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Effective Factors on Runoff Generation and Hydrologic Sensitivity in a Mountainous Watersheds (A Case Study: Farsan Watershed, Upstream of Karoun River)

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ABSTRACT

Aims Affecting factors on runoff generation in mountainous areas, where the hydrological processes are complex, play an important role in the recognition of hydrological phenomena. The aim of the present study was to simulate the water balance of Farsan Basin using the SWAT model.

Materials & Methods In this semi-distributed research, SWAT model was used to simulate the monthly runoff the basin of interest. The study area was Farsan watershed, it is the part of Beheshtabad Basin. Basin's curve number was estimated using a remotely sensed NDVI. The calibration and validation of the model were carried out by using the SUFI2 Algorithm (sequential uncertainty fitting) for two periods, one from 2001 to 2011 and another from 2012 to 2015.

Findings The threshold depth of water in the shallow aquifer to start evaporation (REVAPMN) had the least sensitivity, while the soil evapotranspiration (ESCO), the time delay of the transferring water from the last soil profile to the groundwater level (GW_DELAY), and curve numbers in normal condition (CN2) were the most sensitive factors, respectively. To evaluate the simulation, R2 (coefficient of determination), bR2 (weight correlation coefficient), and NS (Nash Sutcliffe model efficiency) at the calibration stage were 0.63, 0.33, and 0.57, respectively. Whereas at the validation phase, these coefficients were found to be 0.69, 0.68, and 0.52, respectively.

Conclusion A proper specification of these sensitive parameters may be the key factor for runoff simulations. The impact of change in surface parameters may have a great influence in both generating runoff and mountain hydrology.

Keywords Hydrological Modeling; SWAT; SUFI2 Algorithm

CITATION LINKS

[1] Application of the distributed hydrological model, TOPNET, to the Big Darby Creek, ... [2] Hydrology modelling in Taleghan mountainous watershed using ... [3] Comparison of single-site and multi-site based calibrations of SWAT in Taleghan ... [4] Using SWAT model to determine runoff, sediment yield and nitrate loss in Gorganrood ... [5] Modeling of sediment yield from Anjeni-Gauged watershed, Ethiopia using SWAT ... [6] Estimation of hydrologic budget for Gharasou ... [7] Modeling the water balance processes for understanding the components of river ... [8] Application of semi-distributed hydrological model for basin level water balance of the ... [9] Evaluation of SWAT manual calibration and input parameter sensitivity in the ... [10] Assessment of runoff and sediment yield in the Miyun Reservoir catchment by ... [11] Assessing the capability of the SWAT model to simulate snow, snow melt ... [12] Comprehensive hydrologic calibration of SWAT and water balance analysis in ... [13] Assessment of the SWAT model to simulate a watershed with limited available ... [14] Evaluation of the GSMaP_Gauge products using rain gauge observations and SWAT model in ... [15] Comparison of the alternative models source and SWAT for predicting catchment streamflow, sediment and nutrient loads under the effect of land use ... [16] Impact of land use changes on flash flood prediction using a sub-daily SWAT model in five Mediterranean ungauged watersheds ... [17] Reliability of land capability map in watershed hydrological simulation using SWAT ... [18] Soil and water assessment tool; theoretical documentation ... [19] Estimating composite curve number using an improved SCS-CN method with remotely sensed variables in Guangzhou, ... [20] Problems and prospects of SWAT model applications in NILOTIC catchments: A ... [21] An Examination of radar and rain gauge-derived mean areal precipitation ... [22] Application of SWAT model for mountainous ... [23] Application of a SWAT model for estimating runoff and sediment in two ... [24] Factors of runoff generation in the Dongting Lake basin based on a SWAT model ...

Introduction

The concept of using hydrological models to understand the hydrologic processes and runoff predictions are traced back to 4 decades ago. In recent years, basin hydrologists, especially those how are interested in basin hydrology, have shifted their way to more detailed models, to increase model efficiency and ability of these models for different areas with different conditions of soil, topography, land use, etc. Some models can be used as a tool for water and soil resources management at a catchment scale [1]. Recently, to simulate the hydrologic factors of the basins, Soil and Water Assessment Tool (SWAT) model has been widely used in different parts of the world basin [2-4]. Stegen *et al.* [5] evaluated the efficiency of the SWAT model in predicting runoff and also uncertainty analysis of the model in Lake Tana in Ethiopia. The impact of topography, land use, soil, and climatic conditions on the hydrology of this area was studied. Their analysis showed that the base flow process has more contribution to the total flow than runoff.

