



Application of SWAT model and SWAT-CUP software in simulation and analysis of sediment uncertainty in arid and semi-arid watersheds (case study: the Zoshk–Abardeh watershed)

Seyed Hashem Hosseini¹ · Mohammad Reza Khaleghi¹

Received: 20 March 2020 / Accepted: 4 June 2020 / Published online: 18 June 2020
© Springer Nature Switzerland AG 2020

Abstract

This research aimed to appraise the performance of the Soil and Water Assessment Tool (SWAT) model in sediment flow simulation and also to investigate the uncertainty of the model in the watershed areas of arid and semi-arid regions. In this survey, we used the Sequential Uncertainty Fitting ver.2 (SUFI-2) algorithm to assess the uncertainty and calibrate the model. Different factors of water resources are simulated, and we consider the crop yield and water quality at the Hydrological Response Units (HRU) level. Besides, to quantify the water resources, we implemented monthly time intervals. Also, we used monthly time intervals to quantify the water resources. The results showed that in a 3-year validation period (2007–2010), the P -factor and the r -factor were 0.28 and 0.38 respectively, while in the 7-year calibration period (2000–2006), these two factors were 0.29 and 0.39, respectively. The findings of this study proved that in the validation period, statistical indicators of model evaluation comprise R^2 , bR^2 , and the Nash–Sutcliffe efficiency (NSE) coefficients were 0.85, 0.23, and 0.47, respectively, while in the calibration period, these coefficients were 0.46, 0.14, and 0.37, respectively. The results of uncertainty and calibration analysis were acceptable, but in the validation phase, the model has been more applicable and useful. These results show the acceptable efficiency of the SWAT model in simulating the sediment load of the study area. To assess the sensitivities of 22 input parameters, we used SWAT Calibration Uncertainties Program (SWAT-CUP) and achieved three of the most sensitive parameters comprising CN2, SOL_BD, and USLE_P. In contrast, the parameters with the least sensitivity were SLSUBBSN, GW_DELAY, and ESCO. We can use the calibrated model as inputs for SWAT, to assess the impact of climate change on soil erosion.

Keywords SWAT · SUFI-2 · Calibration · Uncertainty analysis · Zoshk–Abardeh watershed

Introduction

In many parts of Iran, the quality and quantity of groundwater have settled and water levels have drawdown, resulting in indiscriminate depletion of water and its potential unfavorable environmental impacts (Gholami et al. 2016; Alizadeh et al. 2018). However, according to some researchers such as Raneesh and Santosh (2011) and also Abbaspour et al. (2015), the trend and phenomenon of climate change create a new level of uncertainty about freshwater resources; to understand the role of rainfall-runoff and

sediment processes and quantify them in watershed areas the use of simulation models in costume (Khaleghi et al. 2011, 2014; Alizadeh et al. 2017; Varvani and Khaleghi 2018; Kargar et al. 2020). Recently many approaches have implemented for estimating suspended sediment load of river systems (Olyaie et al. 2015). Despite the progress of technology in recent decades, an increasing trend in implementing distributed models, the lack of data, and another issue such as the high cost of data provision in Iran, implementing semi-distributed models such as soil and water assessment tool (SWAT), are unavoidable. Investigations in this area show the high performance of these models to the sustainable use of water resources to meet different water demands (Abbaspour et al. 2015). SWAT, as a hydrological model to calculate the basin hydrological response accurately, was formed by integrating a hydrological and basin-scale model with Geographic Information System software

✉ Mohammad Reza Khaleghi
drmrkhaleghi@gmail.com

¹ Torbat-e-Jam Branch, Islamic Azad University,
Torbat-e-Jam, Iran

(ArcGIS 10.3). Investigations in these regards (Ang and Oeurng 2018) show the improvement in the accuracy of the simulated results of the basin hydrological response (discharge flow). This semi-distributed and process-based model (Tobin and Bennett 2009) also play a considerable role in assessing the effect of land-use changes in the watershed area (Li et al. 2010). Arnold et al. (1998) developed this model for the first time and then widely used around the world (Arnold et al. 1998, 2012). Abbaspour et al. (2007) extracted SWAT-CUP (SWAT Calibration Uncertainty Procedures) by connecting three programs to the hydrologic simulator SWAT (Arnold et al. 1998). These three programs, which have been interconnected with SWAT (Hallouz et al. 2018), are Sequential Uncertainty Fitting Ver.2 (SUFI-2) (Abbaspour et al. 2007), ParaSol (Van Griensven and Meixner 2006), and Generalized Likelihood Uncertainty Equation (GLUE) (Beven and Binley 1992; Saleh and Du 2004; Chen and Chau 2019). SWAT-CUP is developed for the calibration of SWAT (Abbaspour et al. 2015). Recently, many types of studies have been implementing the SWAT model (Xiaobo 2008; Setegn et al. 2010; Thampi et al. 2010; Phomcha et al. 2011; Mbonimpa et al. 2012; Havrylenko et al. 2016). Hassen et al. (2016) implemented the SWAT model and earned favorable results concerning flood hydrograph calculation. Ang and Oeurng (2018) used the SWAT model to simulate daily and monthly streamflow in the Stung Pursat River catchment and accessed to high-efficiency results. To find a good model performance for discharges, Hallouz et al. (2018) used the SWAT model to assess the results of implementing the SWAT model in the Upper Tana Basin, and Nkongwe et al. (2014) used the GLUE and SUFI-2 calibration-uncertainty methods and found SUFI-2 as the best method. Recently, the SWAT model has implemented widely in Iran to assess uncertainty and optimize model parameters and to simulate flood hydrograph (Hosseini et al. 2018) and sediment discharge (Khaleghi and Varvani 2018a, b; Varvani and Khaleghi 2019a, b; Varvani et al. 2019). Faramarzi et al. (2009) used SWAT to calculate streamflow hydrology for Iran. Also, Faramarzi et al. (2013) implemented the African SWAT model to investigate the impact of climate change in variations of flood and sediment in Africa.

Above-mentioned literature and feedbacks indicate the successful implementation of the SWAT model in simulation and calculation of the water resource and the features of hydrologic processes. Also, the SWAT-CUP and the SUFI-2 method were selected to calibrate and validate the SWAT model by providing sufficient results. We conducted this study to investigate the efficiency of the SWAT model in estimating and simulating runoff, and investigate the uncertainty of hydrologic parameters in arid and semi-arid regions.

