AQUA

Water Infrastructure, Ecosystems and Society

 AQUA — Water Infrastructure, Ecosystems and Society Vol 72 No 4, 507 doi: 10.2166/aqua.2023.213

A comparison of the SCS-CN-based models for hydrological simulation of the Aghanashini River, Karnataka, India

Harmandeep Singh[a], Mohammad Afaq Alam[a], Priyank J. Sharma[b] and Kuldeep Singh Rautela[b,*]

[a] Department of Civil Engineering, Punjab Engineering College (Deemed to be University), Sector – 12, Chandigarh 160012, India
[b] Department of Civil Engineering, Indian Institute of Technology Indore, Madhya Pradesh 453552, Indore, India
*Corresponding author. E-mail: kuldeeprautela007@gmail.com

ABSTRACT

This present study investigates different techniques for estimating the surface runoff using the Soil Conservation Service Curve Number (SCS-CN) method for the Aghanashini River in Karnataka, India. The SCS-CN method is a simplified approach for runoff estimation, but it does not take into account the actual moisture content in the soil. Consequently, insignificant moisture level changes could induce significant variations in the runoff. The study analyzes six different models based on the SCS-CN method, including the original SCS-CN model and several variations with added features (SCS-CN with slope correction, SCS-CN with λ-optimization, Mishra and Singh, Michel-Vazken -Perrin (MVP), Activation Soil Moisture Accounting SCS-CN). The accuracy of each model was compared using several goodness-of-fit statistics. Furthermore, based on the flood frequency analysis, three large flood events were reported in 2005, 2013, and 2014. The results showed that the MVP model was the best-performing method in simulating runoff. The outcomes of this study can provide valuable information to the local authorities in making informed decisions about flood forecasting and water conservation.

Key words: Aghanashini River, flood frequency, mathematical models, runoff estimation, SCS-CN method

HIGHLIGHTS

- Six mathematical models have been prepared on the basis of SCS-CN for a coastal river basin.
- The long-term hydrological simulation of the Aghanashini River has been carried out by taking AMC changes.
- Seven statistical indices were used to judge the efficiency of the developed models.
- The developed models compute surface runoff with the desired accuracy.

INTRODUCTION

Water is essential for human survival, and rivers have been crucial in shaping human civilization throughout history (Sofi *et al.* 2021). They serve as a vital source of freshwater, providing a crucial resource for various purposes such as water supply, irrigation, and the generation of hydropower (Rautela *et al.* 2022a, 2022b). The climatic and streamflow extremes caused by human and natural factors profoundly impact spring and rain-fed river basins, leading to the drying up of streams and springs and a significant alteration of land use (Sharma *et al.* 2019; Galavi & Mirzaei 2020; Singh *et al.* 2023). These alterations will have a profound impact on the surface and sub-surface water flow dynamics of the basins, significantly affecting their hydrological response (Galavi *et al.* 2019; Sofi *et al.* 2021). The consequences of these changes are significant and highlight the need for an increased understanding and management of our freshwater resources. Hydrologic simulation of surface runoff is a computational approach to predicting the movement of water in catchments, from precipitation to surface water bodies, including rivers. It is particularly useful in ungauged catchments where limited data are available, as it allows for the estimation of flow based on the complex physical and meteorological processes that govern water movement (Kumar & Bhattacharjya 2021).

The simulation process involves mathematical modelling of the physical processes involved in water movement, including precipitation, evaporation, infiltration, and storage (Amini-Zad *et al.* 2018; Rautela *et al.* 2023). These models are based on hydrology, meteorology, and soil science principles and incorporate data on precipitation, temperature, and land use (Kumar & Bhattacharjya 2021). The simulation results provide valuable information on the hydrologic response of a catchment to changes in land use and management practices. With the rapid increase in population, there is a growing need for water conservation and identifying new water resources. Accurate estimates of water flow in a region are crucial for making informed decisions about water management and flood control (Kumar & Bhattacharjya 2021). The results of the hydrologic simulation of surface runoff can be used to estimate the impacts of land use changes on water resources, to identify the best strategies for conserving water, and to reduce the risk of flash flooding, which can cause severe damage to properties near riverbanks.

Empirical models are mathematical formulas that use a limited number of easily measurable variables, such as precipitation and temperature, to estimate runoff. These models are simple and quick to implement and can provide useful estimates for areas where data are limited (Rawat *et al.* 2021). However, empirical models have limitations as they often cannot account for complex processes in a watershed, such as the effect of soil type and land use on runoff (Sen & Altunkaynak 2006). Hydrological models, conversely, are more complex and detailed models that simulate the complete water cycle within a watershed, including precipitation, infiltration, evapotranspiration, and runoff. These models can provide more accurate runoff estimates as they consider a wider range of variables and processes (Bunganaen *et al.* 2021). Examples of hydrological models used for runoff estimation include the Hydrological Modelling System (HEC-HMS) and the Soil and Water Assessment Tool (SWAT) (Murmu & Murmu 2021). However, these models require more data and computational resources and may require more time and expertise. The choice between the two methods depends on the desired accuracy, data availability, and computational resources (Young *et al.* 2009).

In the Soil Conservation Service Curve Number (SCS-CN) method, the curve number is the only parameter that is used for the computation of runoff, which depends on the Land Use Land Cover (LULC), hydrological soil group, and Antecedent Moisture Condition (AMC) (SCS 1956). The RS and GIS techniques are used for LULC and soil classification of the catchment area. The soils are classified into four Groups A, B, C, and D, depending on their runoff generation potential of soils. The curve number is assigned to the hydrologic units formed on intersecting LULC and soil map, which compute the runoff. The curve number depends on the soil's AMC condition, which depends on the previous 5-day precipitation. Very few studies (Mishra *et.al.* 2004; Verma *et al.* 2020; Rawat *et al.* 2021) are available in the literature that presents the comparative application of several SCS-CN-based models for runoff estimation. The present study performs the hydrologic simulation using six mathematical models based on the SCS-CN method. The SCS-CN with slope correction, λ optimization are simple models, while Mishra and Singh (MS) (Mishra & Singh 2004), Michel-Vazken-Perrin (MVP) (Michel *et al.* 2005), and Activation Soil Moisture Accounting SCS-CN (ASMA-SCS-CN) (Verma *et al.* 2020) consider the long-term effect are used for simulation. The model parameters are optimized for the catchment area, and simulation is performed for the period of 18 years (2001–2018) at a daily time scale. The performance of the models is compared with the help of goodness-of-fit statistics. The selected model can be utilized to predict runoff in physioclimatically similar ungauged catchments. This will provide crucial baseline information to local authorities for developing effective water conservation strategies and flood management plans.

