	Land use Land cover	https://earthengine.google.com	Landsat 8 image (OLI TIRS, 30 m resolution)
4	Metrological data	Hydrological Data User Group, Nasik	Daily maximum and minimum temperature, wind speed, solar radiation, relative humidity and rainfall
5	Hydrological data	Central Water Commission, Hyderabad	Daily streamflow

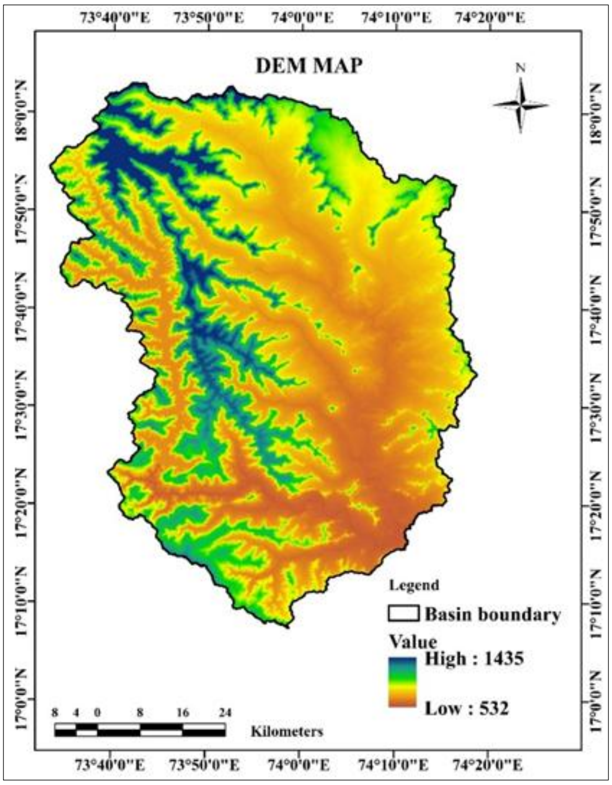

Fig 2: DEM map of study area

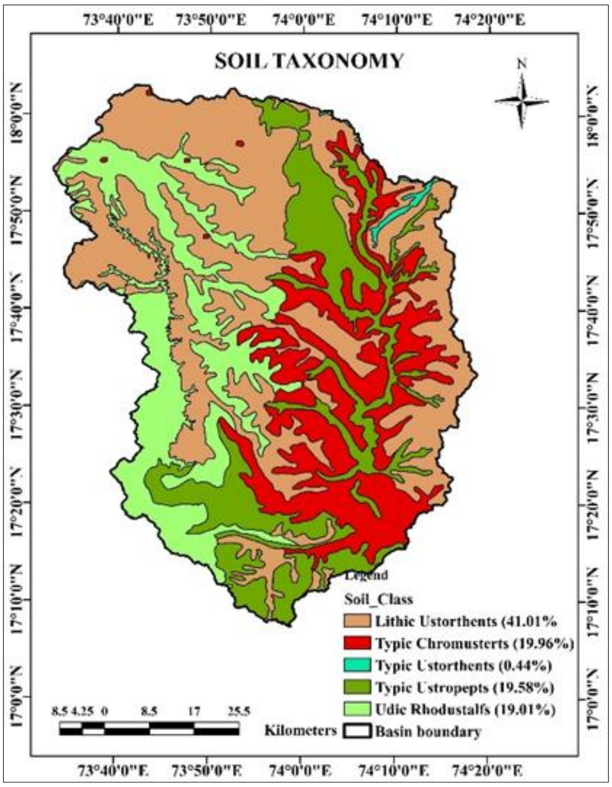

Fig 4: Soil taxonomy of study area

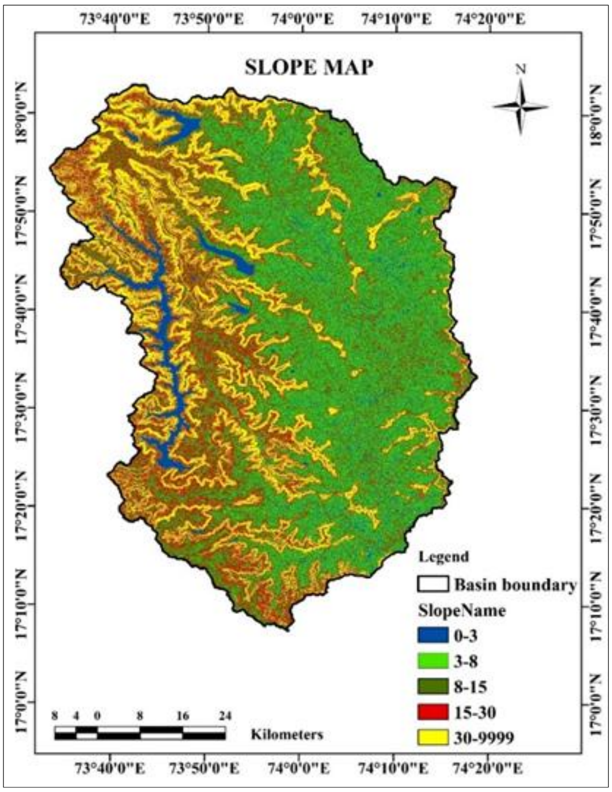

Fig 3: Slope map of study area

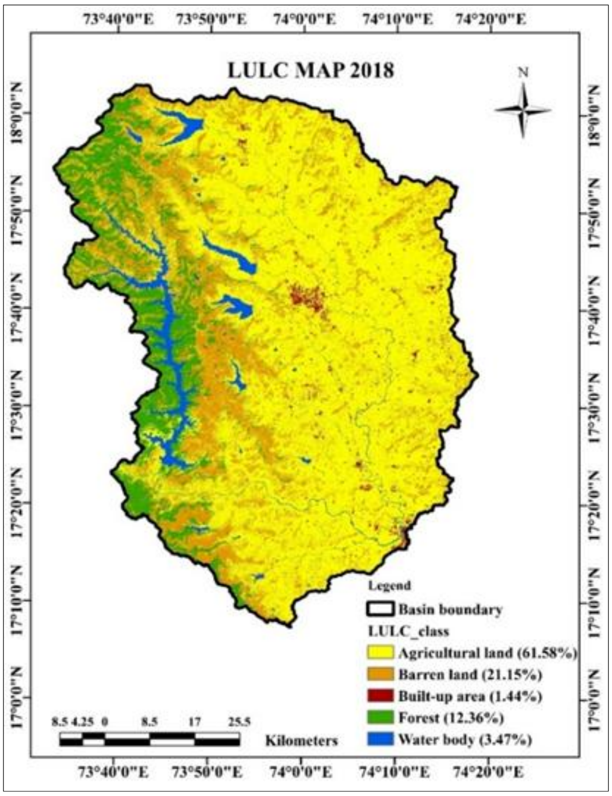

Fig 5: Land use land cover map of study area

When designing the basin representation, ArcSWAT (Winchell *et al.*, 2010) [17] allows users define two different kinds of thresholds. Sub-watershed boundaries are established based on topography using the sub-watershed threshold, which is the minimal area needed to initiate stream networks. After the sub-watersheds have been delineated, the user can either divide the sub-watersheds into several HRUs or model a single soil, land use, and management plan for each sub-watershed. The one-third default threshold area (3622 ha) was chosen for sub-watershed discretization, yielding 75 sub-watersheds and 4176 Hydrologic Response Units (HRUs) for the 0% land use, 0% soil, and 0% slope class threshold.

After setting up the model, the streamflow simulation for the calibration period was conducted in the Karad sub-basin. The calibration periods included daily streamflow data spanning about 17 years (1989 to 2005), with the first four years (1989-1992) being used for the model warm-up. Global sensitivity was used to carry out the optimization procedure that represents