Streamflow Assessment of Mountainous River Basin Using SWAT Model

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1 Introduction

Hydrologic models are valuable tools for planning and managing water resources in the river basin. These models are also helpful in understanding and simulating the hydrologic processes, assessing the effects of climatic and land use and land cover (LULC) changes, and investigating water quality in the river basin [1]. In recent research, hydrologic modeling has emerged as a critical achievement in watershed hydrological simulation with the development and incorporation of new tools like remote sensing (RS) and geographic information systems (GIS). The System Hydrologic European (SHE) model and the Soil and Water Assessment Tool (SWAT) model are a few such model applications widely used for hydrological modeling for river basin studies [2, 3].

Most rivers in the globe originate in high mountain regions, where snow and glaciers retain much water. In high snow and glacier catchments, melting water contributes more streamflow than rain [4, 5]. These rivers provide water for agricultural, industrial, and municipal applications. Recent figures show that over 50% of all disaster, losses are due to connected disasters, with over 70% of flood-related deaths attributed to mountain torrents [6]. Snowmelt floods are frequent, yet they represent severe environmental and economic risks.

Snowmelt hydrology is a crucial element in mountainous watersheds where melting snow is a significant source of stream flows. The simulation complexity leads to a perception that simulating snowmelt runoff in a mountainous area is challenging. Mountainous regions also frequently lack sufficient data, which increases computational simulation requirements [7, 8]. To represent the current complex mountainous

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environmental situation, calibration–validation and uncertainty analysis are necessary to effectively use the distributed hydrologic models [9]. Calibration is done by selecting model input parameters within acceptable ranges to signify the hydrological process accurately. Comparing the model outputs for a particular collection of observed data allows for evaluating this calibration [10]. Once calibrated, watershed models enable evaluation of the effects of environmental changes caused by management or natural processes in a method that is not attainable through field experiments and direct observation. Simulation analysis of situations, before they are implemented, can help reduce management uncertainty.

The two main approaches frequently employed in snowmelt runoff analysis are the temperature index and energy balance techniques. Whereas the energy balance method relies upon the quantity of energy input to the system, the temperature index strategy employs temperature as the primary driving element for snowmelt processes [11, 12]. The energy balance strategy is data-intensive and occasionally inappropriate owing to scarce data or unnecessary information, while the temperature index method is common, straightforward, and simple to utilize [13].

The Sutlej river basin contains many mountainous regions with complex topography. Temperatures rise dramatically in the spring, which causes an increase in flooding frequency. Elevation variations tremendously impact snow cover processes and melt in hilly basins. In watersheds with complex terrain and significant elevation variations, simulated accuracy has been proven to be improved by defining elevation zones within the model's subbasins [8]. The management of the water resources of the high mountain area needs to realize the connections between natural forests, snowpack, snowmelt, and streamflow production. Reliable modeling techniques are crucial for correctly reflecting the impacts of both the forest cover and the dynamics of snowmelt on runoff to calculate the streamflow hydrograph in these conditions. Temperature change is one of the most sensitive input characteristics to calculate snowmelt runoff in the high-altitude basin [14].

The primary snowfall-melting mechanism in SWAT was modified by adding snow accumulation, melting, areal snow coverage, and the ability to input snowfall and temperature as a proportion of elevation bands [8].