Methods and materials

Case study

The Zoshk–Abardeh Watershed with an area of 9225.5 hectares is located in the west of Mashhad in Khorasan Razavi Province, Iran. The studied area was located in the eastern longitude $59^{\circ}4'39''$ to $59^{\circ}16'13''$ and northern latitude $36^{\circ}15'16''$ to $36^{\circ}23'12''$. We present the location of the study area in Fig. 1. The area is under a temperate climate with cool summers and freezing winters. The average annual rainfall and temperature are about 404 mm and 12°C , and the climate of the region based on the Emberger method is cold semi-humid and based on the De Martonne method is the Mediterranean.

Study method

In this study, we implemented the SWAT model to simulate the effects of different climate change scenarios. Data required for SWAT model simulation include digital elevation model (DEM), drainage network map, land use, soil data, and meteorological data. The meteorological data required include rainfall, minimum and maximum temperatures, relative humidity, solar radiation, and wind speed daily for stations within and around the basin. We divide the simulation process in the SWAT model into two phases: the land phase and water for routing phases (Neitsch et al. 2005). Land phases control the loading of the amount of water, sediment, and nutrients, and the second phase defines the movement of water, sediment, and nutrients through the streams of the sub-basins or the Hydrological Response Units (HRU) to watershed outlets. SWAT allows users to define management practices taking place in every HRU (Fig. 2). For ease of simulation, reducing inhomogeneity and increasing accuracy, the basin should be subdivided into sub-basins and then into the hydrological response unit

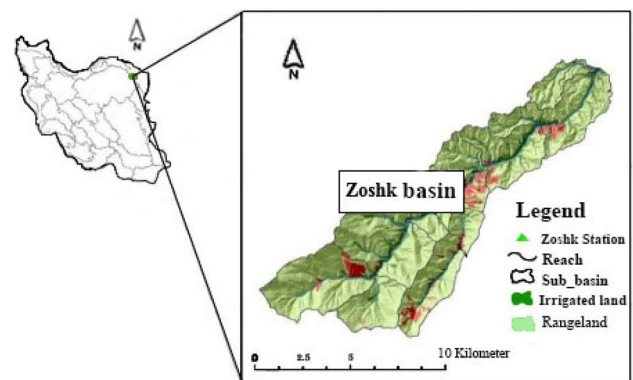


Fig. 1 Location of Zoshk–Abardeh Watershed

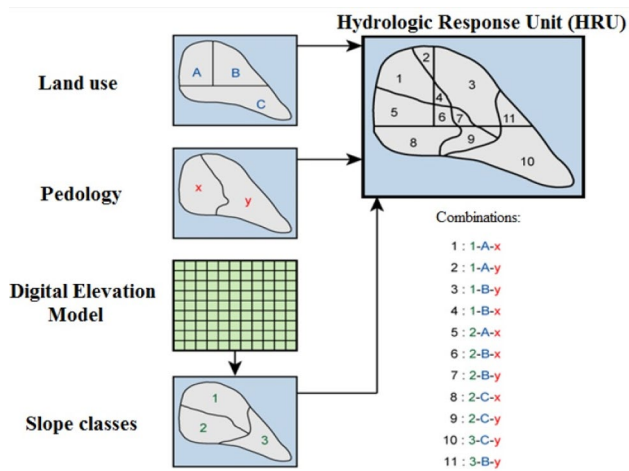


Fig. 2 Principle of discretization of Hydrological Response Units (Briak et al. 2016)

(Robert et al. 2008). The minimum threshold level method was used to determine HRU to remove land uses, soils, and slope within each sub-basin. In this study, 10% of thresholds were set for each slope, soil, and land-use class to include the most detail. Based on the threshold value, we simulated different variables for each HRU and then weighted for the total sub-basins, and after summing, we calculated the total value for that basin (Di Luzio and Arnold 2004). It shows the conceptual process of the SWAT model in Fig. 3.

The SWAT model simulates surface runoff using two alternative methods: the method of the Curve Number (CN) of the Soil Conservation Service (SCS) of the USDA and the method of Green and Ampt. In the SWAT model, erosion caused by rainfall and runoff is calculated using the modified

relationship of the Modified Universal Soil Loss Equation (MUSLE) presented by Wischmeier and Smith (1978):

$$Sed = 11.8(Q_{surf}q_{peak}area_{hru})^{0.56}K_{USLE}C_{USLE}P_{USLE}LS_{USLE}CFRG, \tag{1}$$

where Sed is sediment rate (ton/day), Q_{surf} is runoff (mm in hectare), q_{peak} is the maximum runoff (m^3/s), $area_{hru}$ is the area of each HRU (hectare), K_{USLE} is the soil erodibility factor, C_{USLE} is the cropping management factor, P_{USLE} is a factor of protective methods, LS_{USLE} is the topographic factor, and CFRG is the coefficient of coarse-grained particles.

The sediment routing model consists of two decomposition and sedimentation components that operate simultaneously. In this model, the maximum sediment that can be transported along the route is considered a function of the maximum flow rate:

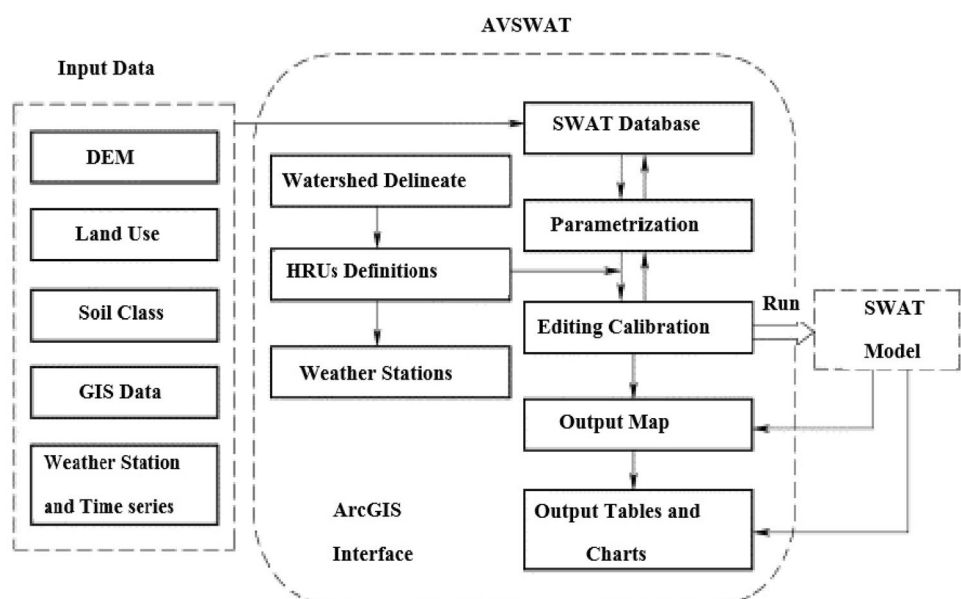
$$Conc_{eded, ch, mx} = C_{sp} v_{ch, pk}^{sp \exp}, \tag{2}$$

where $Conc_{sed, ch, mx}$ is the maximum sediment concentration that can be traversed (ton/m^3). $v_{ch, pk}$ is the maximum flow rate (m/s), and $spexp$ and C_{sp} are empirical coefficients and $spexp$ varies between numbers 1 and 2. If the sediment concentration exceeds the maximum calculated sediment concentration, the sediment is deposited in the path and the sediment content is calculated from the following relation:

$$Sed_{dep} = (conc_{sed, ch, i} - conc_{sed, ch, mx})V_{ch}. \tag{3}$$

If the sediment concentration in the path is lower than the calculated maximum sediment concentration, the decomposition process occurs and the amount of sediment decomposed is calculated from the following relation:

