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Uncertainty Analysis of Hydrological Parameters in the Sarbaz Watershed Using the SWAT Model and the SUFI-2 Algorithm

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ABSTRACT

The SWAT model was used to simulate the monthly runoff of the Sarbaz watershed (6324 Km^2) located in Sistan-va- Baluchestan province of Iran. The main objective of the study was to evaluate the accuracy of the SWAT model simulation in the calibration and validation stages and to analyze the uncertainty of input parameters of the model. A hydrological modeling approach was used to identify the sensitive hydrological input parameters of the watershed through the SUFI-2 algorithm. The important parameters of the model were determined by the general sensitivity analysis, and the model was, then, calibrated for 1997-2005 with two years as the warm-up (1997–1998) by a multi-objective optimization approach using the SWAT-CUP program. Subsequently, the model was validated on a dataset of five years (2006–2010). To reduce the uncertainty, different components of the water balance were considered in the calibration stage, and data from the Pishin station were used. Based on the p-value and t-stat, the most sensitive parameters were the curve number and the parameter of alpha in return flow, and the parameter with the lowest sensitivity was the percentage of deep aquifer feeding on the shallow aquifer. The performance of the model was tested using two objective functions of Nash–Sutcliffe efficiency (NSE) and coefficient of determination (R^2). R^2 and NSE were estimated at 0.83 and 0.80 in calibration and 0.53 and 0.38 in validation, respectively. Acceptable values were also obtained for the uncertainty assessment indicators. The p-factor and r-factor were calculated to be 0.76 and 1.53 for the calibration stage and 0.72 and 1.23 for the validation stage, respectively. In addition to confirming the goodness of fit for the conditions of the Sarbaz watershed, these results indicate that the model can positively affect the simulated runoff in future projects due to the dynamics of the model parameters in the specified uncertainty interval.

1. Introduction

Currently, one of the most important challenges faced by watershed managers is the frequency of floods and droughts, most of which are associated with the hydrological behavior of watersheds or intense changes in land use and vegetation destruction by human activities in watersheds. Therefore, water and soil conservation and proper land use will greatly affect the prediction of floods and natural phenomena due to the large number of hydrological parameters that are subject to uncertainty. Today, one of the most important concerns in predicting natural phenomena, e.g., floods, is to assess uncertainty and identify patterns that govern their behavior, and this is possible through their simulation with the help of hydrological models.

Limited measurement methods in hydrology (in arid and semi-arid watersheds) and the need to have a way to generalize existing statistics to non-statistical basins or places without hydrometric stations, as well as the simulation of future hydrological changes, are other reasons for hydrological simulation (Beven and Freer, 2001). Therefore, in large watersheds, such as Kajo and Kahir river basins adjacent to the Sarbaz watershed, if these hydrological models, such as those used in this study area (in the Sarbaz watershed), achieve good results, they can be generalized to adjacent and similar river basins due to similar climatic conditions and statistical limitations.

Higher life standards, demographic changes, water and land-use policies, and other external factors increase local, regional, and national pressure on water supply for irrigation, energy production, industrial use, domestic use, and the environment (Abbaspour et al., 2015). Hydrological models are important tools for sustainable planning of water resources in response to changes in their demand (Arnold et al., 1998). For planning and implementation of water-related projects, it is essential to use new models and methods to determine the components of the water balance

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of watersheds (Sepehri et al., 2018). Given the recent droughts, it has also become increasingly valuable to plan for water resources management and conservation, as well as the protection of local communities (Khosravian et al., 2019). Many researchers have even used different models to investigate the influence of such parameters as climate change and population growth on water consumption (Akbarpour and Ghoochanian, 2019). These parameters and components are reviewed in the following paragraphs.

Today, there are many hydrological models to calculate water discharge more accurately and faster than traditional measurement methods. One of these models is the SWAT (Water and Soil Assessment Tool), which is a basin-scale model integrated with GIS to improve simulated flow results from precipitation and physical properties of the basin (Ang and Oeurng, 2017). This model is successfully used to simulate runoff, sediment load, and soil nutrients in many basins across Asia, the Americas, and Europe (Di Luzio and Arnold, 2004). Some of the most important studies on runoff simulation and identification of uncertainty of various parameters of watersheds, which have especially been conducted by the SWAT model, are reviewed below.