SWAT has been widely used for water balance simulations [6]. A study to find the contribution of different parts of a river on total daily flow in the Shibostu Basin was conducted by Jiang *et al.* [7]. The efficiency of simulated base flow, monthly total flow, surface runoff, and Evapotranspiration (ET) was found satisfactory by this model. Murty *et al.* [8] applied the semi-distributed hydrologic model of SWAT to predict water balance in Ken Basin in India Basin. The yearly and monthly calibration and validation of the model showed how the average annual precipitation in the area (1132mm) contributes to hydrological components. They concluded that 23% is allocated to surface flow, 4% to groundwater flow, and 73% to evapotranspiration.

Sensitivity analysis is a method to determine the inputs, which are more involved in the output variation and finding the parameters that have a satisfactory correlation with the output [8]. Through the sensitivity analysis, one can recognize the most important and sensitive parameter/variable so that after the identification of such a parameter, calibration computationally can be more efficient. Feyereisen *et al.* [9] have listed the most sensitive parameters on total streamflow as the following: Curve number factors, available soil water, and evaporation compensation index from soil layers. Xu *et al.* [10] stated that CN parameters, flow evaporation constant from the channel, evaporation compensation coefficient factor from soil layers, available soil water, soil depth, and surface flow lag time are the most sensitive parameters in the SWAT model.

Grusson *et al.* [11] used the SWAT model an Alpine Watershed (i) to explore the various snow representation possibilities, including elevation bands, offered by SWAT; (ii) to validate SWAT snow simulations using MODIS data supplemented with in situ data; (iii) to assess the impact of different snow dynamics computation on SWAT water budgets. The results showed that the implementation of elevation bands and their associated altitudinal lapse rates had a positive impact on the hydrological simulation of the Upper Garonne watershed. SWAT produced a good spatial and temporal representation of the snow cover, using MODIS data, despite a slight overestimation at the end of the snow season on the highest elevation bands. Elevation bands brought consistent changes in water distribution within the hydrological cycle of implemented watersheds, which are more in line with expected flow paths.

Romagnolia *et al.* [12] used the SWAT model in the Pampas region, Argentina. In this application, limited hydrologic data has resulted in limited water-resources assessment. Under such a condition, analysis of field and remote sensing data characterizing hydrology, water quality, soil types, land use/land cover, management practices, and crop yield, guarantee a comprehensive SWAT modeling approach. A combined manual and automated calibration and validation process incorporating sensitivity and uncertainty analysis is performed using information concerning interior watershed processes. This work provides, for the first time in Argentina, a reliable tool to simulate yield response to soil quality and water availability capable to meet defined environmental targets to support decision making on planning public policies and private activities on the Pampas region. Lu *et al.* [13] proposed a comprehensive method to calibrate the SWAT model in the Yingluoxia watershed, upstream area of the Heihe River basin; it was based on multi-temporal, multi-variable, and multi-site integrated drainage characteristics. The comprehensive calibration method based on multi-temporal, multi-variable, and multi-site integrated drainage characteristics can better portray the hydrological processes of the watershed and improve the model simulation; and the output of the model then provides a reliable reference for assessing and managing water resource of the watershed.

In recent years, some studies were performed by Deng *et al.* [14]; Nguyen *et al.* [15], and Jodar-Abellan *et al.* [16] on predicting catchment streamflow under the effect of land use changes using SWAT model. However, in spite of the importance of quantitative assessment of water balance in mountainous regions, model calibration and sensitivity analysis especially are difficult in the highlands. Such areas are mostly ungauged and data-scarce.

The aim of the present study was to simulate the water balance of Farsan Basin using the SWAT model.

Materials and Methods

In the present study, a sensitivity analysis was performed to determine the important and effective factors. The obtained results were analyzed both quantitatively and qualitatively. Also, the calibration and verification of the SWAT model were done by using the SUFI2 Algorithm. Then, the effective factors on runoff generation could be determined and prioritized.