One of the more popular models is the SWAT, utilized in numerous nations worldwide [15, 16]. The physical foundation of the hydrological model SWAT is semi-distributed and continuous time. The SWAT model design and evolutionary methodology make it a good tool for examining how the management of rocky mountain forests affects the region's water supplies. However, the SWAT has not been explored much with rocky mountain river basins, which have significant elevation differences and are mainly covered with snowfall, technologies that have considered elevations to improve SWAT capacity to model snowmelt processes.
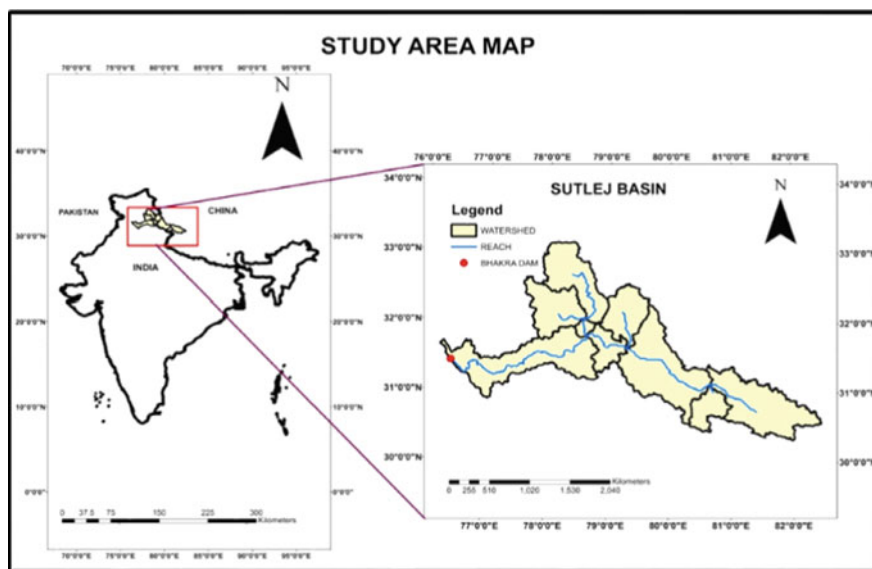
Fig. 1 Pictorial representation of the study area

2 Study Area

The present study is performed for the Sutlej River Basin, which receives its water from Manasorovar Lake, located on the southern flanks of Mount Kailash on the Tibetan Plateau at an altitude of more than 4500 m above sea level. Moreover, it covers several regions with varied topographic and climatic characteristics, including Punjab in northern India. In addition, runs through several regions of Pakistan [23, 24]. The area of the present study is 55,000 km^2. In addition, the Bhakra gauging station is considered an output gauging station to calibrate and validate the model (Fig. 1).

3 Methodology

3.1 Model Setup

This model was created to evaluate the effects on the water system in complex basins of long-term changes to the soil, Landover, and management practices. The flexible architecture of SWAT was created to employ easily accessible data to define a watershed's physical and climatic properties. In remote, ungagged basins where calibration is impossible, SWAT can estimate reasonable outcomes using physically-based

inputs. Because of the code's high computing efficiency makes continuous simulation over vast areas and lengthy timespan possible. The influence of management strategies can be assessed by simulating watershed processes over an extended period [10].

Digital Elevation Maps (DEM), land uses (LULC), soil maps, and details on meteorological data are the input data that the SWAT model requires. The watershed delineation was done using Shuttle radar topography mission (SRTM) data with a 30 m × 30 m resolution. The Soil map taken from the FAO database with a 1 × 1 km grid resolution and land use data from the NRSC/WRIS with a 1 × 1 km grid resolution was used. The meteorological data such as Rainfall data, maximum and low-temperature data, relative humidity, and sunshine hours data over 35 years were collected from the CFSR database (1979–2013) with a warmup period of three years. The soil and water conservation service (SCS) curve number (CN) approach has been adapted to calculate stormwater runoff. For calculating evapotranspiration, the Penman–Monteith approach has been used in this model [17] (PET). The Muskingum routing technique approach determines channel routing [3]. Furthermore, the temperature index algorithm has been used to evaluate snowfall and snowmelt routine. The model has also been evaluated using two situations, one with elevation bands taken into account and the other without considering elevation bands in the model.

3.2 Sensitivity Analysis

In SUFI-2, the sequential and fitting approach based on the Bayesian framework is used to accomplish calibration and validation, respectively [18]. Observed data, model input, and model structure are just a few examples of the parameter uncertainty sources considered and described as uniform distributions in SUFI-2 [19]. Their *p-factor* and *r-factor* are indices used to evaluate the model's accuracy and uncertainty. The level of uncertainty is gauged using the *p-factor*, calculated via Latin hypercube sampling. The range of the *p-factor* is 0 to 100%, while the *r-factor* has an infinite range and should ideally be 1 and 0, respectively, whenever the model successfully reflects the observed data. An objective function is made, and the required termination rule is applied before doing an uncertainty analysis.

3.3 Objective Function

The present study KGE has been taken as the objective function to assess the degree to which actual and simulated streamflow was accurate. Since NSE uses the recorded mean as its baseline, it tends to overestimate model performance for solid seasonal parameters. To solve this problem between simulated and actual discharge, a new performance measure [20], KGE, based on the identical results of 3 significant

components those are bias ratio (α), linear correlation (γ), and variance (β).

$$KGE = 1 - \sqrt{(\gamma - 1) + (\alpha - 1) + (\beta - 1)^2} \tag{1}$$

where, $\alpha = \frac{\sigma_{sim}}{\sigma_{obs}}$, $\beta = \frac{X_{mean}^{sim}}{X_{mean}^{obs}}$

γ Is the coefficient of the linear regression between the simulated and observed value.