Fig. 3 Processing and display concept for SWAT model (Wangpimool et al. 2013)



$$\text{Sed}_{\text{deg}} = (\text{conc}_{\text{sed, ch, mx}} - \text{conc}_{\text{eded, ch, i}}) V_{\text{ch}} K_{\text{CH}} C_{\text{CH}}, \quad (4)$$

where K_{CH} is erosion factor (cm/h/Pascal) and C_{CH} is channel coverage factor. The amount of sediment is obtained from the following relation:

$$\text{Sed}_{\text{ch}} = \text{Sed}_{\text{ch, i}} - \text{Sed}_{\text{deg}} + \text{Sed}_{\text{deg}}, \quad (5)$$

where sed_{ch} is the amount of suspended sediment (ton), $\text{sed}_{\text{ch, i}}$ is the amount of sediment suspended at the beginning of the time step (ton), and V_{ch} is the volume of water suspended in the track (cubic meters). Finally, the amount of sediment that gets out of the way is calculated from the following equation:

$$\text{sed}_{\text{out}} = \text{sed}_{\text{ch}} \frac{V_{\text{out}}}{V_{\text{ch}}}. \quad (6)$$

Statistical indicators of model evaluation

To evaluate the model, R^2 , bR^2 , and the Nash–Sutcliffe efficiency (NSE) coefficients (Nash and Sutcliffe 1970) are used:

$$R^2 = \frac{[\sum_{i=1}^n (\text{Simulated}_i - \text{Simulated}_{\text{avg}})(\text{Measured}_i - \text{Measured}_{\text{avg}})]^2}{\sum_{i=1}^n (\text{Simulated}_i - \text{Simulated}_{\text{avg}})^2 \sum_{i=1}^n (\text{Measured}_i - \text{Measured}_{\text{avg}})^2}, \quad (7)$$

$$bR^2 = \begin{cases} |b|R^2 & \text{if } |b| \leq 1 \\ |b|^{-1}R^2 & \text{if } |b| > 1 \end{cases}, \quad (8)$$

$$E_{\text{NS}} = 1 - \frac{\sum_{i=1}^n (\text{Measured}_i - \text{Simulated}_i)^2}{\sum_{i=1}^n [\text{Measured}_i - 1/n \sum_{i=1}^n \text{Measured}_i]^2}, \quad (9)$$

where $\text{Simulated}_{\text{avg}}$ and $\text{Measured}_{\text{avg}}$ are average simulated and measured values, respectively.

The SWAT model uncertainty analysis, calibration, and validation

In this study, because of high potential and efficiency of the SUFI-2 program for time-consuming large-scale models, it was implemented for sensitivity analysis, model calibration and validation, and uncertainty analysis in the SWAT-CUP program (Abbaspour et al. 2007; Yang et al. 2008; Abbaspour et al. 2015; Ang and Oeurng 2018; Shamsirband et al. 2019). To perform the calibration and validation processes, it was used from runoff data. To perform the sensitivity analysis based on linear approximation and uncertainty, we used it from two factors called the R -factor and P -factor. The P -factor is the percentage of observation

data covered equal to the estimated 95% uncertainty band (PPU95). The R -factor is the average PPU95 bandwidth divided by the measured standard deviation (Khalid et al. 2016). The 95PPU has calculated at 2.5% and 97.5% levels of the cumulative distribution of an output variable got through Latin hypercube sampling (Memarian et al. 2013a). The closer the P -factor to 100% and the R -factor to zero, the more accurate is the simulation (Shimelis et al. 2008). To analyze the quantity and quality of calibration, validation, and sensitivity assessment, we implemented three measures: (a) the percentage of data excluded by the 95% prediction uncertainty (95PPU) (P -factor); (b) the ratio of the band 95PPU's medium thickness (Hallouz et al. 2018). Using the SUFI-2 program allows us to implement ten different aim functions such as mean square error (MSE), Nash–Sutcliffe (NS), and r^2 . So long as most observational data are in the 95% uncertainty band and the band thickness is as small as possible, the process of computations in the SUFI-2 algorithm continues (Memarian et al. 2013b).

Results

Sensitivity analysis of parameters affecting sediment load

We used SUFI2 software only for sensitivity analysis. In the first step, we considered 22 potential and effective parameters in the production of watershed sediment. We introduced these parameters in the model along with their permissible range of variation and we performed 300 simulations to optimize the model outputs. For each of these parameters, a t -stat value was provided by the SUFI2 program, and based on them, the sensitive parameters were determined. The higher the t -stat values, the greater the relative sensitivity. P values are used to determine the significance of the sensitivity, so that the closer the P values to zero, the more important the parameters become. The outcomes of t -stat and the P values for each of the parameters affecting sediment outflow are presented in Figs. 4 and 5, respectively.

Table 1 shows these values for the various parameters. Analyzing and the analogy of the obtained t -stat values for each parameter show that the parameters CN2, SOL_BD, and USLE_P have the highest relative sensitivity, and SLSUBBSN, GW_DELAY, and ESCO have the least relative sensitivity. Based on this algorithm, about 22 effective parameters in the sediment have been investigated, which have been tried to be selected based on the results of previous research and the suggestions of researchers in other countries.