Study area and data collection

The catchment of the River Aghanashini (up to the Santeguli station) in Uttara Kannada, Karnataka, is considered the study domain (Figure 1). The Aghanashini River originates from Shankara Honda in the Gadihalli (Sirsi) at 676 m Above Mean Sea Level (AMSL). It is one of the virgin rivers of the world because of its unobstructed flow through the Western Ghats and travels 117 km to join the Arabian Sea near Kumta while draining an area of 998.02 km^2 up to Santeguli. The study region is located between the longitudes 74° 34′ 21″ E–74° 55′ 7″ E and the latitudes 14° 15′ 36″ N–14° 37′ 33″ N. The evergreen trees in the forest create swamps in the area, which help maintain the perennial flow of the river. The Myristica swamps act as a sponge by absorbing the water during the monsoon period and releasing the same in the dry period. This also reduces the impact of floods since the area already has water in its soil pores.

The daily district-level precipitation data of Uttara Kannada district and daily streamflow data at Santeguli Station are obtained from the India-WRIS web portal from 1 January 2001 to 31 December 2018. The 30 m resolution Digital Elevation Model (DEM) is obtained from the CARTOSAT-1 satellite of the Indian Space Research Organization (ISRO). For the LULC classification, the Web Map Service layer from ISRO with a resolution of 50 K prepared during 2015–16 is used. The soil map used in this study is obtained from the National Bureau of Soil Survey and Land Use Planning (NBSS and LUP), Nagpur, in cooperation with the Department of Agriculture, Karnataka, on a scale of 1:500000.

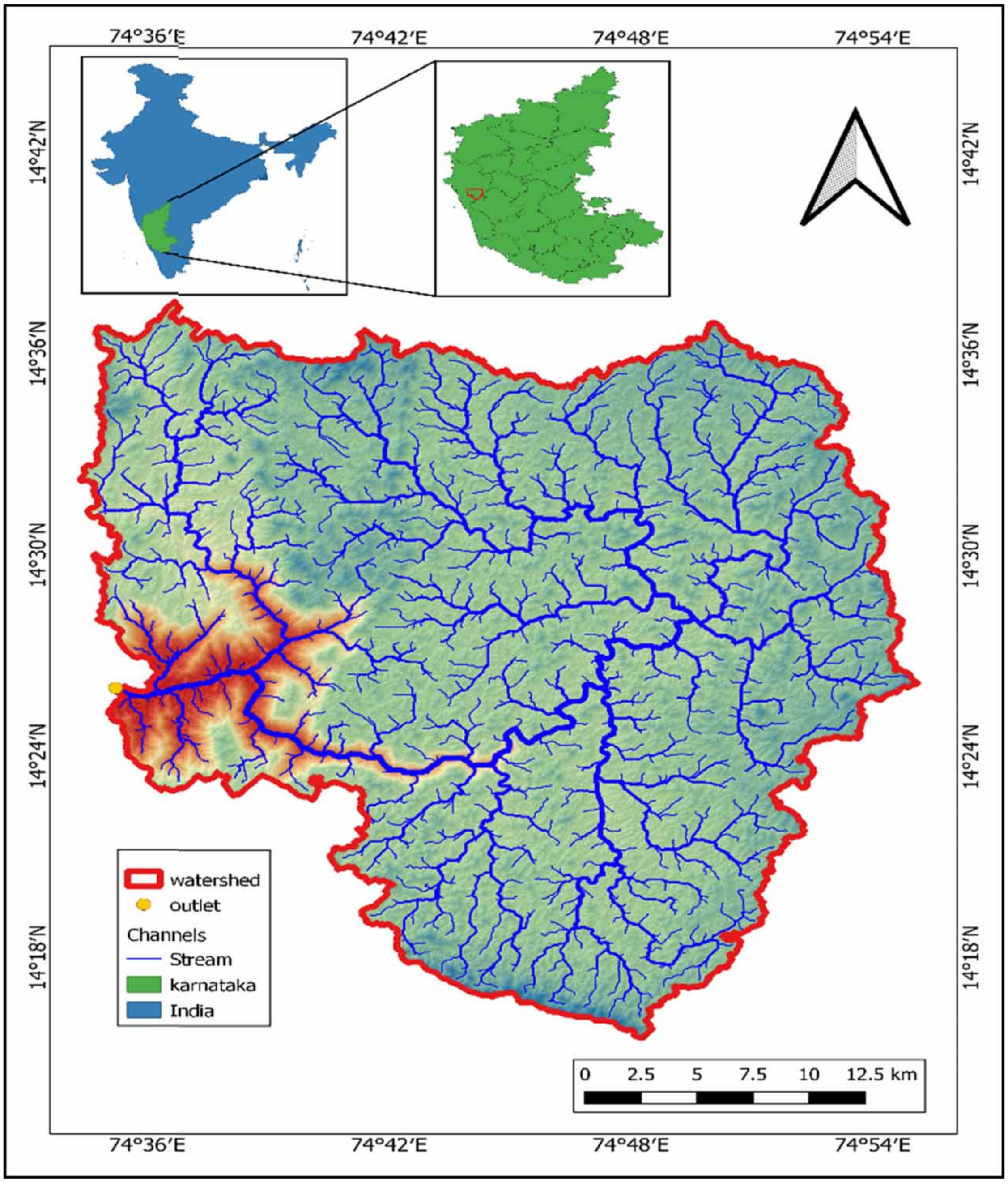

Figure 1 | Location map of the Aghanashini River Basin.

METHODOLOGY

Baseflow separation

The Web-based Hydrograph Assessment Tool (WHAT) is used to carry out the baseflow separation from observed streamflow to compute the surface runoff (Lim *et al.* 2005). In the WHAT programme, the recursive digital filter algorithm is used considering the values of the filter parameter and maximum baseflow index as 0.98 and 0.80, respectively.

LULC classification

The LULC is the main parameter affecting the curve number in the SCS-CN method for the simulation of runoff. This study assumes that the LULC is invariant during the simulation period from 2014 to 2018. The catchment area is divided into eight

LULC classes, viz., residential, cultivated, plantation, dense forest, scrub forest, pasture, wasteland, and water body (Figure 2(a)). The dense forest is found to be the prominent land use in the catchment covering an area of 753.35 km^2, which is 75.98% of the total catchment area.

Hydrological soil classification

The soil map is geo-referenced and digitized using the QGIS tool. The hydrological soil classification is done depending on the texture of the soil and the soil is divided into Groups B, C, and D, hydrological soil groups (Figure 2(b)). Group B soil covers 27.22 km^2, Group C soil covers 681.53 km^2, and Group D soil covers 289.26 km^2 of the catchment area. The largest area is covered by Group C hydrological soil type with moderately high runoff-producing potential.