3.4 Performance Indicators

NSE: The normalized statistic difference between the residual variance and total variance of the observed and simulated data is how it is expressed [21]. Its values range from -1.0, with 1 representing the model's optimal performance.

$$\text{NS (Maximize)} = 1 - \frac{\sum\limits_{i=1}^{n} (X_m - X_s)_i^2}{\sum\limits_{i=1}^{n} \left(X_{m,i} - \overline{X}_s\right)^2} \tag{2}$$

where, X_m = observed discharge, X_s = simulated discharge.

R²: It is a statistic that expresses how closely calibrated data resembles the best-fit observed data. An improved model is indicated by a higher value ranging from 0 to 1.

$$R^2(\text{Maximize}) = \frac{\text{Variance of the model}}{\text{Total variance}} = 1 - \frac{SS_{res}}{SS_{tot}} = \frac{S_{xy}^2}{S_{xy} * S_{yy}} \tag{3}$$

P-BIAS is the biased error percentage for both actual and simulated data. It is taken into account to be zero when choosing the most appropriate behavioral model. The performance of the model improves as the value decreases.

$$\text{PBIAS (Minimize)} = \left[\frac{\sum\limits_{i=1}^{n} (X_m - X_s)}{\sum\limits_{i=1}^{n} X_m} * 100 \right] \tag{4}$$

where, X_m = observed discharge, X_s = simulated discharge.

4   Result and Discussion

The sensitivity analysis has been conducted using global sensitivity analysis, which explores the design space using a large set of samples. SWAT-CUP uses the values of *t-stat* and *p-value* to determine the relative importance of various parameters. High absolute values indicate greater sensitivity, whereas near zero indicates high significance levels. The most sensitive input parameters were identified using the global sensitivity technique has performed 1500 iterations using SUFI-2. Over 200 hydrological parameters are included in the SWAT model. However, not all of them are likely to impact the results significantly. It is required to determine the most sensitive input parameters to simulate the streamflow and the ranges within which they fall. 22 parameters were identified initially, and their initial ranges were chosen in this study. The streamflow simulations produced by the SUFI-2 were satisfactory, showing some uncertainty in the calibration and validation results. The ground-water and soil parameters GWQMN, SOL-K, and SOL-AWC are identified as the most sensitive parameters influencing model output results. Because the present study area lies in a snow-dominated mountainous region, moreover SWAT model has the limitation that the infiltration in frozen soil (snowpack and glacier) is neglected. In an actual situation, it does not exist. Table 1 shows the top 10 sensitive parameters with their sensitive ranking in *t-stat and p-value.*

The Himalayas mountain region of a river basin, i.e., the Sutlej river basin up to Bhakra, was modeled to determine how they would respond. Before applying elevation bands, the main problem was a persistent underestimation of both low and high flows during the calibration period.

Figure 2 shows that the simulated streamflows in the Sutlej river basin were still below observed streamflows. Furthermore, the correlation statistics were poor (KGE: 0.21 and NSE: 0.16). The underestimating issue was resolved using the elevation band approach [8]. An elevation band allows the model to consider their lapse rates according to elevation variance. The values of KGE and NSE for the calibration

Table 1 Sensitive ranking of SWAT parameters identified using SUFI-2

Parameters	Sensitivity rank	*t-stat*	*p-value*
R_GWQMN	1	-27.52	0.00
R-SOL-K	2	-26.51	0.00
R_SOL_AWC	3	-18.09	0.00
V-ALPHA_BF	4	-3.25	0.00
R_GW_REVAP	5	-2.88	0.00
R_CN$_2$	6	-2.81	0.00
R_SUB_SMFMN	7	1.88	0.05
V_CH_K2	8	1.59	0.11
V_GW_DELAY	9	1.34	0.17
R_MSK_CO$_1$	10	1.08	0.27