Arnold et al. (1998) were among the first to simulate the hydrological balance of the Mississippi River Basin in the United States using the SWAT model. Their results showed that large-scale hydrological balance can realistically be simulated using the SWAT model. Zhixiang et al. (2015) simulated the water balance in a mountainous watershed in the northwest of China using the SWAT model calibration. Their research results showed that the model outputs were a suitable and reliable reference for evaluation and water resources management in such basins.

Abbaspour et al. (2007) also used the SWAT model to simulate the processes affecting water, sediment, and nutrient balance in the Tour Basin of Switzerland. The results revealed that the runoff and nitrate simulations performed very well and the sediment and phosphorus simulations performed relatively well. They concluded that the SWAT model can be a very useful tool for watershed management. Alansi et al. (2009) used the SWAT model to simulate river flow in the Barnam watershed with an area of 1,097 Km^2. The coefficient of determination (R^2) and the Nash-Sutcliffe coefficient were 0.65 and 0.62 in the monthly runoff calibration stage and 0.93 and 0.92 in the validation stage, respectively. This study shows that the SWAT model is capable of successfully simulating flow in humid tropical areas and can be used to study the effects of land-use change.

In another study, Chantha et al. (2011) used the SWAT model to predict daily runoff, sediment, and organic carbon levels in an agricultural watershed in southwestern France with an area of 1110 Km^2. The SWAT model predicted that the average annual rainfall (726 mm) of the watershed for the whole simulation period would be divided into evapotranspiration (78.3%), infiltration (14.1%), loss (0.5%), and surface runoff (7.1%). The average surface runoff for the whole simulation period was 138 mm compared to the observed value (136 mm). Finally, they concluded that the SWAT model simulated the daily runoff values better than the daily sediment values and that it could be a good instrument to study the water balance components in the watersheds, which are heavily affected by the intense agricultural activities, for water management approaches.

Lirong and Jianyung (2012) simulated the monthly flow of the Beijiang River using the SWAT model. The river basin with an area of 38831.95 km^2 is located in southern China. The studied watershed was divided into 29 sub-watersheds and 345 hydrological response units (HRU). The statistical data for 20 years (1961 to 1990) were used to validate the model. The results showed that the model was capable of accurately simulating the monthly flow of the river.

Also, Salmani et al. (2013) used the SWAT model to optimize rainfall-runoff parameters in the Ghazaghli watershed of Golestan province, Iran. After identifying the sensitive parameters, the flow model was simulated with a relatively average coefficient of determination (0.69 and 0.86). Their results showed the low uncertainty and high accuracy of the model so that most of the observational data were in the range of 95% uncertainty.

Most studies that were reviewed above have been mainly focused on runoff simulation using the SWAT model. Basirani et al. (2015) addressed the sensitivity analysis of the SWAT model for estimating sediment load in the Doiraj watershed. The results as to the estimation of the monthly sediment load using the default coefficients were not satisfactory, but after using the SUFI-2 algorithm and inverse modeling and determining the optimal values of the input parameters to the model, the coefficients of determination and the Nash Sutcliffe improved model performance to an acceptable level.

Another category of research has focused on using the SWAT model to estimate hydrological and hydrogeological parameters. An example is the work of Mostafazadeh et al. (2016) in the Balkhlu Chay watershed in Ardabil province. The results indicated that the most sensitive parameters included curve number, evaporation coefficient from the soil surface, available soil water, precipitation, snowmelt temperature, and lag time of aquifer feeding, which were accurately estimated by the model. Also, in an attempt to estimate the parameters of the model in the Golestan Ghazagli watershed, Jafarzadeh et al. (2016) introduced the curve number as the most sensitive parameter in that watershed. They concluded from the statistical indicators such as coefficient of determination and Nash-Sutcliffe coefficient that the SWAT model could accurately estimate the runoff. In addition, ZareGarizi and Talebi (2017) simulated the water balance of the Qarahsoo watershed in Golestan province using the SWAT model. Their results showed that the SWAT model was suitable for simulating the hydrological parameters of the watershed.

The efficiency of the SWAT model for runoff simulation in large watersheds such as the Talar river basin in Mazandaran province has also been investigated. In this regard, Gholami et al. (2017) obtained results similar to Jafarzadeh et al. (2016) so that they also introduced the runoff curve number as the most sensitive parameter of the model. In 2018, a lot of studies were conducted. For example, Aalami et al. (2018) used two types of algorithms, i.e., GLUE and SUFI-2, to calibrate and analyze the uncertainty of hydrological parameters and estimate runoff and suspended load in the Sufi Chai basin in East Azerbaijan. The SUFI-2 method was found to be a more effective algorithm for calibration and determination of the model uncertainty.