the sensitivity of the twenty SWAT input parameters (Table 2). Five hundred iterations of the global sensitivity methods were chosen in order to obtain the most sensitive input parameters. The sensitivity analysis in this study was conducted using the licensing version of SWAT-CUP. By enabling eight simultaneous simulation processes at once, SWAT-CUP's parallel processing technology accelerated the simulation operations. Using Parallel Computing Technology, SWAT-CUP parallel processing currently enables SUFI-2 to operate more quickly.

5. Sensitivity Analysis

Twenty hydrological parameters [CN2.mgt (SCS runoff curve number for moisture condition II), SOL_AWC.sol (Available soil capacity of soil layer (mm/mm of soil)), ALPHA_BF.gw (Base flow alpha factor), CH_N2.rte (Manning’s coefficient for channel), RCHRG_DP.gw (Deep aquifer percolation factor), CH_K2.rte (Effective hydraulic conductivity in main channel alluvium (mm/h), GW_DELAY.gw (Groundwater delay), HRU_SLP.hru (Average slope steepness), GWQMN.gw (Threshold depth of water in the shallow aquifer for return flow to occur), EPCO.hru (Average slope steepness), SLSUBBSN.hru (Average slope length), GW_REVAP.gw (Groundwater delay (days)), REVAPMN.gw (Threshold depth of water in the shallow aquifer for revap to occur (mm)), SOL_K.sol (Saturated hydraulic conductivity (mm/h)), OV_N.hru (Manning’s value for overland flow), ESCO.bsn (Plant evaporation compensation factor), SURLAG.bsn (Surface runoff lag time), SOL_BD.sol (Moist bulk density), ALPHA_BF.gw (Base flow alpha factor (days)), TLAPS.sub (Temperature laps rate (^{0}C/km))] related to runoff were selected to perform the global sensitivity analysis as outline in Table 2.