Slope classification

The slope of the land is also a significant factor affecting the runoff. The catchment is divided into six zones from slope 0 to 144% based on the slope class having an equal slope interval (Figure 2(c)). From the slope map, it is observed that about 705.10 km^2 area has a slope ranging between 0 and 24%. The steep slopes of the order of 120–144% occupy a very small area (i.e. 0.3 km^2).

Mathematical models

The six mathematical models based on the SCS-CN method are used for hydrologic simulation. The SCS-CN is a simple method that uses LULC, soil type, and AMC conditions to compute the curve number (Chow *et al.* 2010). In the SCS-CN with slope correction, a slope factor is applied on the curve number, which takes the effect of the slope of the catchment into account (Shi & Wang 2020). It is observed from the studies that the value of the coefficient for the initial abstraction of 0.3 is substantial (Woodward *et al.* 2003). In the SCS-CN with λ (initial abstraction coefficient) optimization method, the value of the initial abstraction coefficient is optimized for the catchment. The MS model modifies the existing SCS-CN model by including the cumulative static infiltration component in the formulation and simulates runoff for the long-term (Mishra & Singh 2004). The soil moisture accounting procedure is incorporated into the MVP method by using the initial soil moisture (Michel *et al.* 2005). In the ASMA-SCS-CN method, the concept of activation soil moisture is used by combining the soil moisture accounting with static infiltration for long-term runoff simulation (Verma *et al.* 2020).

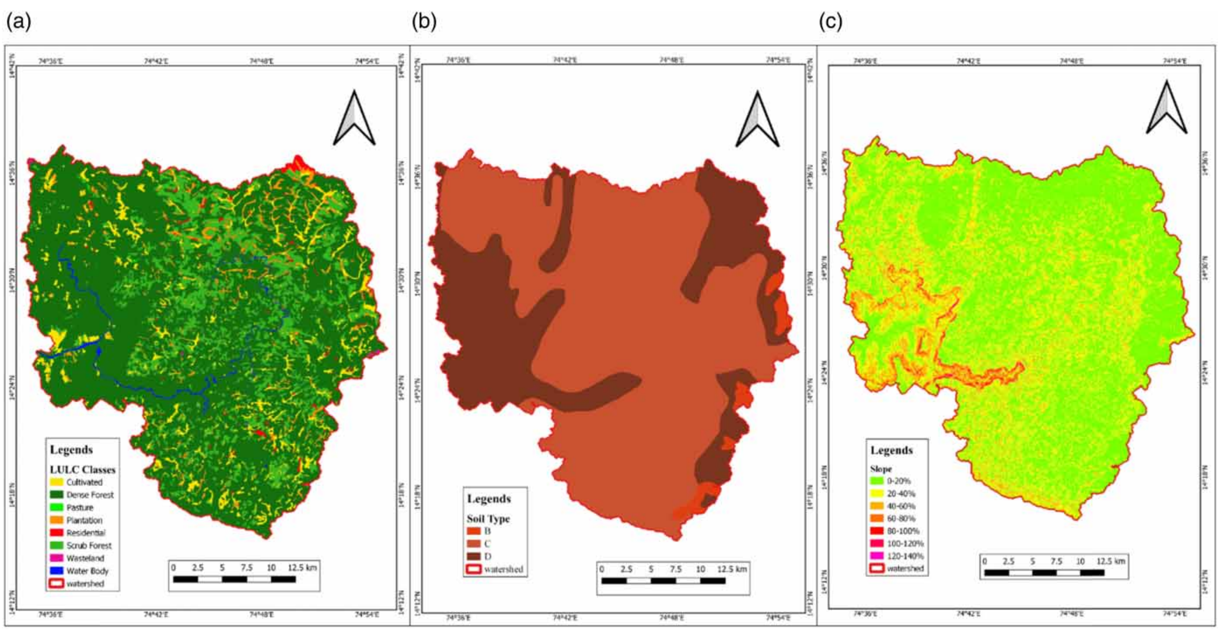

Figure 2 | (a) LULC map; (b) hydrological soil map; and (c) slope map of the Aghanashini River Basin.

In the above mathematical models (Table 1), Q is the daily surface runoff, P is the daily precipitation, I_a is the initial abstraction, S is the amount of potential maximum retention in soil, λ is initial abstraction coefficient, F_c is cumulative static infiltration, S_a is the threshold soil moisture, V_o is the initial soil moisture, and V_{et} is the revised threshold soil moisture.

The parameters V_o, $S_{a,}$ and F_c used in the above mathematical models are estimated using the expressions of Mishra *et al.* (2006) and Singh *et al.* (2015) as in the following Equations (1)–(3).

$$V_o = \alpha\sqrt{P_5 S} \tag{1}$$

$$S_a = \beta S \tag{2}$$

$$F_c = f_c T \tag{3}$$

where α is the coefficient for initial soil moisture, β is the coefficient for threshold soil moisture, P_5 is the cumulative precipitation of the preceding 5 days, f_c is the minimum infiltration rate, and T is the duration of precipitation.

Parameter optimization

In the mathematical models, the parameters need to be optimized for the given catchment area and give the maximum efficiency in terms of goodness-of-fit statistics. The SOLVER tool is used for optimization, which uses the Generalized Reduced Gradient (GRG) non-linear method of optimization (Hirpurkar & Ghare 2015). The initial values and optimized values of all parameters are shown in Table 2.

Performance evaluation

The goodness-of-fit statistics such as Nash–Sutcliffe Efficiency (NSE) (Equation (4)), Root Mean Square Error (RMSE) (Equation (5)), Normalized RMSE (nRMSE) (Equation (6)), Percent Bias (PBIAS) (Equation (7)), Mean Absolute Error (MAE) (Equation (8)), Standard Error (SE) (Equation (9)), and RMSE to Standard Deviation Ratio (RSR) (Equation (10))

Table 1 | Mathematical models used in the study with method of formulation

S. No.	Method name	Case	Method formulation
1.	SCS-CN	$P \geq I_a$	$Q = \frac{(P - I_a)^2}{(P - I_a + S)}$
		$P < I_a$	$Q = 0$
2.	SCS-CN with slope correction	$P \geq I_a$	$Q = \frac{(P - I_a)^2}{(P - I_a + S)}$
		$P < I_a$	$Q = 0$
3.	SCS-CN with λ optimization	$P \geq \lambda S$	$Q = \frac{(P - \lambda S)^2}{(P + (1 - \lambda)S)}$
		$P < \lambda S$	$Q = 0$
4.	Mishra and Singh	$P \geq (I_a + F_c)$	$Q = \frac{(P - I_a - F_c)^2}{(P - I_a - F_c + S)}$
		$P < (I_a + F_c)$	$Q = 0$
5.	MVP	$V_o \leq (S_a - P)$	$Q = 0$
		$(S_a - P) < V_o < S_a$	$Q = \frac{(P + S_a - V_o)^2}{(P + V_o - S_a + S)}$
		$(S_a \leq V_o \leq (S_a + S)$	$Q = P\left[1 - \frac{(S + S_a - V_o)^2}{S^2 + (S + S_a - V_o)P}\right]$
6.	Activation Soil Moisture ASMA-SCS-CN	$V_o \leq (V_{et} - P)$	$Q = 0$
		$(V_{et} - P) < V_o < V_{et}$	$Q = \frac{(P + V_o - V_{et})^2}{(P + V_o - V_{et} + S)}$
		$(V_{et} \leq V_o \leq (V_{et} + S)$	$Q = P\left[1 - \frac{(S + V_{et} - V_o)^2}{S^2 + (S + V_{et} - V_o)P}\right]$