Tejaswini and Sathian (2018) also calibrated the SWAT model for the Kunthipuzha watershed using the SUFI-2 algorithm. Calibration was performed for a 7-year period from 2000 to 2006 and validation for a 3-year period from 2007 to 2009. The values of the Nash-Sutcliffe coefficient and the coefficient of determination (R^2) were 0.81 and 0.82 for the calibration period and 0.73 and 0.88 for the validation period, respectively, implying the very good performance of the model in hydrological simulation. The p-factor and r-factor were 0.69 and 0.47 for the calibration period and 0.57 and 0.51 for the validation period, respectively. SUFI-2 was found to be very convenient and easy to use versus the other automatic calibration methods.

Other examples of research conducted on the SWAT model include Agakhani et al. (2019) in the Taleghan watershed, Tajbakhsh et al. (2018) in Zoshk, Nouri et al. (2019) in the Mehrgard watershed of Semirom, and Rezaei Moghaddam et al. (2019) in the Lenbaran Chay watershed. According to the above studies, the performance of the SWAT model in estimating runoff has been described to be satisfactory. The GLUE and SUFI-2 algorithms have also successfully estimated the model parameters in the validation and calibration stages.

Du et al. (2019) simulated the runoff of the Dagu River Basin in Qingdao, Shandong Province, using the SWAT model. In this study, like other researchers, they used the SWAT hydrological model using Arc GIS software with the inputs including DEM, soil, land use, meteorological and runoff data (observational). The simulations were then performed based on runoff data for 1986-2000 and the sensitive parameters were determined by SWAT-CUP-2012. The coefficient of determination (R^2) and the efficiency coefficient of Nash-Sutcliffe were determined to be more than 0.8 and 0.70, respectively. Then, the effect of land-use change and climate change on the surface runoff of the Dagu River Basin was investigated. The simulation results had an important reference value and scientific and practical importance for the sustainable development of this basin in the future and the reasonable allocation of water resources.

Salimirad et al. (2020) identified and analyzed the uncertainty of hydrological parameters in the Kardeh watershed using the SWAT model. According to the values of the Nash-Sutcliffe efficiency coefficient of 0.64 in the calibration periods and 0.68 in the validation periods, the developed SWAT model showed good efficiency for simulating runoff in this watershed. The GLUE algorithm also determined the calibration and validation periods of 68% and 93%, respectively. The results of this study confirmed the good fit of the model and the hydrological parameters had a good fitness with the conditions of the watershed of Kardeh Dam.

Considering the above review of the literature, it should be stated that the SWAT model is a robust tool in the field of soil and water studies (Nasserabadi et al., 2016). Also, the results of recent studies have shown that this model is widely used for various purposes around the world. In other words, it is inferred from the above researches that the SWAT model has worked well both in estimating runoff and suspended sediments and in determining the amount of pollution caused by mineral elements in large river basins. Even in some cases, the performance of the SWAT model in simulating river flow in watersheds with poor hydrological statistics has been reported to be satisfactory (Rode et al., 2010). Therefore, considering the vast area of the Sarbaz watershed (6324 Km^2) and the poor statistical data that exist in most basins of Balochistan, estimating runoff and determining the uncertainty of hydrological parameters of the watershed is not far from expectation. Therefore, the main purpose of this study is to apply and implement the SWAT model to the monthly runoff simulation of the Sarbaz watershed and to evaluate the accuracy of the model simulation in the calibration and validation stages using the SUFI-2 algorithm in SWAT-CUP software.

2. Materials and Methods

2.1. Study area

The great Sarbaz watershed is located in the southeast of Iran between longitudes 60º56' and 61º35' E. and latitudes 26º and 27º05' N. The average elevation of the Sarbaz watershed is 932 meter above sea level, and the area of this basin up to the Pishin hydrometric station is 6324.29 km^2. According to the statistics of the stations within the watershed, i.e., Sarbaz and Bahouklat stations, the average annual rainfall of the watershed varies from 179.4 to 102.1 mm. This region is subject to frequent monsoons and heavy summer rains. The direction of the river is from north to south and its average annual discharge is about 6.63 m^3/s at the Pishin hydrometric station. The longest main waterway of the watershed is 172 km. The average maximum temperature is 29ºC, and the average minimum temperature is 15ºC. In general, there are 10 main land uses in the region. The highest percentage of land area is poor rangelands (54%) and the lowest is water surfaces (0.1%) (Damadi, 2017). Figure 1 shows the location of the watershed with its hydrographic network and sub-watersheds.