Fig. 6 displays the final ranking of sensitive parameters derived from the SUFI-2 iterations. These parameters were then chosen as the starting set for calibration of the model. Table 2 shows the comprehensive ranking of streamflow sensitivity analysis parameters together with the related t-statistic and p-value that were found after 500 simulation runs in the SWAT-CUP’s SUFI-2 algorithm.

The results indicated that the parameters affecting surface runoff, groundwater recharge, soil moisture, and channel processes have significant effects on streamflow simulation, based on a global sensitivity analysis performed for the Karad sub-basin. While REVAPMN.gw, SOL_K.sol, OV_N.hru, and ESCO.bsn demonstrated significant sensitivity, parameters like SURLAG.bsn, SOL_BD.sol, ALPHA_BF.gw, and TLAPS.sub had little effect on the model response. Additionally, the parameters GWQMN.gw, EPCO.hru, SLSUBBSN.hru, and GW_REVAP.gw showed moderate sensitivity and were involved in evapotranspiration and subsurface flow. However, it was discovered that the most sensitive parameters influencing streamflow control were those related to surface runoff (CN2.mgt, CH_N2.rte), soil moisture capacity (SOL_AWC.sol), and groundwater interaction (ALPHA_BNK.rte, RCHRG_DP.gw). Additionally, variables like CH_K2.rte, GW_DELAY.gw, and HRU_SLP.hru also had a substantial contribution to changes in the simulated discharge. In order to mitigate the model's tendency for overestimation and underestimation, interdependence between some parameters was also noted, where changes in one parameter affected the response of others. It was discovered that the most sensitive factor affecting streamflow was the SCS Curve Number for moisture condition II (CN2).

The CN2.mgt had a t-stat value of 26.73, which was significantly higher than the majority of the parameters. The CN2.mgt's P-value was 0.00. The t-stat value for the least sensitive parameter, TLAPS.sub, was 0.09, which was significantly lower than the values for the other parameters. The TLAPS.sub's P-value was 0.93.

Table 2: Streamflow parameters used and their ranking after global sensitivity analysis

Parameter code	t-stat	P-value	Rank	Range	Definition
r_CN2.mgt	-26.73	0.00	1	-0.20 - 0.20	SCS runoff curve number for moisture condition II
r_SOL_AWC.sol	4.27	0.00	2	-0.50 - 0.50	Available soil capacity of soil layer (mm/mm of soil)
v_ALPHA_BNK.rte	-3.07	0.00	3	0.0 - 1.0	Base flow alpha factor for bank storage
v_CH_N2.rte	2.04	0.04	4	0.0 - 0.5	Manning’s coefficient for channel
v_RCHRG_DP.gw	-1.99	0.05	5	0.0 - 1.0	Deep aquifer percolation factor
v_CH_K2.rte	1.54	0.13	4	0.0 - 150.0	Effective hydraulic conductivity in main channel alluvium (mm/h)
v_GW_DELAY.gw	1.42	0.16	7	0.0 - 500.0	Groundwater delay (days)
r_HRU_SLP.hru	-1.32	0.19	8	0.0 - 0.2	Average slope steepness
v_GWQMN.gw	-1.23	0.22	9	0 - 5000.0	Threshold depth of water in the shallow aquifer for return flow to occur (mm)
v_EPCO.hru	1.08	0.28	10	0.01 - 1	Plant evaporation compensation factor
r_SLSUBBSN.hru	1.06	0.29	11	-0.5 - 0.5	Average slope length
v_GW_REVAP.gw	0.78	0.44	12	0.0 - 500.0	Groundwater revap coefficient
v_REVAPMN.gw	0.69	0.49	13	0.0 - 500.0	Threshold depth of water in the shallow aquifer for revap to occur (mm)
r_SOL_K.sol	-0.62	0.53	14	-0.50 - 0.50	Saturated hydraulic conductivity (mm/h)
r_OV_N.hru	-0.61	0.54	15	0.01 - 30	Manning’s value for overland flow
v_ESCO.bsn	0.59	0.56	16	0.01 - 1	Plant evaporation compensation factor
v_SURLAG.bsn	0.54	0.59	17	0.0 - 10.0	Surface runoff lag time
r_SOL_BD.sol	0.36	0.72	18	1.1 - 1.9	Moist bulk density
v_ALPHA_BF.gw	0.26	0.79	19	0.0 - 1.0	Base flow alpha factor (days)
v_TLAPS.sub	-0.09	0.93	20	-10 - 10	Temperature laps rate (^{0}C/km)