Study Area

The study area was Farsan watershed with an area of 83035.5ha, it is the part of Beheshtabad Basin. The area was located between 50˚45'15" to 50˚22'28" of eastern longitude and 32˚29'20" to 32˚6'4" northeast. The lowest elevation of the area is 1970m with a maximum altitude of 3610m and the average elevation of 2399m. The average annual rainfall in the area is 461.7mm/year, which ranges from 96mm/month in April to less than 5 mm/month in summer. The monthly rainfall increases during the autumn and winter. The average annual temperature is 12.5°C (Figure 1).

SWAT Model

The SWAT model was selected to simulate hydrological processes in this mountainous and large basin where soil, land use, and weather conditions variability is relatively high and the changes should be taken into consideration. SWAT model is a conceptual semi-distributed model used in basin domain and is has been validated for such applications [4, 9, 15-17]. Moreover, the model can be run hourly, monthly or yearly time scales.

SWAT is an integrated complete model that can be used for several purposes. For instance, it has been used by American Agricultural Research Service to predict different management practices on long-term flow, sediment, nutrient elements, and chemical changes, especially in areas with different soil, land use and conditions. This model can be classified as one of physically-based models that relays on the physical equations of large-scale simulations. Most existing relationships in this model have a physical basis, SWAT is a computationally efficient model for quantitative basin management. The water balance equation used in the model is as follows [18]:

$$SW_t = SW_0 + \Sigma(Rday - Qsurf - Ea - Wseep - Qgw) \quad (1)$$

Where “SW_t” is the final soil water content (mm H_2O), “t” is time (days), SW_0 is the initial soil water content on day (mm H_2O), “Rday” is the amount of precipitation per day I (mm H_2O), “Qsurf” is the amount of surface runoff on day I (mm H_2O), “Ea” is the amount of evapotranspiration on day I (mm H_2O), “Wseep” is the amount of water entering the vadosezone from the soil profile on day I (mm H_2O) “Qgw” is the amount of return flow on day I (mm H_2O).

In the conceptualization of this model, every basin is divided into several sub-basins and each of sub-basins is divided into several Hydrological Response Units (HRUs), which are considered as a homogeneous unit in term of land use, topography, and soil type. The study area was divided into 27 sub-basins. The required meteorological information, for period 1996 to 2010, including precipitation, minimum, maximum daily temperatures, radiation, wind speed, and average humidity were collected from local stations (Table 1). The data source for rainfall data is from ten rain gauge stations, three synoptic station, and five climatological stations. The temperature data comes from three synoptic stations and five climatological stations. In addition, the hydrometric station Darkesh-Varkash is located at the outlet of Farsan watershed, hence it was considered as the flow observatory station.

Sensitivity analysis: Due to the number of inputs of the model, a sensitivity analysis was carried out. Also, this simplifies the calibration procedure. The mean monthly flow for the period of 2001 to 2011 was used to complete sensitivity analysis of as many as 17 parameters of the model. Then based on the orders under the average condition for other parameters, the most sensitive inputs were selected. The results lead to a faster calibration and a time efficient optimization. Since the normal curve number was found to be a sensitive parameter, similar to Fan *et al.* [19] curve numbers was estimated based on remotely sensed NDVI (Table 2).