period after considering elevation bands are 0.91 and 0.81; moreover, validation values are between 0.87 and 0.75 and can be regarded as very good [22]. In addition, 82 and 71% of observed data lie within the uncertainty band. Figure 3 despite not accurately replicating the peaks and the recession limbs, the hydrograph shape could be replicated satisfactorily overall (Fig. 4). Figure 5 is a uniform distribution of points observed about the 1:1 line connecting the recoded and estimated monthly streamflow in the calibration and validation data scatter plot. Some data points were not in line but mostly lay on the line, which indicates the excellent correlation coefficient between observed and simulated streamflow. As a result, the SWAT model can be treated as a valuable tool for simulating the discharge hydrograph and many components of the water balance for a mountainous river basin (Fig. 6).
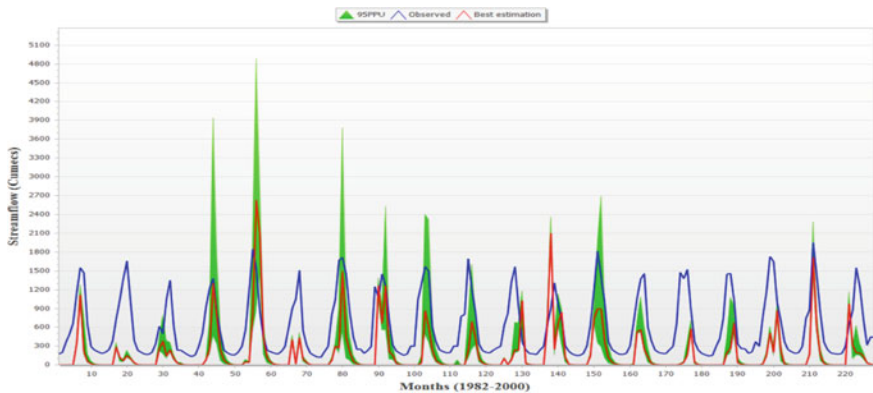
Fig. 2 95PPU plot of Sutlej river basin dung calibration period (1982–2000) before implementing elevation bands with KGE as the objective function
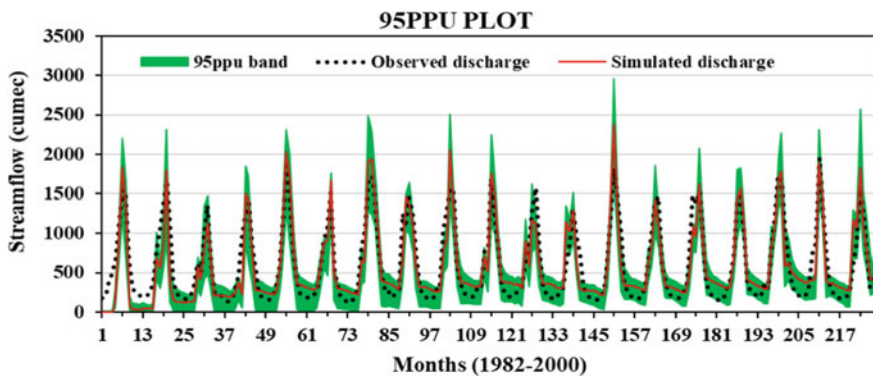
Fig. 3 95PPU plot of Sutlej river basin dung calibration period after implementing elevation bands with KGE as the objective function
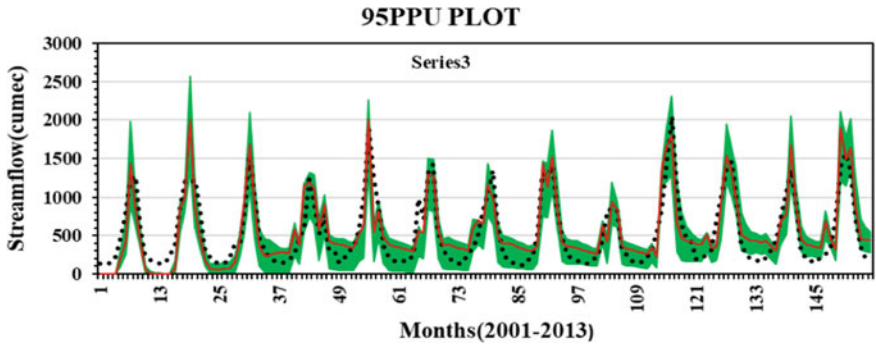
Fig. 4 95PPU plot of Sutlej river basin dung validation period after implementing elevation bands with KGE as the objective function
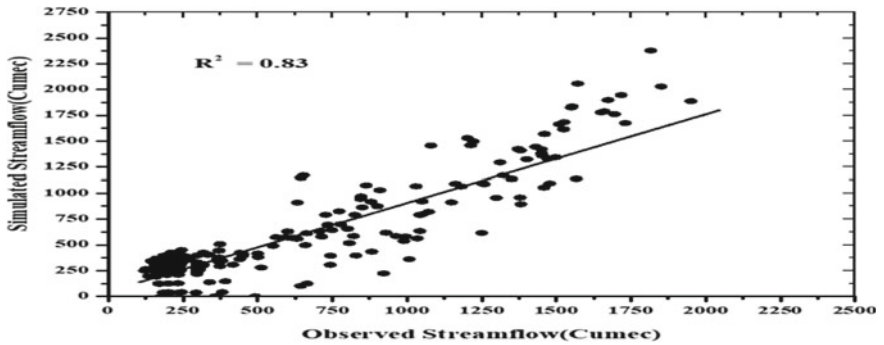