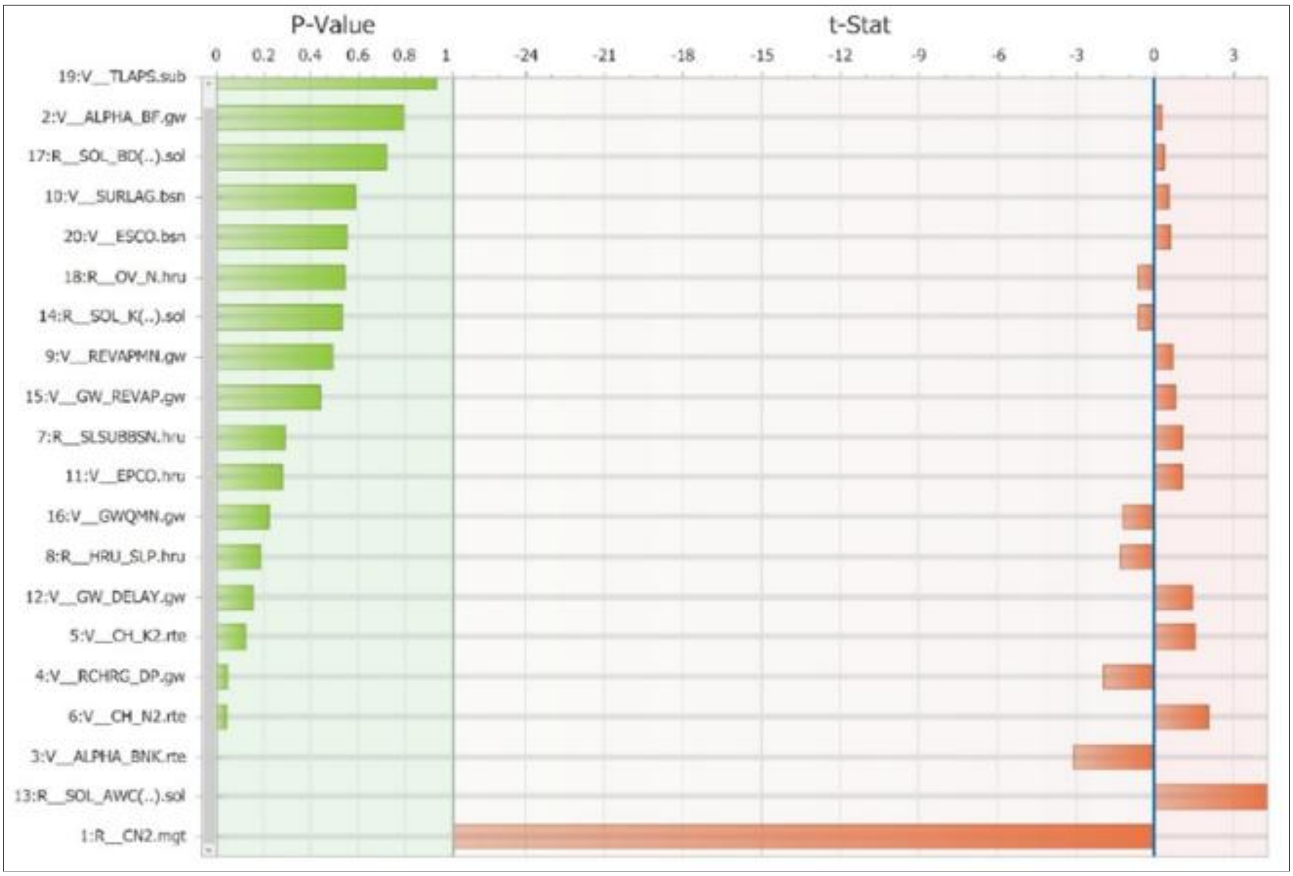

Fig 6: Streamflow sensitivity analysis from SWAT-CUP

6. Conclusion

The sensitivity analysis conducted during the calibration of the SWAT model yielded critical insights into the dominant hydrological processes influencing runoff generation in the study watershed. The SUFI-2 algorithm of SWAT-CUP proved successful in performing sensitivity analysis of streamflow parameters within the Karad sub-basin. The SWAT-CUP parallel processing technology accelerated simulation processes by permitting eight simultaneous simulation executions. The SCS Curve Number for moisture condition II (CN2) emerged as the most sensitive parameter affecting streamflow among the twenty parameters evaluated for the Karad sub-basin. The results showed that the parameters affecting surface runoff, groundwater recharge, soil moisture, and channel processes had a substantial impact on streamflow modelling. The input parameters identified as the five most sensitive parameters include CN2.mgt, SOL_AWC.sol, ALPHA_BNK.rte, CH_N2.rte, and RCHRG_DP.gw. All sensitive input parameters were considered during the calibration and validation processes of the watershed modelling prior to the model's implementation for any scenario study. These parameters are also recommended for application to identical geographical distributions in other watersheds.

References

1. Abbaspour KC. User manual for SWAT-CUP, SWAT calibration, and uncertainty analysis programs. Swiss Federal Institute of Aquatic Science and Technology, Eawag, Duebendorf, Switzerland. 2012. p. 93.
2. Abbaspour KC, Johnson CA, Van Genuchten MT. Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. Vadose Zone J. 2004;3(4):1340-1352.
3. Abbaspour KC, Rouholahnejad E, Vaghefi S, Srinivasan R, Yang H, Kløve B. A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. J Hydrol. 2015;524:733-752.
4. Abbaspour KC, Yang J, Maximov I, Siber R, Bogner K, Mieleitner J, *et al*. Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. J Hydrol. 2007;333(2-4):413-430.
5. Ali MF, Abd Rahman NF, Khalid K, Liem ND. Langat river basin hydrologic model using integrated GIS and ArcSWAT interface. Appl Mech Mater. 2014;567:86-91.