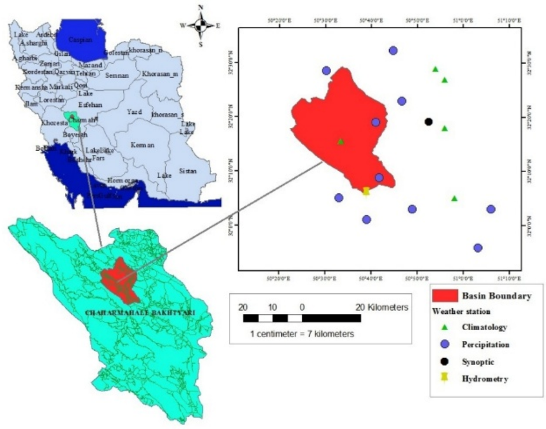

Figure 1) The location of the study area

Table 1) The location of the available meteorological stations

No	Name of station	Type	X	Y	H (m)
1	Joonghan	Raingauge	470000	3557000	2027
2	Chaleshtor	Raingauge	479000	3853000	2100
3	Ben	Raingauge	475000	3600000	2228
4	Dehno	Raingauge	509433	3546163	2034
5	Rustamabad	Raingauge	457526	3549942	1872
6	Ardal	Raingauge	466939	3542517	1875
7	Soreshjan	Raingauge	470185	3575762	2130
8	Marghmalek	Raingauge	451430	3590615	2556
9	Shalamzar	Raingauge	482685	3546173	2041
10	Farkhshahr	Climatology	493716	3573872	2085
11	Shahrekord	Synoptic	485875	3577575	2050
12	Farsan	Climatology	460743	3568404	2059
13	Broujen	Synoptic	528329	3540656	2260
14	Bolldaje	Raingauge	505000	3533000	2231
15	Paul-Zaman Khan	Climatology	490596	3594197	1883
16	Saman	Climatology	493726	3590499	2075
17	Dezak Abad	Climatology	497000	3550000	2054
18	Koohrang	Synoptic	416950	3588993	2365

Table 2) CN value in relation to NDVI [2]

Vegetation	NDVI	Vegetation Vigor	CN A	CN B	CN C	CN D
Forest	NDVI>0.65	Poor: V<50%	45	66	77	83
		Fair: 50%<V<75%	36	60	73	79
		Good: V>75%	30	55	70	77
Grass and Bush	0.57<NDVI<0.65	Poor: V<50%	57	73	82	86
		Fair: 50%<V<75%	43	65	76	82
		Good: V>75%	32	58	72	79
Farmland	0.4<NDVI<0.57	Poor: V<50%	72	81	88	91
		Good: V>50%	67	78	85	89
None-Vegetated	NDVI<0.4		59	74	82	86

Calibration and Validation: Calibration of the SWAT model can be implemented either manually or by using auto-calibration methods. In the present study, calibration was done automatically by using the SUFI2 Algorithm for a period of 2001 to 2011 (the year 2000 was considered as the Warm-up period). After running SUFI2 Algorithm, the most sensitive parameters and optimal values were determined. To calibrate the model, this algorithm was run for several times, and it was checked if the results are logical or not. In case the results were not logical, the optimization was repeated again. To calibrate the model, the SUFI2 Algorithm was run 3000 times. The validation step was performed using the obtained values for the optimized parameters in the calibration phase. The model was validated for the period of 2012 to 2015.

Assessing the model performance

To evaluate model efficiency three measures, including R^2 (Coefficient of determination), bR^2 (weight correlation coefficient), and NS (Nash-Sutcliff) were used. Coefficient of determination was applied to assess simulation results in calibration and validation phases:

$$R^2 = \frac{[\Sigma_{i=1}^{n}(Sim_i - Sim_{avg})(Meas_i - Meas_{avg}]^2}{\Sigma_{i=1}^{n}(Sim_i - Sim_{avg})^2 \Sigma_{i=1}^{n}(Meas_i - Meas_{avg})^2} \quad (2)$$

Where "Sim_{avg}" is the average simulated values and $Meas_{avg}$ is the average measured values. Coefficient of determination ranges from 0 to 1 and its optimal value is 1.

The second evaluation metric was the coefficient bR2 that explains the difference between observed and simulated values as well as the dynamics between them. This coefficient is the product of the coefficient of determination by the slope of the fitted trend line between simulated and observation points.

The third criteria for evaluation was Nash-Sutcliffe coefficient that shows the relative difference between observed data and simulated results:

$$E_{NS} = 1 - \frac{\Sigma_{i=1}^{n}(Means_i - Sim_i)^2}{\Sigma_{i=1}^{n}[Means_i - {}^{1}/_{n}\Sigma_{i=1}^{n}Means_i]^2} \quad (3)$$

To calibrate the model in this way, the E_{NS} was used as an objective function. The values of the Nash-Sutcliffe coefficient, ranges from 1 to negative infinity. Although, the optimal value is 1 but it should be mentioned that values higher than 0.75 are favorable, between 0.75 and 0.36 acceptable and, values less than 0.36 are considered as unacceptable [20].

Findings

Both sensitivity analysis and calibration for SWAT model were done in two ways, firstly manual and secondly by using the SUFI2 Algorithm, an automatically sensitivity analysis/calibration tool provided by SWAT-CUP. In order to calibrate the model, the 10 years of time series (2001 to 2011) of rainfall, temperature, and daily flow were used.

It was observed that the peak flows were generally had taken place during period or rainy months of the present study (Diagram 1a). The main mismatching points in hydrograph were related to peak points. Also, analysis of hydrograph model was not able to capture low flows during the dry period. The results obtained from sensitivity analysis lead to finding out the effective parameters as intermediate outputs for calibration (Tables 2, 3, and 4; Figure 2).