Table 2 | Optimized parameters of different mathematical models

S. No.	Method	Parameter		Initial value	Optimized value
1.	SCS-CN with λ optimization	λ	Initial abstraction ratio	0.2	0.037
2.	MS	f_c	Minimum infiltration rate	1	0.02
		S	Amount of potential maximum retention in soil	125	41.95
3.	MVP	α	Coefficient for initial soil moisture	0.01	0.22
		β	Coefficient for threshold soil moisture	0.01	0.02
		S	Amount of potential maximum retention in soil	125	217.5
4.	ASMA-SCS-CN	α	Coefficient for initial soil moisture	0.01	0.11
		β	Coefficient for threshold soil moisture	0.01	0.01
		f_c	Minimum infiltration rate	1	0.1
		S	Amount of potential maximum retention in soil	125	109

are used to evaluate the performance of models.

$$\mathrm{NSE} = \left[1 - \frac{\sum_{i=1}^{N}(Q_{obs} - Q_{comp})_i^2}{\sum_{i=1}^{N}(Q_{obs} - \bar{Q}_{obs})_i^2}\right] \quad (4)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Q_{obs} - Q_{comp})_i^2} \quad (5)$$

$$\mathrm{nRMSE} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Q_{obs} - Q_{comp})_i^2}}{\bar{Q}_{obs}} \quad (6)$$

$$\mathrm{PBIAS} = \left[\frac{\sum_{i=1}^{N}(Q_{obs} - Q_{comp})_i}{\sum_{i=1}^{N}(Q_{obs})_i}\right] \quad (7)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|Q_{obs} - Q_{comp}|_i \quad (8)$$

$$\mathrm{SE} = \frac{1}{(N - m + 1)}\sqrt{\sum_{i=1}^{N}(Q_{obs} - Q_{comp})_i^2} \quad (9)$$

$$\mathrm{RSR} = \frac{\sqrt{\sum_{i=1}^{N}(Q_{obs} - Q_{comp})_i^2}}{\sqrt{\sum_{i=1}^{N}(Q_{obs} - \bar{Q}_{obs})_i^2}} \quad (10)$$

where Q_{obs} is the observed flow, Q_{comp} is the computed flow, $\bar{Q}_{obs}$ is the mean observed flow, m is the degree of freedom, and N is the total number of datasets.

Flood frequency analysis

Flood frequency analysis is a statistical method used to estimate the probability of flood events of various magnitudes occurring at a particular location. The annual maximum discharge series was derived from the daily observed discharge to conduct flood frequency analysis using the Gumbel's method (Subramanya 2017). The distribution fitting tool in the 'Statistics and Machine Learning Toolbox' of MATLAB has been adopted for assessing the goodness-of-fit of different probability distributions for the annual maximum discharge series. After fitting the distribution, the goodness-of-fit is evaluated using a quantile–quantile plot. Sensitivity analysis is performed to assess the impact of different distribution functions and parameter estimation methods on the results. Based on the criteria suggested by Kale & Hire (2004), the flood events can be classified based on the return period (T) as: small floods ($T \leq 2.33$ years), moderate floods ($2.33 < T < 6.33$ years), and large floods ($T \geq 6.33$ years).

RESULTS AND DISCUSSION

Baseflow

The baseflow of the Aghanashini River changes noticeably because of the diverse soil characteristics of the study area. The higher baseflow was obtained due to soil moisture holding capacity. Generally, the Groups B and C type soil hold the higher moisture and release it in the dry periods as baseflow, but during wet seasons the soil is fully saturated, and it gives the higher baseflow and leads to higher discharge in the river. From our analysis, the baseflow index is obtained as 0.71, which gives the total baseflow of 37,054 mm and total direct runoff of 15,387 mm (Figure 3).

Simulation results

The simulation of the surface runoff is performed for six different mathematical models in Microsoft Excel. In the present study, the calibration is performed for the years 2001–2009, while the validation is carried out for the years 2010–2018.

In the SCS-CN method, the observed and simulated runoff show poor agreement (Figure 4(a)). The simulated runoff is less than the observed runoff because of the high initial abstraction ratio of 0.3, which reduces the simulated runoff significantly. A significant difference of -16.17 m^3/s is observed for the average discharge, while a deviation of -425.89 m^3/s is observed for the peak discharge. Significant deviations between observed and simulated values are noticed in this method (Figure 4(a)). The coefficient of determination (R^2) of the SCS-CN method was found to be 0.61 (Figure 5(a)).

The SCS-CN with slope correction method considers the catchment's mild slope and shows slightly good results compared to the SCS-CN method. The simulated curve lies below the observed curve showing a difference of -15.86 m^3/s in the average value and a deviation of -415.76 m^3/s in the maximum value (Figure 4(b)). A slight rise in the simulated values is observed compared to the SCS-CN method due to the consideration of the effect of the mild slope. The scatter plot shows a trend similar to the SCS-CN method, which shows an R^2 of 0.61 (Figure 5(b)).

A good fit between observed and simulated values is noticed for the SCS-CN with λ the optimization method as compared to previous methods (Figure 4(c)). The optimized value of 0.017 of the initial abstraction ratio increases the simulated runoff and decreases the deviation as compared to previous methods. In calibration, a difference of -6.23 m^3/s is observed in the average value and a deviation of -445.78 m^3/s is observed for the maximum value of the runoff. While in validation, a difference of -3.97 m^3/s (-240.25 m^3/s) is observed for the average (peak) runoff value (Figure 4(c)). From Figure 4(c), the runoff values show good agreement for the calibration period, while some deviations are noticed for the validation period due to the lower peak flows. The scatter plot shows the R^2 of 0.72 and 0.61 for the calibration and validation period, respectively (Figure 5(c) and 5(d)).