6. Arnold JG, Moriasi DN, Gassman PW, Abbaspour KC, White MJ, Kannan N. SWAT: Model use, calibration and validation. Trans ASABE. 2012;55(4):1491-1508.
7. Arnold JG, Srinivasan R, Muttiah R, Williams JR. Large area hydrologic modeling and assessment: Part I. Model development. J Am Water Resour Assoc. 1998;34:73-89.
8. Beven KJ, Binley AM. The future of distributed models: model calibration and uncertainty prediction. Hydrol Process. 1992;6:279-298.
9. Gassman PW, Reyes MR, Green CH, Arnold JG. The soil and water assessment tool: Historical development, applications, and future directions. Trans ASABE. 2007;50(4):1211-1250.
10. Gassman PW, Arnold JG, Srinivasan R, Reyes M. The worldwide use of the SWAT model: Technological drivers, networking impacts, and simulation trends. In: Proc. 21st Century Watershed Technology: Improving Water Quality and Environment. ASABE Publication No. 701P0210cd; 2010.

11. Griensven A, Meixner T. Methods to quantify and identify the sources of uncertainty for river basin water quality models. Water Sci Technol. 2006;53(1):51-59.
12. Khalid K, Ali MF, Abd Rahman NF, Mispan MR, Rasid MZA, Haron SH, *et al*. Optimization of the spatial input parameter in distributed hydrological model. ARPN J Eng Appl Sci. 2015;10(15):6628-6633.
13. Kuczera G, Parent E. Monte Carlo assessment of parameter uncertainty in conceptual catchment models: the Metropolis algorithm. J Hydrol. 1998;211(1-4):69-85.
14. Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RG, Veith TL. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans ASABE. 2007;50(3):885-900.
15. Neitsch SL, Arnold JG, Kiniry JR, Williams JR. Soil and Water Assessment Tool Theoretical Documentation. Version 2005. USDA Agricultural Research Service and Texas A&M Blackland Research Center, Temple, TX.
16. Shi P, Hou Y, Xie T, Chen C, Chen X, Li Q, *et al*. Application of a SWAT model for hydrological modeling in the Xixian watershed, China. J Hydrol Eng. 2013;18:1522-1529.
17. Winchell MR, Srinivasan M, Lazio D, Arnold JG. ArcSWAT Interface for SWAT 2009: User's Guide. Texas Agricultural Experiment Station, Texas, and USDA Agricultural Research Service, Temple, Texas; 2009.
18. Yang JP, Reichert P, Abbaspour KC, Xia JH, Yang. Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China. J Hydrol. 2008;358:1-23.