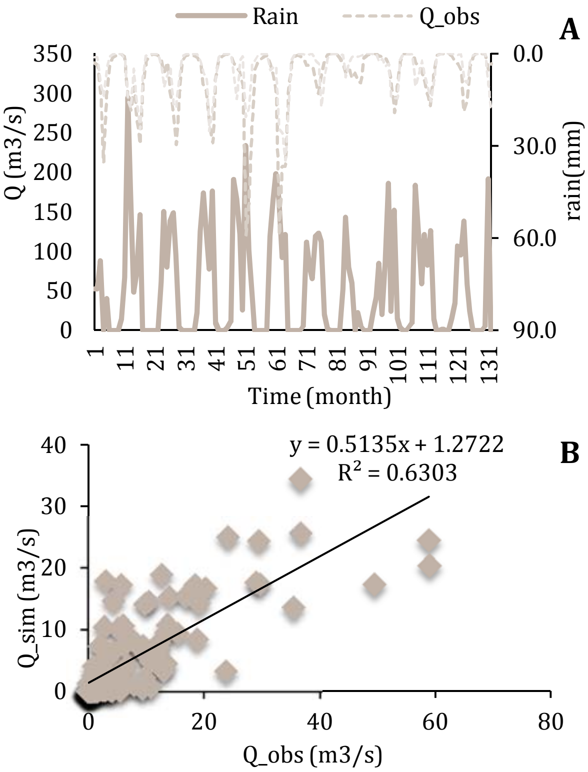

Diagram 1) A: Comparison of simulated hydrographs with observed discharge (2001 to 2011); B: Correlation diagram of observed versus simulated discharge values at calibration stage

Table 3) Evaluation of model performance for calibration

Evaluation criterion	Optimum value
Nash-Sutcliff coefficient (NS)	0.57
Coefficient of determination	0.63
Coefficient bR2	0.33

Table 4) Sensitivity analysis of SWAT model for runoff simulation in Farsan Watershed

Rank	Parameter	Unit	Symbol
1	Threshold depth of water in the shallow aquifer for "revap" to occur	mmH_2O	V__REVAPMN
2	Soil evaporation compensation factor		V__ESCO
3	Groundwater delay	day	V__GW_DELAY
4	Initial SCS runoff Curve number for moisture condition ll		R__CN2
5	Surface runoff lag time	day	V__SURLAG
6	Manning "n" value for the main channel		V__CH_N2
7	Available water capacity of soil layer	mm/mm	R__SOL_AWC
8	Baseflow alpha factor for bank storage	day	V__ALPHA_BNK
9	Plant uptake compensation Factor		V__EPCO
10	Effective hydraulic conductivity in main channel alluvium	mm/hr	V__CH_K2
11	Saturated hydraulic conductivity of soil	mm/hr	R__SOL_K
12	Minimum amount of required water supply in the table for the base flow event (mmH_2O)		V__GWQMN
13	Groundwater "revap" coefficient		V__GW_REVAP
14	Moist bulk density of soil layer	mg/m^3	R__SOL_BD
15	Snowfall temperature	°C	V__SFTMP
16	Snow melt base temperature	°C	V__SMTMP
17	Base flow alpha factor	day	V__ALPHA_BF

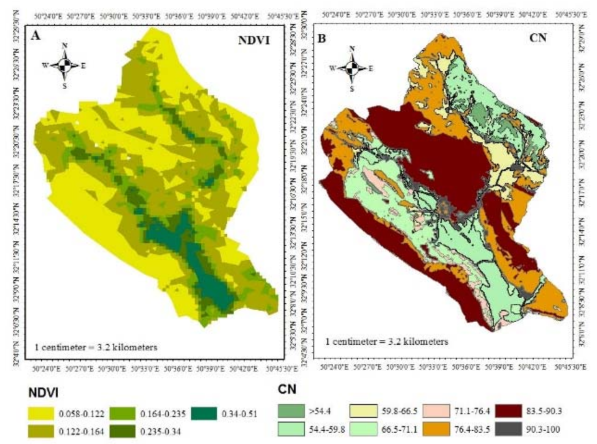

Figure 2) A: NDVI map of the study area; B: CN values in the study area

The study area, with an area of 83035.5ha, consists of 27 sub-basins. Comparison of simulated flow at the output and the monthly precipitation values for the calibration period (2001 to 2011) showed that peak discharges occurred synchronously with rainy months (Diagram 1). In term of time, there was no delay but in term of flow levels, the simulated discharges were slightly under-estimated. In view of influencing factors, one can state that soil moisture plays a significant role in the simulation process. Minimal effect of the soil moisture can be a reason for under-estimation of the near-zero simulated base-flow during the dry seasons.