Fig. 5 Scatter plot between observed and simulated streamflow hydrographs during the calibration period after implementing elevation bands
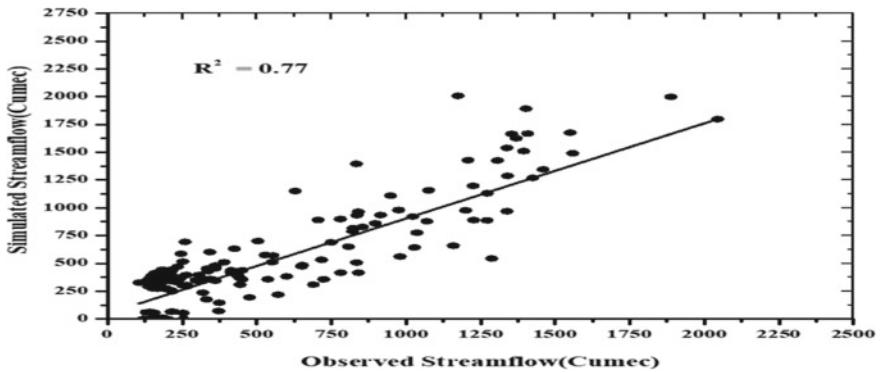

Fig. 6 Scatter plot between observed and simulated streamflow hydrographs during the validation period after implementing elevation bands

5 Summary and Conclusions

The semi-arid and mountainous watersheds in the Sutlej drainage basin, which are significantly influenced by snowmelt, are improved by the SUFI-2 technique employing KGE as the fitness function and combined with the SWAT model. Before implementing elevation bands to the model, the main problem was a persistent underestimating of low and high flows for the calibration period. Due to the SWAT model's failure to account for the impact of snow melt, the estimated streamflows in the Sutlej river basin were still below the observed streamflows. Additionally, the correlation statistics were poor. The systematic underestimating issue was resolved using the elevation band technique, and the outcomes were supported [8]. In NSE, the observed mean is utilized as a baseline and may lead to an overestimation of model performance for extremely seasonal variables. KGE was designed to address this issue. As a result, the KGE would be a better choice to employ as the objective function in a watershed where mountainous snowmelt predominates, such as the Sutlej watershed [25]. Despite producing good results, the present model does not adequately signify the infiltration and runoff processes related to snowmelt since it is predicted that infiltration does not occur in frozen soils. The model also performs poorly at times of base flow. By improving the components of the simulation that reflect groundwater discharge, snowmelt infiltration, and runoff in base flow, the performance of the model, as well as the actual representation of hydrologic processes in this and comparable mountain streams, has been greatly improved.

Further, a total of 35 years (1979 to 2013) of monthly streamflow data was collected from the Bhakra gauging station of the SRB and used for SWAT model calibration and validation. The results obtained with the elevation band use in the SWAT model proved better compared to the model without elevation band use. The model performance statistics, such as KGE, R^2, *p-bias, and p-factor*, show 0.91, 0.83, 2.30, and 0.82, respectively, with the use of elevation band, and 0.21, 0.47, 0.85, and 0.01, respectively, for without the elevation band use in the model, signifies the SWAT model poorly performed without the use of elevation band or natural topography of the river basin. It confirms that the topography shows a significant effect on the streamflows of the mountainous river basins. Therefore, this work will undoubtedly help the researchers to make them aware of the limitations of the SWAT model use while applying it to the mountainous river basins.