Fig. 4 The *t*-stat values for each of parameters affecting sediment outflow

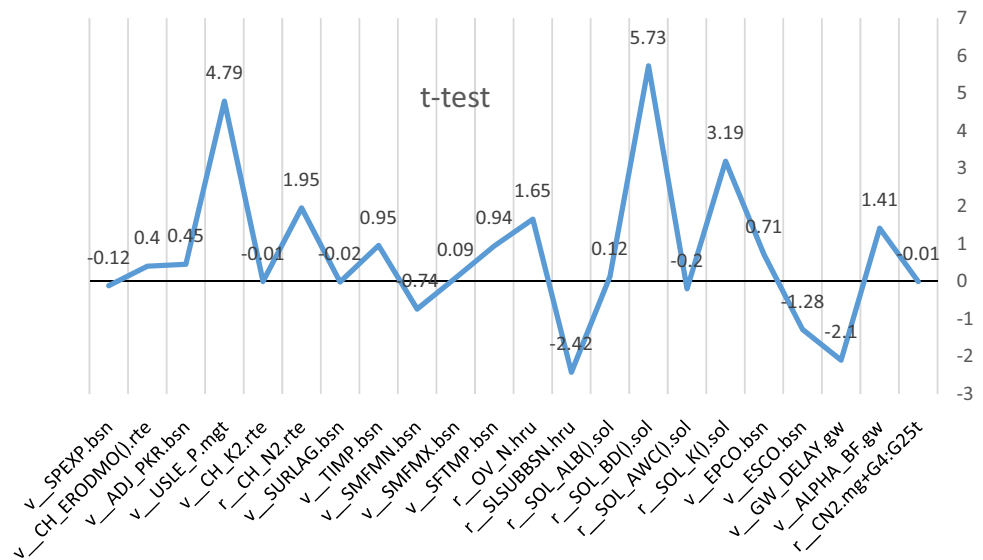
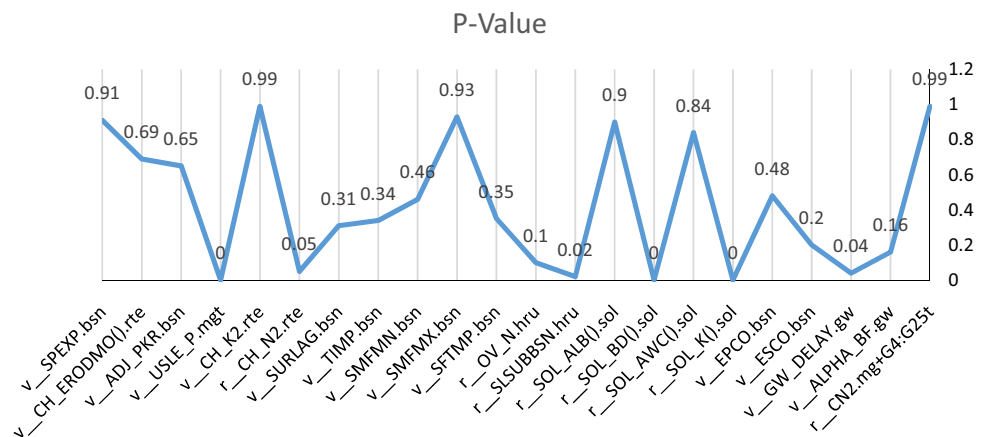


Fig. 5 The *P* values for each of parameters affecting sediment outflow



Model calibration and validation

We performed the calibration and validation of the SWAT model to amend the simulation results of the sediment load. 7-year (2000–2006) and 3-year (2007–2010) monthly sedimentation statistics were implemented to perform calibration and validation processes, respectively. The *P*-factor and the *r*-factor values for the calibration period calculated 0.29 and 0.39, respectively, while the validation period was 0.28 and 0.38, respectively. The findings of this study proved that in the validation period, the coefficients of R^2 , bR^2 , and *Ns* were 0.85, 0.23, and 0.47, respectively, while in the calibration period, these coefficients were 0.46, 0.14, and 0.37, respectively. The results of uncertainty and calibration analysis were acceptable, but in the validation phase, the model has been more applicable and useful. These results show the acceptable efficiency of the SWAT model in simulating the sediment load of the study area. The results of optimal

values of the effective parameters on sediment load, *t*-stat, and *P* value are presented in Table 2.

Runoff calibration and validation results

Statistical indicators of model evaluation include R^2 , bR^2 , and *NS* coefficients were implemented to evaluate model performance. The results of these indices in the calibration and validation steps have been presented in Table 3.

As shown in Figs. 6 and 7, during the calibration and validation periods, diagrams of observed and simulated daily (Spruill et al. 2000) sediment load values were drawn to simulate minimum and maximum sediment loads and also to check their temporal compliance with real data. The analysis of these diagrams shows that the model well-simulated maximum and minimum deposition times. The average rates of simulated monthly sediment load during the calibration and validation period are 14,790 and 13,597 tons, respectively,

Table 1 Parameters entered into the model and the minimum, maximum and results of *t*-stat and *P* value values after sensitivity analysis

	<i>t</i> -stat	<i>P</i> value	Minimum	Maximum	Parameter acronym	Parameters
1	- 0.01	0.99	- 0.2	1	r__CN2.mgt	Curve number
2	1.41	0.16	0	1	v__ALPHA_BF.gw	Groundwater Reaction Factor
3	- 2.1	0.04	0	500	v__GW_DELAY.gw	Delay time of groundwater supply flow
4	- 1.28	0.2	0	1	v__ESCO.bsn	Compensation factor for evaporation from soil
5	0.71	0.48	0	1	v__EPCO.bsn	Plant water harvesting factor
6	3.19	0	- 0.5	0.5	r__SOL_K().sol	Saturated hydraulic conductivity of soil (mm/h)
7	- 0.2	0.84	- 0.5	0.5	r__SOL_AWC().sol	Available water capacity in the soil layer
8	5.73	0	- 0.5	0.5	r__SOL_BD().sol	Density of soil mass
9	0.12	0.9	- 0.5	0.5	r__SOL_ALB().sol	Wet soil albedo coefficient
10	- 2.42	0.02	- 0.5	0.5	r__SLSUBBSN.hru	Average slope length (m)
11	1.65	0.1	- 0.5	0.5	r__OV_N.hru	Coefficient of roughness of range
12	0.94	0.35	- 5.0	5.0	v__SFTMP.bsn	Degree of snowfall (°C)
13	0.09	0.93	0	10	v__SMFMX.bsn	Degree of melting snow (°C)
14	- 0.74	0.46	0	10	v__SMFMN.bsn	Degree of melting snow (°C)
15	0.95	0.34	0	10	v__TIMP.bsn	Snow mass temperature delay coefficient
16	- 1.02	0.31	1	24	v__SURLAG.bsn	Surface flow delay coefficient
17	1.95	0.05	- 0.5	0.5	r__CH_N2.rte	Manning coefficient in the main channel
18	- 0.01	0.99	0.0	150	v__CH_K2.rte	Hydraulic conductivity in the main channel
19	4.79	0	0.0	1	v__USLE_P.mgt	Factor related to soil conservation operations in the USLE equation
20	0.45	0.65	0.5	2	v__ADJ_PKR.bsn	Peak rate adjustment factor for sediment routing in sub-basin
21	0.4	0.69	0	1	v__CH_ERODMO().rte	Channel erodibility coefficient
22	- 0.12	0.91	1	1.5	v__SPEXP.bsn	Exponential re-entrainment coefficient for channel sediment routing

v means replacing existing parameter values with a given value and *r* means multiplying existing parameter values by (+ 1 given value)

while these values for real data are 6124 and 17,463 tons, respectively.