Validation of the model

To verify the appropriateness of calibrated parameters, the same (optimized) values were used to simulate streamflow at the outlet of the basin over 2012 to 2015. The model performance of the simulations over the above-mentioned independence period was evaluated using three coefficients (Table 5). The result indicated that the model performs acceptably against the validation data set (Diagram 2).

Table 5) Evaluation of model performance for validation

Evaluation Criterion	Amount
Nash-Sutcliff coefficient (NS)	0.52
Coefficient of determination	0.69
Coefficient bR2	0.68

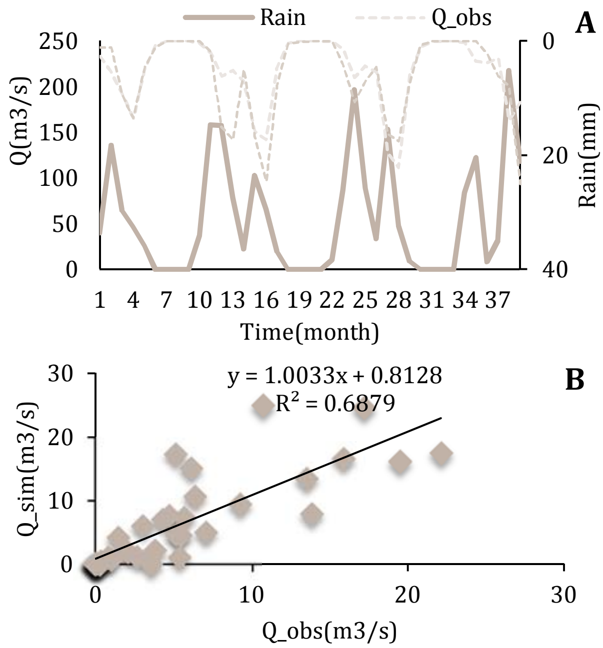

Diagram 2) A: Comparison of monthly simulated and observed hydrographs. The blue line also the rain of the area at validation period (2012-2015); B: Correlation diagram of observed vs. simulated discharge values (validation period)

Discussion

In this research, both manual and the SUFI2 Algorithm were used to calibrate the model. Monthly discharges, for a period (from 2001 to 2011) were used as calibration series while monthly discharges from 2012 to 2015 were used for validation. The results obtained from the first phase of the SWAT modeling showed that the model had performed well in this mountainous basin. Moreover, a more detailed look showed that SWAT has been capable to simulate times to peak, however, it was not able to capture peak flows in the given basin. For calibration period the model has underestimated peak discharges which may be explained by the averaging nature of the model structure, distribution of rain gauge stations and the way of locating rainfall as it has been mentioned by Stellman *et al.* [21]. However, this may be also related to the high gradient of the steep slopes in the basin.

The statistical comparison showed acceptable results for simulated and observed hydrographs with a Nash-Sutcliffe correlation coefficient of 57%. Regarding important hydrograph features such as instantaneous peak discharge, runoff volume, and time to peak, there was a good agreement between two hydrographs. Therefore, it might be inferred as a positive point for SWAT model application in the mountainous region like the basin of the interest. The results of sensitivity analysis for 17 effective parameters on runoff showed that V__ALPHA_BF (base-flow coefficient) had the least sensitivity. For soil controlling factors, including V__REVAPMN (threshold depth of water in the shallow aquifer for "revap" to occur), V__ESCO (Soil evaporation compensation coefficient), V__GW_DELAY (Groundwater delay time), and R__CN2 (Curve number) were found as the most sensitive parameters. This finding suggests that soil moisture plays a critical role in the modeling that is in line with the findings of other studies [20, 22-24].

Conclusion

A proper specification of these sensitive parameters may be the key factor for runoff simulations. The impact of change in surface parameters may have a great influence in both generating runoff and mountain hydrology.

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