References

1. Paul M, Impacts of land use and climate changes on hydrological processes in South Dakota Watersheds
2. Beven KJ, Warren ROSS, Zaoui JACQUES (1980) SHE: towards a methodology for physically-based distributed forecasting in hydrology. IAHS Publ 129:133–137
3. Arnold JG, Srinivasan R, Muttiah RS, Williams JR (1998) Large area hydrologic modeling and assessment part I: model development 1. JAWRA J Am Water Resour Assoc 34(1):73–89

4. Gascoin S, Kinnard C, Ponce R, Lhermitte S, MacDonell S, Rabatel A (2011) Glacier contribution to streamflow in two headwaters of the Huasco River. Dry Andes Chile Cryosphere 5(4):1099–1113
5. Pelto MS (2015) Quantifying glacier runoff contribution to Nooksack River, WA in 2013–15. In: AGU fall meeting abstracts, vol. 2015. pp C33E-0862
6. Lian J, Gong H, Li X, Zhao W, Hu Z (2009) Design and development of flood/waterlogging disaster risk model based on Arcobjects. J Geo-Inf Sci 11:376–381
7. Hartman MD, Baron JS, Lammers RB, Cline DW, Band LE, Liston GE, Tague C (1999) Simulations of snow distribution and hydrology in a mountain basin. Water Resour Res 35(5):1587–1603
8. Fontaine TA, Cruickshank TS, Arnold JG, Hotchkiss RH (2002) Development of a snowfall–snowmelt routine for mountainous terrain for the soil water assessment tool (SWAT). J Hydrol 262(1–4):209–223
9. Abbaspour KC, Rouholahnejad E, Vaghefi S, Srinivasan R, Yang H, Kløve B (2015) A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. J Hydrol 524:733–752
10. Arnold JG, Fohrer N (2005) SWAT2000: current capabilities and research opportunities in applied watershed modelling. Hydrol Process: Int J 19(3):563–572
11. Tanasienko AA, Chumbaev AS (2008) Features of snowmelt runoff waters in the Cis-Salair region in an extremely snow-rich hydrological year. Contemp Probl Ecol 1(6):687–696
12. Neitsch SL, Arnold JG, Kiniry JR, Williams JR (2011) Soil and water assessment tool theoretical documentation version 2009. Tex Water Resour Inst
13. Hock R (2003) Temperature index melt modelling in mountain areas. J Hydrol 282(1–4):104–115
14. Tahir AA, Chevallier P, Arnaud Y, Neppel L, Ahmad B (2011) Modeling snowmelt-runoff under climate scenarios in the Hunza River basin, Karakoram Range, Northern Pakistan. J Hydrol 409(1–2):104–117
15. Gassman PW, Reyes MR, Arnold JG (2005) Review of peer-reviewed literature on the SWAT model. In: Proceeding of the 3rd international SWAT Conference. pp 13–15
16. Gassman PW, Reyes MR, Green CH, Arnold JG (2007) The soil and water assessment tool: historical development, applications, and future research directions. Trans ASABE 50(4):1211–1250
17. Monteith JL (1965) Evaporation and environment. In: Symposia of the society for experimental biology, vol 19. Cambridge University Press (CUP) Cambridge, pp 205–234
18. Khoi DN, Thom VT (2015) Parameter uncertainty analysis for simulating streamflow in a river catchment of Vietnam. Glob Ecol Conserv 4:538–548
19. Gupta HV, Kling H, Yilmaz KK (2009) Martinez GF decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. J Hydrol 377:80–91
20. Nash JE (1970) Sutcliffe JV river flow forecasting through conceptual models part I-A discussion of principles. J Hydrol 10:282–290
21. Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans ASABE 50(3):885–900
22. Singh P, Jain SK (2002) Snow and glacier melt in the Satluj River at Bhakra Dam in the western Himalayan region. Hydrol Sci J 47(1):93–106
23. Singh P, Jain SK (2003) Modelling of streamflow and its components for a large Himalayan basin with predominant snowmelt yields. Hydrol Sci J 48(2):257–276
24. Paul M, Negahban-Azar M (2018) Sensitivity and uncertainty analysis for streamflow prediction using multiple optimization algorithms and objective functions: San Joaquin Watershed, California Model. Earth Syst Environ 4:1509–1525