Uncertainties in simulating sediment load

After performing the calibration process, we calculated the probability of data uncertainty between 92.5% and 97.5% and the runoff uncertainty band showed that in this graph, both simulated and observed discharges were determined within the 95% uncertainty band. However, Fig. 8 shows that the outputs of the model were not accurately and favorably got.

Conclusion and discussion

In this study, we implemented the SWAT model and integrated it with the spatial variability of ArcGIS 10.3 to appraise the performance of the SWAT model in sediment flow simulation and also to investigate the uncertainty of the model in the watershed areas of arid and semi-arid regions. The results of the statistical indicators of model evaluation (R^2 and NS) illustrate the efficiency of the SWAT model in simulating the sediment load of the study area which is acceptable. Also, analysis of related graphs of the calibration

and validation periods of the sediment load shows the high capability of the model in the maximum's modeling and minimum sediment load occurrences. This finding is consistent with the results of the study by Abbaspour (2005) and Abbaspour et al. (2015) about the high capability of the SWAT model in simulating the seasonal changes of sediment. Another ability of this model is in simulating water phenomena and sediment transfer processes. This finding is consistent with the results of the study by Ang and Oeurng (2018) and Hallouz et al. (2018).

Also, the results of the uncertainty diagrams show that after the calibration and validation processes, there was a high difference in simulated and observed values. This high uncertainty, particularly in the results of sedimentation, is observed in studies that can be attributed to several reasons. First, there are no exact statistics for sedimentation. Second, there are no statistics on the amount of water harvested in gardens and upstream of the basin. Third, there are a lot of wells in upstream of the basin that does not have any statistics on discharge. In general, several factors are involved in the accuracy of modeling results. One group of these factors was related to the climatic and geological conditions of the basin (Gholami et al. 2017; Khaleghi 2018) and the information collected, and the other group was related to the weaknesses of the model in the simulation. In terms of geology,

Table 2 Effective parameters on sediment load and their optimal values, *t*-stat, and *P* value

	Parameter	Optimal value	Min	Max	<i>t</i> -stat	<i>P</i> value
1	R_CN2.mgt	0.602	- 0.200	0.700	58.562	0.000
2	V_ALPHA_BF.gw	0.284	0.000	1.000	3.355	0.001
3	V_GW_DELAY.gw	188.250	0.000	500.000	- 0.424	0.672
4	V_ESCO.bsn	0.775	0.010	1.000	- 0.252	0.801
5	V_EPCO.bsn	0.234	0.010	1.000	- 0.263	0.793
6	R_SOL_K (..).sol	0.344	- 0.500	0.500	7.543	0.000
7	R_SOL_AWC (..).sol	0.362	- 0.500	0.500	- 0.965	0.335
8	R_SOL_BD (..).sol	- 0.158	- 0.500	0.500	15.074	0/000
9	R_SOL_ALB (..).sol	- 0.484	- 0.500	0.500	- 0.395	0.693
10	R_SLSUBBSN.hru	0.078	- 0.500	0.500	- 2.135	0.033
11	R_OV_N.hru	0.011	- 0.500	0.500	- 0.028	0.978
12	V_SFTMP.bsn	3.235	- 5.000	5.000	1.184	0.237
13	V_SMFMX.bsn	1.635	0.000	10.000	0.640	0.522
14	V_SMFMN.bsn	5.155	0.000	10.000	- 0.838	0.402
15	V_TIMP.bsn	3.685	0.000	10.000	0.071	0.944
16	V_SURLAG.bsn	18.515	1.000	24.000	0.104	0.917
17	R_CH_N2.rte	0.396	- 0.500	0.500	2.054	0.040
18	V_CH_K2.rte	107.475	0.000	150.000	1.470	0.142
19	V_USLE_P.mgt	0.693	0.000	1.000	5.018	0.000
20	V_ADJ_PKR.bsn	1.482	0/500	2.000	1.316	0.88
21	V_CH_ERODMO (..).rte	0.442	0.000	1.000	1.826	0.068
22	V_SPEXP.bsn	1.003	1.000	1.500	- 1.328	0.184

v means replacing existing parameter values with a given value and *r* means multiplying existing parameter values by (+ 1 given value)

Table 3 Values of the model evaluation index in the calibration and validation steps

Evaluation indicators and stages of model implementation	Calibration step	Validation step
Coefficient of determination (R^2)	0.46	0.85
Nash–Sutcliffe coefficient (NS)	0.37	0.47
Br^2 coefficient	0.140	0.23
<i>P</i> -factor	0.29	-
<i>r</i> -factor	0.39	-

it seems that most of the sedimentation load of this basin is related to the bed load, which will increase the possibility of increasing the error due to the lack of collected statistics and data reconstruction.

Evaluation of SWAT_CUP and SWAT model for simulation of sediment load variable of the Zoshk–Abardeh watershed shows that uncertainty about sediment is higher. This result is consistent with the results of Xu et al. (2009) and Khalid et al. (2016). These results show the acceptable efficiency of the SWAT model in simulating the sediment

Fig. 6 Comparison of monthly values of runoff observed and simulated after calibration

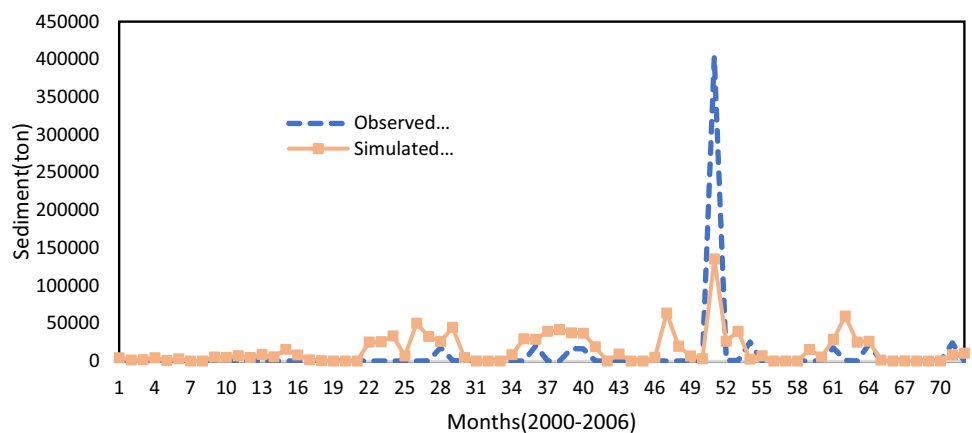


Fig. 7 Comparison of monthly values of runoff observed and simulated after validation