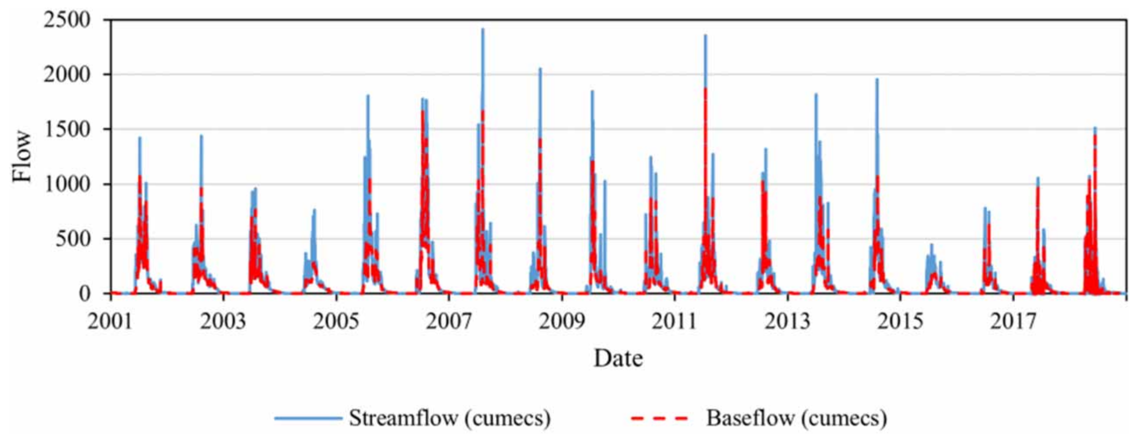

Figure 3 | Baseflow separation using WHAT for the study area during 2001–2018.

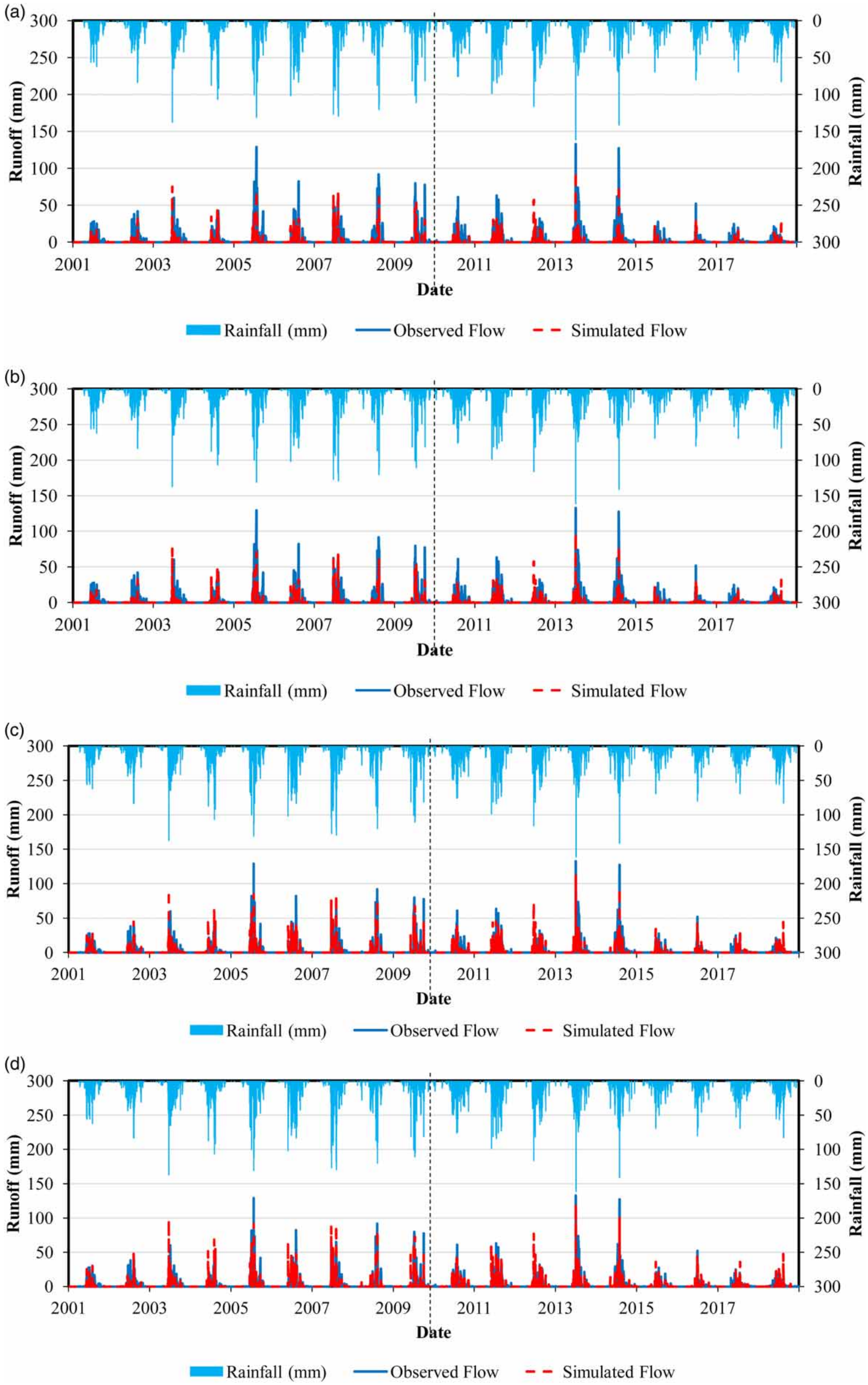

Figure 4 | Comparison of observed and computed runoffs through time series plots for (a) SCS-CN; (b) SCS-CN with slope correction; (c) SCS-CN with λ optimization; (d) MS; (e) MVP; and (f) ASMA-SCS-CN. (*continued.*).

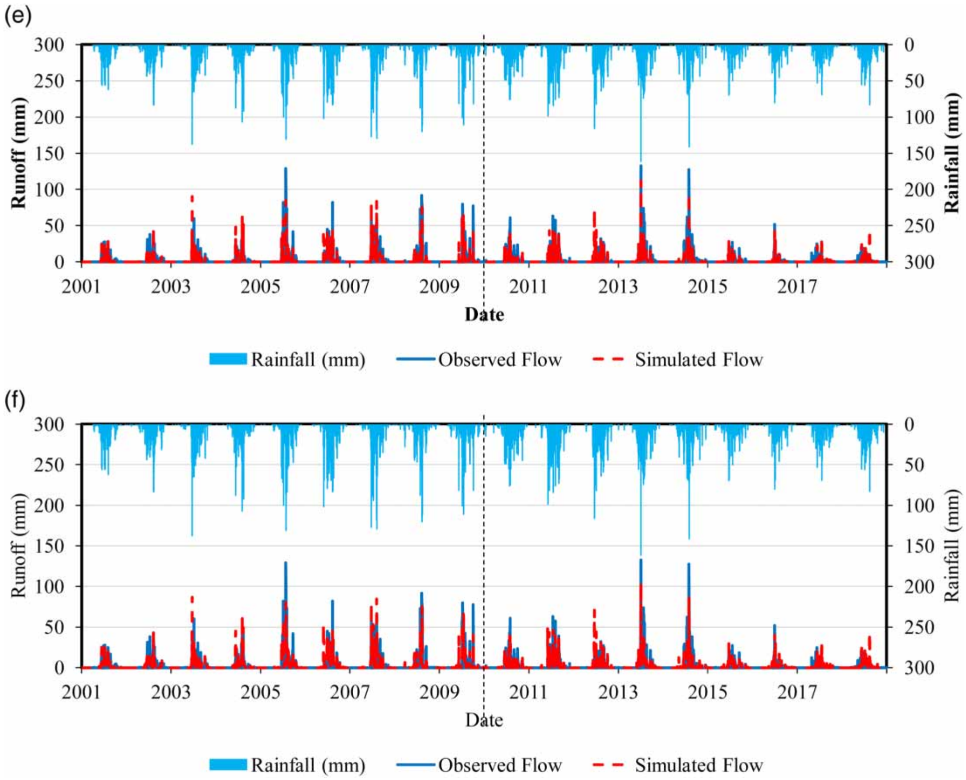

Figure 4 | Continued.

In the Mishra and Singh method, the observed and simulated values exhibit better conformity compared to previous methods (Figure 4(d)). In calibration, the simulated average and peak values exhibited deviations of −6.95 and −369.51 m^3/s, respectively, with respect to the corresponding observed values. A similar result was derived for the validation phase also. This method yielded an improvement in RMSE, NSE, PBIAS, and MAE compared to the SCS-CN and SCS-CN with slope correction; however, it could not outperform the SCS-CN with λ-optimization method. The scatter plot shows the R^2 of 0.69 and 0.58 for the calibration and validation periods, respectively (Figures 5(e) and (f)).

The MVP method shows better statistical performance in terms of NSE, RMSE, PBIAS, MAE, and RSR than all previous methods. The MVP method significantly improves the PBIAS than the previous methods, indicating superior model performance (Table 3). The best fit is observed in the MVP method compared to other methods between observed and simulated values (Figure 4(e)). The MVP method improves the accuracy in estimating average runoff as the deviations from the observed values during the calibration (−0.7 m^3/s) and validation (1.67 m^3/s) periods were minimal. On the other hand, the estimation of peak runoff exhibited marginally higher deviations as compared to the other methods. The scatter plot shows better agreement of observed and simulated runoff with higher R^2 of 0.73 and 0.63 for the calibration and validation periods, respectively (Figures 5(g) and (h)).

In the ASMA-SCS-CN method, the result shows slightly higher deviations from peak values than the MVP method. (Figure 4(f)). During calibration, the mean simulated value exceeded the mean observed value by −1.37 m^3/s, and a deviation of −487.72 m^3/s was observed between the maximum values of runoff. In the validation period, a difference of 0.93 m^3/s was observed between average values, and a deviation of −331.05 m^3/s was observed between the maximum values of runoff. The scatter plot shows similar results to the MVP method, as R^2 of 0.73 and 0.62 for the calibration and validation period, respectively (Figures 5(i) and (j)). In general, all the methods used in the study produced satisfactory to good R^2, NSE, RMSE, nRMSE, PBIAS, SE, and RSR values, which means that the simulated discharge was able to closely follow the observed discharge. In certain cases, the models are not able to accurately capture the peak discharge because of the significant contribution of baseflow to the river discharge.

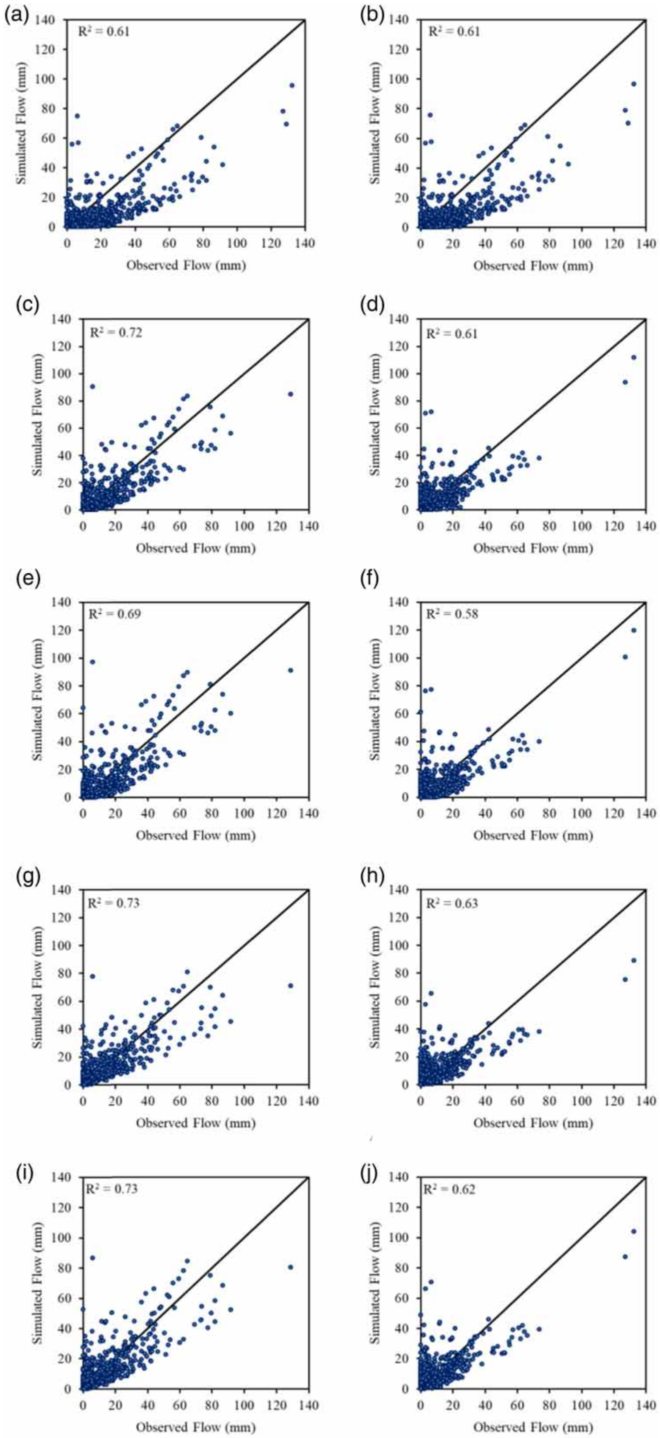

Figure 5 | Comparison of observed and computed runoff using scatter plot for (a) SCS-CN; (b) SCS-CN with slope correction; (c) SCS-CN with λ optimization (calibration); (d) SCS-CN with λ optimization (validation); (e) MS (calibration) (f) MS (validation); (g) MVP (calibration); (h) MVP (validation); (i) ASMA-SCS-CN (calibration); and (j) ASMA-SCS-CN (validation).