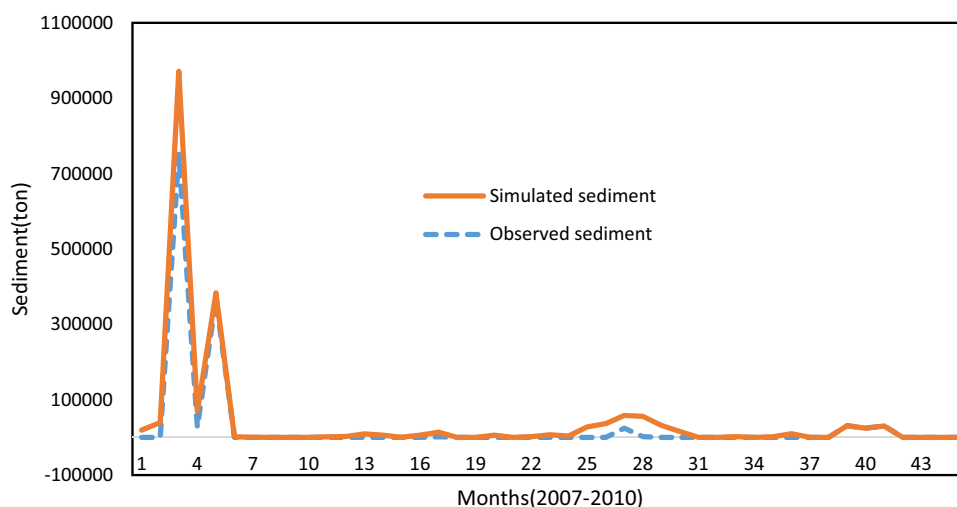
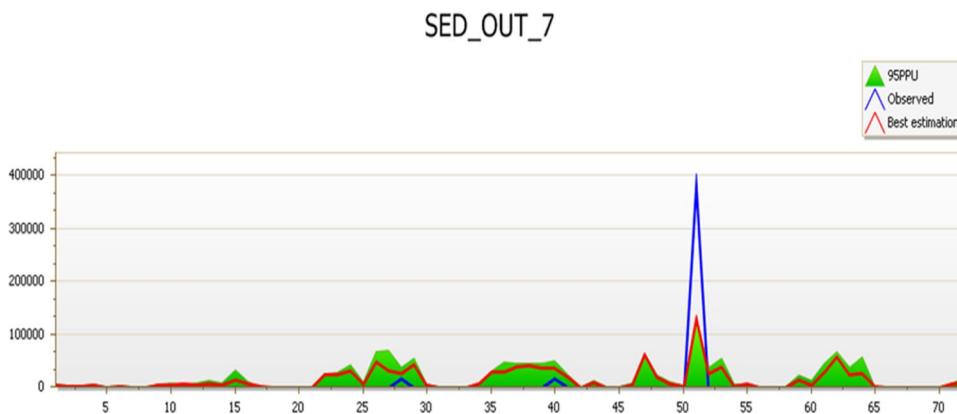


Fig. 8 Runoff uncertainty band of Zoshk–Abardeh watershed after calibration



load of the study area. To assess the sensitivities of 22 input parameters, we used SWAT-CUP and achieved three of the most sensitive parameters comprising CN2, SOL_BD, and USLE_P. In contrast, the parameters with the least sensitivity were SLSUBBSN, GW_DELAY, and ESCO. We can use the calibrated model as inputs for SWAT, to assess the impact of climate change on soil erosion. To the validation of the modeling results, many factors are involved. Some of them are linked to climatic and geological conditions of the basin and the collected data, and other factors are related to model weaknesses in the simulation. We can implement the outcomes of this research to predict the effects of climate change on the hydrological patterns of watersheds and also the management practices needed to deal with them in the region (as a scenario in the proposed model).

In general, the SWAT model, as a comprehensive model for natural resource studies, can be a powerful tool in macro planning and management. The multifunctionality, or in other words, the prediction of different goals for this model, including hydrological processes, water quality, soil erosion, rangeland management, and climate change effects, and the greater accuracy of the model's results on

a large scale, confirms this model. The compatibility of the model with different software environments such as Arc View and Arc GIS has increased the efficiency of this model. The results of research conducted in different parts of the world also show that this model can be introduced as a standard model in the world. However, it should be noted that compared to other models, this model requires a lot of input information, which is one of the weaknesses of the model.

Finally, model validation and validation have been introduced as a key factor in reducing uncertainty and increasing user confidence in simulation and more effective forecasting and as a factor to help watershed models in developing the SWAT model to achieve watershed management goals. The calibrated model can be used to simulate the effects of climate change and land use, as well as various management scenarios on runoff and soil erosion.

Due to the proper performance of the SWAT model in stimulating the flow of runoff and sediment load of Zoshk–Abardeh basin as well as its extensive capabilities, other study fields in this basin are suggested as follows:

- Comparison of SWAT efficiency with other models about the simulation of different basin variables.
- Simulation of river flow basins with natural and climatic conditions similar to the Zoshk–Abardeh basin in terms of data access limitation using the SWAT weighed model.
- Using a calibrated model to study the effects of climate change, land use, vegetation, and various management scenarios on runoff and soil erosion of the basin to determine the best land-use pattern and allocate water resources.
- Investigating the effects of climate change on water resources using the SWAT model to reduce and compensate for the harmful effects of climate change.
- Prioritization of sub-basins based on soil loss ratios to take protective measures.
- Analysis of parameter sensitivity assessment in different climatic conditions and time scales.
- Determining the importance of baseline flow and surface runoff as important components of total discharge and determining the number of watershed losses due to evaporation and transpiration.
- According to the required information of the SWAT model, this model can be used to simulate discharge and sediment load in Iran's watersheds, although the lack of accurate meteorological statistics and land-use maps with appropriate accuracy and appropriate to the similar period hurts the accuracy of results.

Acknowledgements The authors would like to thank the officers of the LDD, RID, and RTSD for supplying the original data used in this study and also the reviewers for their valuable comments.