Performance evaluation

The performance of these models is evaluated through goodness-of-fit statistics such as NSE, RMSE, nRMSE, PBIAS, MAE, SE, and RSR, as shown in Table 3. As per Moriasi *et al.* (2007), all six models perform satisfactorily as their NSE values lie

Table 3 | Performance evaluation of the mathematical models for runoff estimation

S. No.	Mathematical model	NSE	RMSE (m^3/s)	nRMSE	PBIAS (%)	MAE (m^3/s)	SE (m^3/s)	RSR
1	SCS-CN	0.54	117.99	4.36	59.80	71.50	2.76	0.68
2	SCS-CN with slope correction	0.55	117.05	4.33	58.67	71.01	2.74	0.67
3	SCS-CN with λ-optimization calibration	0.72	72.02	2.33	20.20	30.98	1.69	0.53
4	SCS-CN with λ-optimization validation	0.61	68.17	2.94	17.11	29.50	1.60	0.63
5	MS calibration	0.68	77.15	2.50	22.53	33.49	1.81	0.57
6	MS validation	0.57	71.65	3.09	21.14	30.66	1.68	0.66
7	MVP calibration	0.73	70.34	2.28	2.28	30.26	1.65	0.52
8	MVP validation	0.63	66.42	2.86	−7.19	29.88	1.55	0.61
9	ASMA-SCS-CN calibration	0.72	71.07	2.30	4.44	30.38	1.66	0.53
10	ASMA-SCS-CN validation	0.62	67.31	2.90	−4.00	30.09	1.58	0.62

Table 4 | Summary of flood events in the Aghanashini River

Return period (T)	Type of flood	No of events	Years
$\leq$2.33	Small	10	2001, 2002, 2004, 2008, 2009, 2010, 2012, 2015, 2017, 2018
$2.33 < T < 6.33$	Moderate	5	2003, 2006, 2007, 2011, 2016
$\geq$6.33	Large	3	2005, 2013, 2014

between 0.5 and 0.65. The MVP method shows superior performance compared to other methods with the least RMSE and nRMSE values. According to criteria suggested by Moriasi *et al.* (2007) and Durbude *et al.* (2011), the MVP and ASMA-SCS-CN models give better performance with a PBIAS value of less than 10%, while the MS method and SCS-CN with λ optimization reflected fair performance having a PBIAS less than 25%. All the other methods show unsatisfactory performance having PBIAS greater than 25%. Table 3 shows the lowest values of MAE and SE for the MVP method. All the models' performances are satisfactory, with an RSR value between 0.6 and 0.7 (Moriasi *et al.* 2007; Durbude *et al.* 2011).

Flood frequency analysis

The distribution fitting tool in MATLAB 2018a was adopted for modelling the annual maximum discharge series. In this study, the Gumbel's Extreme Value, Generalized Extreme Value (GEV), Log Normal 2 Parameter (LN2P) and Weibull distribution are used to fit the annual maximum series. The results indicated that GEV and LN2P are the best-performing distributions for the annual maximum series; however, we adopted LN2P for the flood frequency analysis due to parsimony considerations. The location (μ) and scale (σ) parameters for the LN2P distribution are 6.1 and 0.89, respectively. From the analysis, the computed magnitude of mean annual flood was 613.8 m^3/s corresponding to a return period (T) of 2.78 years. Table 4 shows that three large flood events have been observed in the Aghanashini catchment in the years 2005, 2013, and 2014. The results of this study provide valuable information for designing flood protection measures. This information can be used to set design standards for flood walls or determine the height of riverbanks, depending on the specific location and the level of protection required.

CONCLUSIONS

The study assesses the magnitude and the temporal variations in the stream discharge using six mathematical models based on the SCS-CN method for the Aghanashini River catchment for the period of 18 years. The baseflow contribution in the Aghanashini River is considerable due to the predominance of dense forests, pasture land, and the presence of soils with moderately low runoff potential, thus allowing considerable infiltration. The simulation results reflect that the MVP model, exhibiting the highest predictive efficiency and lowest errors, is superior for long-term hydrologic simulations in the Aghanashini River catchment compared to other models. The flood frequency analysis reflects the frequent occurrence of moderate and high floods in the catchment, which stresses the importance of serving flood mitigation and protection measures. The Aghanashini River catchment, unaffected by human interventions, presents a valuable opportunity for developing small- and medium-scale water resources. This study is helpful for the concerned policymakers and stakeholders to adopt a suitable method to simulate the runoff for water resources and flood management in the catchment.

ACKNOWLEDGEMENTS

The authors express their heartfelt gratitude and appreciation to the Director of Punjab Engineering College (Deemed to be University) and the PG coordinator of the Water Resources Engineering Department for providing the necessary facilities to conduct the present study. Without their support, this research would not have been possible. Additionally, the authors would like to express their sincere appreciation to the Indian Institute of Technology, Indore for their valuable support and assistance throughout the course of the study. Their contributions have been indispensable in the success of this research. The authors also extend their thanks to the Central Water Commission (CWC) India for providing the discharge data through the India-WRIS portal. The authors are truly grateful for the support and encouragement received from all these institutions.

AUTHORS' CONTRIBUTIONS

Harmandeep Singh and Kuldeep Singh Rautela developed and designed the manuscript and wrote it under the supervision of Mohammad Afaq Alam and Priyank J. Sharma. All authors read and approved the final manuscript.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Amini-Zad, A., Galavi, H. & MohammadRezaPoor, O. 2018 Hydrological modeling of Pishin dam watershed using SWAT. *Development and Applications of Soil and Water Assessment Tool (SWAT) in WAter Resources Management* 26–30. https://civilica.com/doc/820016/ (accessed on 12 November 2022).

Bunganaen, W., Frans, J. H., Seran, Y. A., Legono, D. & Krisnayanti, D. S. 2021 Rainfall-runoff simulation using HEC-HMS model in the Benanain Watershed, Timor Island. *Journal of the Civil Engineering Forum* **7** (3), 359–368. https://doi.org/10.22146/jcef.64782.

Chow, V. T., Maidment, D. R. & Mays, L. W. 2010 *Applied Hydrology*. McGraw-Hill Education, New York.

Durbude, D. G., Jain, M. K. & Mishra, S. K. 2011 Long-term hydrologic simulation using SCS-CN-based improved soil moisture accounting procedure. *Hydrological Processes* **25** (4), 561–579. https://doi.org/10.1002/hyp.7789.

Galavi, H. & Mirzaei, M. 2020 Analyzing uncertainty drivers of climate change impact studies in tropical and arid climates. *Water Resources Management* **34**, 2097–2109.

Galavi, H., Kamal, M. R., Mirzaei, M. & Ebrahimian, M. 2019 Assessing the contribution of different uncertainty sources in streamflow projections. *Theoretical and Applied Climatology* **137**, 1289–1303.

Hirpurkar, P. & Ghare, A. D. 2015 Parameter estimation for the nonlinear forms of the Muskingum model. *Journal of Hydrologic Engineering* **20** (8), 04014085. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001122.

Kale, V. S. & Hire, P. S. 2004 Effectiveness of monsoon floods on the Tapi River, India: role of channel geometry and hydrologic regime. *Geomorphology* **57** (3–4), 275–291.

Kumar, D. & Bhattacharjya, R. K. 2021 Change in rainfall patterns in the hilly region of Uttarakhand due to the impact of climate change. *Applied Environmental Research* **43** (1), 1–3.

Lim, K. J., Engel, B. A., Tang, Z., Choi, J., Kim, K. S., Muthukrishnan, S. & Tripathy, D. 2005 Automated web GIS based hydrograph analysis tool, WHAT. *JAWRA Journal of the American Water Resources Association* **41** (6), 1407–1416. https://doi.org/10.1111/j.1752-1688.2005.tb03808.x.

Michel, C., Andréassian, V. & Perrin, C. 2005 Soil conservation service curve number method: how to mend a wrong soil moisture accounting procedure? *Water Resources Research* **41** (2). https://doi.org/10.1029/2004WR003191.

Mishra, S. K. & Singh, V. P. 2004 Long-term hydrological simulation based on the Soil Conservation Service curve number. *Hydrological Processes* **18** (7), 1291–1313. https://doi.org/10.1002/hyp.1344.

Mishra, S. K., Jain, M. K. & Singh, V. P. 2004 Evaluation of the SCS-CN-based model incorporating antecedent moisture. *Water Resources Management* **18** (6), 567–589.

Mishra, S. K., Sahu, R. K., Eldho, T. I. & Jain, M. K. 2006 An improved Ia-S relation incorporating antecedent moisture in SCS-CN methodology. *Water Resources Management* **20** (5), 643–660. https://doi.org/10.1007/s11269-005-9000-4.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D. & Veith, T. L. 2007 Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE* **50** (3), 885–900. doi: 10.13031/2013.23153.

Murmu, R. & Murmu, S. 2021 Simulation of runoff for subarnarekha catchment using SWAT model. In: *Water Security and Sustainability: Proceedings of Down To Earth 2019*. (C. Bhuiyan, W. A. Flügel & S. K.Jain, eds.) Springer, Singapore, pp. 157–168.

Rautela, K. S., Kuniyal, J. C., Alam, M. A., Bhoj, A. S. & Kanwar, N. 2022a Assessment of daily streamflow, sediment fluxes, and erosion rate of a Pro-glacial Stream Basin, Central Himalaya, Uttarakhand. *Water, Air, & Soil Pollution* **233**, 136.

Rautela, K. S., Kumar, M., Khajuria, V. & Alam, M. A. 2022b Comparative geomorphometric approach to understand the hydrological behaviour and identification of the Erosion prone areas of a coastal watershed using RS and GIS tools. *Discover Water* **2** (1), 1–6.

Rautela, K. S., Kumar, D., Gandhi, B. G. R., Kumar, A. & Dubey, A. K. 2023 Long-term hydrological simulation for the estimation of snowmelt contribution of Alaknanda River Basin, Uttarakhand using SWAT. *Journal of Water Supply: Research and Technology-Aqua* **72** (2), 139–159.

Rawat, K. S., Singh, S. K. & Szilard, S. 2021 Comparative evaluation of models to estimate direct runoff volume from an agricultural watershed. *Geology, Ecology, and Landscapes* **5** (2), 94–108. https://doi.org/10.1080/24749508.2020.1833629.

Sen, Z. & Altunkaynak, A. 2006 A comparative fuzzy logic approach to runoff coefficient and runoff estimation. *Hydrological Processes: An International Journal* **20** (9), 1993–2009. https://doi.org/10.1002/hyp.5992.

Sharma, P. J., Patel, P. L. & Jothiprakash, V. 2019 Impact of rainfall variability and anthropogenic activities on streamflow changes and water stress conditions across Tapi Basin in India. *Science of the Total Environment* **687**, 885–897.

Shi, W. & Wang, N. 2020 An improved SCS-CN method incorporating slope, soil moisture, and storm duration factors for runoff prediction. *Water* **12** (5), 1335. https://doi.org/10.3390/w12051335.

Singh, P. K., Mishra, S. K., Berndtsson, R., Jain, M. K. & Pandey, R. P. 2015 Development of a modified SMA based MSCS-CN model for runoff estimation. *Water Resources Management* **29** (11), 4111–4127. https://doi.org/10.1007/s11269-015-1048-1.

Singh, S., Goyal, M. K. & Jha, S. 2023 Role of large-scale climate oscillations in precipitation extremes associated with atmospheric rivers: nonstationary framework. *Hydrological Sciences Journal* 1–17.

Sofi, M. S., Rautela, K. S., Bhat, S. U., Rashid, I. & Kuniyal, J. C. 2021 Application of geomorphometric approach for the estimation of hydro-sedimentological flows and cation weathering rate: towards understanding the sustainable land use policy for the Sindh Basin, Kashmir Himalaya. *Water, Air, & Soil Pollution* **232**, 280. https://doi.org/10.1007/s11270-021-05217-w.

Soil Conservation Service 1956 *Hydrology, National Engineering Handbook*, Supplement A, Section 4, Chapter 10, Soil Conservation Service.

Subramanya, K. 2017 *Engineering Hydrology*, 4th edn. The McGraw-Hill Company, New Delhi.

Verma, S., Singh, P. K., Mishra, S. K., Singh, V. P., Singh, V. & Singh, A. 2020 Activation soil moisture accounting (ASMA) for runoff estimation using soil conservation service curve number (SCS-CN) method. *Journal of Hydrology* **589**, 125114. https://doi.org/10.1016/j.jhydrol.2020.125114.

Woodward, D. E., Hawkins, R. H., Jiang, R., Hjelmfelt Jr., A. T., Van Mullem, J. A. & Quan, Q. D. 2003 Runoff curve number method: Examination of the initial abstraction ratio. In *World Water & Environmental Resources Congress 2003*. pp. 1–10. https://doi.org/10.1061/40685(2003)308.

Young, C. B., McEnroe, B. M. & Rome, A. C. 2009 Empirical determination of rational method runoff coefficients. *Journal of Hydrologic Engineering* **14** (12), 1283–1289. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000114.

First received 30 November 2022; accepted in revised form 12 March 2023. Available online 29 March 2023