References

- Abbaspour KC (2005) Calibration of hydrologic models: when is a model calibrated? In: Zenger A, Argent RM (eds) In: Proceedings of the international congress on modelling and simulation (MODSIM'05), 2449–2455. Melbourne, Australia: Modelling and Simulation Society of Australia and New Zealand
- Abbaspour KC (2007) User manual for SWAT-CUP, SWAT calibration, and uncertainty analysis programs. Swiss Federal Institute of Aquatic Science and Technology, Eawag, Dübendorf, Switzerland
- Abbaspour KC, Yang J, Maximov I, Siber R, Bogner K, Mieleitner JZ, Srinivasan R (2007) Modeling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. *J Hydrol* 333(2–4):413–430. <https://doi.org/10.1016/j.jhydrol.2006.09.014>
- Abbaspour KC, Rouholahnejad E, Vaghefi S, Srinivasan R, Yang H, Klove BA (2015) 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. <https://doi.org/10.1016/j.jhydrol.2015.03.027>
- Alizadeh MJ, Jafari Nodoushan E, Kalarestaghi N, Chau KW (2017) Toward multi-day-ahead forecasting of suspended sediment concentration using ensemble models. *Environ Sci Pollut Res* 24(36):28017–28025. <https://doi.org/10.1007/s11356-017-0405-4>
- Alizadeh MJ, Kavianpour MR, Danesh M, Adolf J, Shamshirband S, Chau KW (2018) Effect of river flow on the quality of estuarine and coastal waters using machine learning models. *Eng Appl Comput Fluid Mech* 12(1):810–823. <https://doi.org/10.1080/19942060.2018.1528480>
- Ang R, Oeurng C (2018) Simulating streamflow in an ungauged catchment of Tonlesap LakeBasin in Cambodia using Soil and Water Assessment Tool (SWAT) model. *Water Sci* 32:89–101. <https://doi.org/10.1016/j.wsj.2017.12.002>
- Arnold JG, Srinivasan R, Muttiyah RS, Williams JR (1998) Large-area hydrologic modeling and assessment: Part I. Model development. *J Am Water Resour Assoc* 34(1):73–89. <https://doi.org/10.1111/j.1752-1688.1998.tb05961.x>
- Arnold JG, Moriasi DN, Gassman PW, Abbaspour KC, White MJ, Srinivasan R, Santhi C, Harmel RD, Griensven AV, Liew MWV, Kannan N, Jha MK (2012) SWAT: model use, calibration, and validation. *Trans ASABE* 55(4):1491–1508. <https://doi.org/10.13031/2013.42256>
- Beven K, Binley A (1992) The future of distributed models: model calibration and uncertainty prediction. *Hydrol Process* 6(3):279–298. <https://doi.org/10.1002/hyp.3360060305>
- Briak H, Moussadek R, Aboumaria K, Mrabet R (2016) Assessing sediment yield in Kalaya gauged watershed (Northern Morocco) using GIS and SWAT model. *Int Soil Water Conserv Res* 4(3):177–185. <https://doi.org/10.1016/j.iswcr.2016.08.002>
- Chen XY, Chau KW (2019) Uncertainty analysis on hybrid double feedforward neural network model for sediment load estimation with LUBE method. *Water Res Manag* 33(10):3563–3577. <https://doi.org/10.1007/s11269-019-02318-4>
- Di Luzio M, Arnold JG (2004) Formulation of a hybrid calibration approach for a physically based distributed model with NEXRAD data input. *J Hydrol* 298(1–4):136–154
- Faramarzi M, Abbaspour KC, Schulin R, Yang H (2009) Modeling blue and green water resources availability in Iran. *Hydrol Process* 23:486–501
- Faramarzi M, Abbaspour KC, Vaghefi SA, Farzaneh MR, Zehnder AJB, Yang H (2013) Modelling impacts of climate change on freshwater availability in Africa. *J Hydrol* 480:85–101. <https://doi.org/10.1016/j.jhydrol.2012.12.016>
- Gholami V, Khaleghi MR, Sebgati M (2016) A method of groundwater quality assessment based on fuzzy network-CANFIS and geographic information system (GIS). *Appl Water Sci* 7:3633–3647. <https://doi.org/10.1007/s13201-016-0508-y>
- Gholami V, Torkaman J, Khaleghi MR (2017) Dendrohydrogeology in paleohydrogeologic studies. *Adv Water Resour* 110:19–28
- Hallouz F, Meddia M, Mahéb G, Alirahmanic S, Keddar A (2018) Modeling of discharge and sediment transport through the SWAT model in the basin of Harraza (Northwest of Algeria). *Water Sci* 32:79–88. <https://doi.org/10.1016/j.wsj.2017.12.004>
- Hassen MY, Assefa MM, Gete Z, Tena A (2016) Streamflow prediction uncertainty analysis and verification of SWAT model in a tropical watershed. *Environ Earth Sci* 75:806. <https://doi.org/10.1007/s12665-016-5636-z>
- Havrylenko SB, Bodoque JM, Srinivasan R, Zuccarelli GV, Mercuri P (2016) Assessment of the soil water content in the Pampas region using SWAT. *CATENA* 137:298–309. <https://doi.org/10.1016/j.catena.2015.10.001>
- Hosseini SH, Khaleghi MR, Jami H, Baygi S (2018) Comparison of hybrid regression and multivariate regression in the regional flood frequency analysis: a case study in Khorasan Razavi province. *Environ Health Eng Manag J* 5(2):93–100
- Kargar K, Samadianfard S, Parsa J, Nabipour N, Shamshirband S, Musavi A, Chau KW (2020) Estimating longitudinal dispersion coefficient in natural streams using empirical models and

- machine learning algorithms. *Eng Appl Comput Fluid Mech* 14(1):311–322. <https://doi.org/10.1080/19942060.2020.1712260>
- Khaleghi MR, Gholami V, Ghodusi J, Hosseini SH (2011) Efficiency of the geomorphologic instantaneous unit hydrograph method in flood hydrograph simulation. *CATENA* 87(2):163–171
- Khaleghi MR, Ghodusi J, Ahmadi H (2014) Regional analysis using the geomorphologic instantaneous unit hydrograph (GIUH) method. *Soil Water Res* 9(1):25–30
- Khaleghi MR (2018) Application of dendroclimatology in evaluation of climatic change. *J For Sci* 64(3):139–147
- Khaleghi MR, Varvani J (2018a) Sediment rating curve parameters relationship with watershed characteristics in the semiarid river watersheds. *Arab J Sci Eng* 43(7):3725–3737
- Khaleghi MR, Varvani J (2018b) Simulation of relationship between river discharge and sediment yield in the semi-arid river watersheds. *Acta Geophys* 66(1):109–119
- Khalid K, Ali MF, Abd Rahman NF, Mispan MR, Haron SH, Othman Z, Bachok MF (2016) Sensitivity analysis in the watershed model using SUFI-2 algorithm. International conference on efficient & sustainable water systems management toward worth living development, 2nd EWaS 2016. *Procedia Eng* 162:441–447. <https://doi.org/10.1016/j.proeng.2016.11.086>
- Li C, Qi J, Feng Z, Yin R, Songbing Z, Zhang F (2010) Parameters optimization based on the combination of localization and auto-calibration of the SWAT model in a small watershed in Chinese Loess Plateau. *Front Earth Sci China* 4(3):296–310. <https://doi.org/10.1007/s11707-010-0114-5>
- Mbonimpa EG, Yuan Y, Mehaffey MH, Jackson MA (2012) SWAT model application to assess the impact of intensive corn farming on runoff, sediments and phosphorous loss from an agricultural watershed in Wisconsin. *J Water Resour Prot* 4:423–431. <https://doi.org/10.4236/jwarp.2012.47049>
- Memarian H, Balasundram SK, Abbaspour KC, Talib J, Alias S, Teh CBS (2013a) SWAT-based hydrological modeling of tropical land-use scenarios. *Hydrol Process J* 59(10):1808–1829. <https://doi.org/10.1080/02626667.2014.892598>
- Memarian H, Tajbakhsh M, Balasundram SK (2013b) Application of swat for impact assessment of land use/cover change and best management practices: a review. *Int J Adv Earth Environ Sci* 1(1):25–34
- Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual models. Part I. A discussion of principles. *J Hydrol* 10(3):282–290
- Neitsch SL, Arnold JG, Kiniry JR, Williams JR, King KW (2005) Soil and water assessment tool theoretical documentation—version 2005. In: Soil and Water Research Laboratory, Agricultural Research Service. US Department of Agriculture, Temple
- Nkonge LK, Sang JK, Gathenya JM, Home PG (2014) Comparison of two calibration-uncertainty methods for soil and water assessment tool in stream flow modelling. *J Sustain Res Eng* 1(2):40–44
- Olyae E, Banejad H, Chau KW, Melesse AM (2015) A comparison of various artificial intelligence approaches performance for estimating suspended sediment load of river systems: a case study in United States. *Environ Monit Assess* 187:189. <https://doi.org/10.1007/s10661-015-4381-1>
- Phomcha P, Wirojanagud P, Vangpaisal T, Thaveevouthti T (2011) Predicting sediment discharge in an agricultural watershed: a case study of the Lam Sonthi watershed, Thailand. *SCI ASIA* 37(1):43–50. <https://doi.org/10.2306/scienceasia1513-1874.2011.37.043>
- Raneesh KY, Santosh GT (2011) A study on the impact of climate change on streamflow at the watershed scale in the humid tropics. *Hydrol Sci J* 56(6):946–965. <https://doi.org/10.1080/0262667.2011.595371>
- Robert SA, Scot WW, Hans RZ (2008) Hydrologic calibration and validation of SWAT in a snow dominated rocky mountain watershed, Montana, USA. *J Am Water Resour Assoc* 44(6):1411–1430
- Shimelis GS, Srinivasan R, Dargahi B (2008) Hydrological modeling in the Lake Tana Basin, Ethiopia using SWAT model. *Open Hydrol J* 2:49–62
- Spruill CA, Workman SR, Taraba JL (2000) Simulation of daily and monthly stream discharge from small watersheds using the SWAT model. *Trans Am Soc Agric Eng* 43(6):1431–1439. <https://doi.org/10.13031/2013.3041>
- Saleh A, Du B (2004) Evaluation of SWAT and HSPF within basins program for the upper North Bosque River watershed in central Texas. *Trans Am Soc Agric Eng* 47(4):1039–1049. <https://doi.org/10.13031/2013.10387>
- Shamshirband S, Jafari Nodoushan E, Adolf J, Abdul Manaf A (2019) Ensemble models with uncertainty analysis for multi-day ahead forecasting of chlorophyll a concentration in coastal waters. *Eng Appl Comput Fluid Mech* 13(1):91–101. <https://doi.org/10.1080/19942060.2018.1553742>
- Thampi SG, Raneesh KY, Surya TV (2010) Influence of scale on SWAT model calibration for streamflow in a river basin in the humid tropics. *Water Resour Manag* 24(15):4567–4578. <https://doi.org/10.1007/s11269-010-9676-y>
- Setegn SG, Shimelis G, Dargahi B, Srinivasan R, Melesse AM (2010) Modeling of sediment yield from Anjeni-Gauged watershed, Ethiopia using the SWAT model. *J Am Water Resour Assoc* 46:514–526. <https://doi.org/10.1111/j.1752-1688.2010.00431.x>
- Tobin KJ, Bennett ME (2009) Using SWAT to model stream flow in two river basins with ground and satellite precipitation data. *J Am Water Resour Assoc* 45(1):253–271. <https://doi.org/10.1111/j.1752-1688.2008.00276.x>
- Van Griensven A, Meixner T (2006) Methods to quantify and identify the sources of uncertainty for river basin water quality models. *Water Sci Technol* 53(1):51–59
- Varvani J, Khaleghi MR (2019a) Investigation of application of storm runoff harvesting system using geographic information systems (GIS): a case study of the Arak watershed, Markazi (Iran). *Appl Water Sci* 8(6):180
- Varvani J, Khaleghi MR (2019) A performance evaluation of neuro-fuzzy and regression methods in estimation of sediment load of selective rivers. *Acta Geophys* 67(1):205–214
- Varvani J, Khaleghi MR, Gholami V (2019) Investigation of the relationship between sediment graph and hydrograph of flood events (case study: Gharachay River Tributaries, Arak, Iran). *Water Resour* 46(6):883–893
- Wangpimool W, Pongput P, Sukvibool C, Sombatpanit S (2013) The effect of reforestation on stream flow in Upper Nan river basin using Soil and Water Assessment Tool (SWAT) model. *Int Soil Water Conserv Res* 1(2):53–63. [https://doi.org/10.1016/S2095-6339\(15\)30039-3](https://doi.org/10.1016/S2095-6339(15)30039-3)
- Wischmeier WH, Smith DD (1978) Predicting rainfall erosion losses—a guide for conservation planning. U.S. Department of Agriculture, Agriculture Handbook, vol 537
- Xiaobo J (2008) Impacts of land cover changes on runoff and sediment in the Cedar Creek Watershed, St. Joseph River, Indiana, United States. *J Mt Sci* 5(2):113–121. <https://doi.org/10.1007/s11629-008-0105-0>

- Xu ZX, Pang JP, Liu CM, Li JY (2009) Assessment of runoff and sediment yield in the Miyun reservoir catchment by using SWAT model. *Hydrol Process* 23:3619–3630. <https://doi.org/10.1002/hyp.7475>
- Yang J, Abbaspour KC, Reichert P, Yang H (2008) Comparing uncertainty analysis techniques for a SWAT application to

Chaohe Basin in China. *J Hydrol* 358(1–2):1–23. <https://doi.org/10.1016/j.jhydrol.2008.05.012>

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.