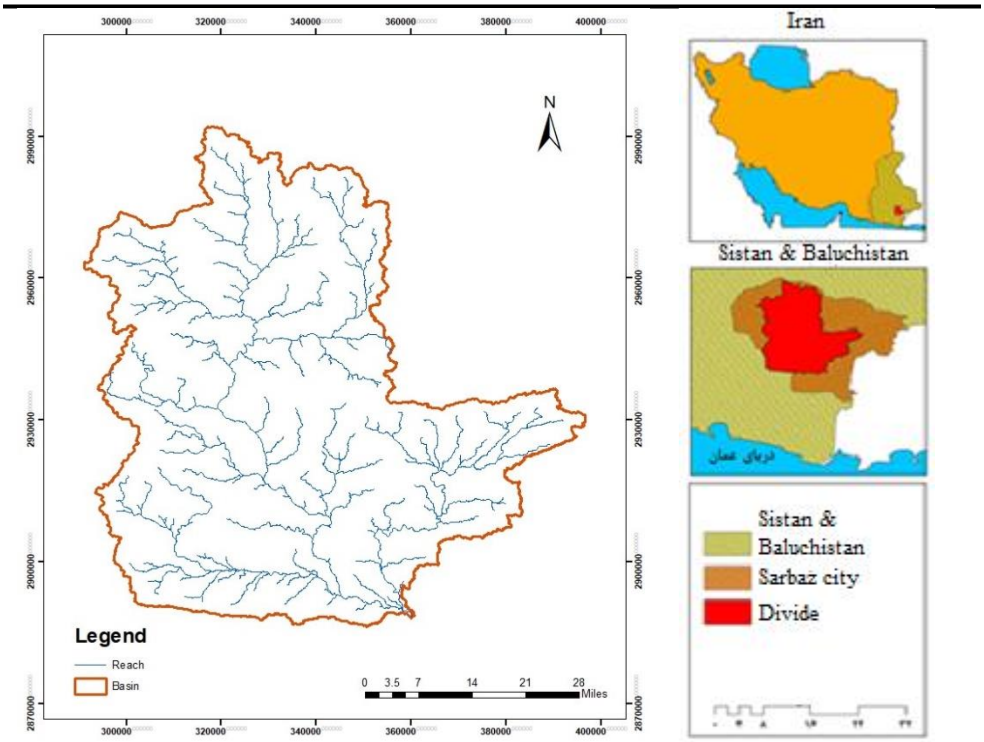

Fig. 1. The location of the great Sarbaz watershed in Sistan-va-Baluchistan province, Iran

2.2. Introducing the SWAT model

SWAT, which stands for Soil and Water Assessment Tool, was first developed and established by Jeff Arnold at the USDA United State Department of Agricultural in 1990 (Arnold et al., 1998). SWAT is a semi-distributed, process-based hydrological model that can simulate hydrological processes, particularly precipitation-runoff. The SWAT model simplifies hydrological processes using balance equations and has many parameters that must be estimated before applying the model (Bayat et al., 2018). The simulation of the watershed system in the SWAT model can be divided into two general sections, including the ground phase and the water phase. The terrestrial phase is related to surface processes and the entry of water, sediment, and chemical elements into the main waterway of each sub-watershed. The aqueous phase (routing) simulates the processes of streams and canals, including the movement of water, sediment, and chemicals (Neitsch et al., 2005). Important model processes are as follows:

2.3. Hydrological cycle

In the SWAT model, the hydrological cycle is simulated based on the water balance equation (Arnold et al., 2012). The components of the water balance are shown in Equation 1:

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

in which

SW_t: Final amount of water in soil (mm),

SW_0: Initial amount of water in the soil (mm),

R_{day}: Daily rainfall (mm),

Q_{surf}: Amount of surface runoff (mm),

E_a: Evapotranspiration rate (mm),

W_{seep}: The amount of water entering from the soil profile into the unsaturated zone (mm),

Q_{gw}: Groundwater flow into the main channel (mm)

The water balance for each HRU in the SWAT model is calculated by four storage volumes, including snow, soil profile layer (0-2 m depth), shallow aquifer layer, and deep aquifer layer (Basaltupour and Hosseinzadeh, 2016).

2.4. Surface runoff

In the SWAT model, there are two methods to estimate surface runoff: a) the curve number method and b) the Green-Ampt infiltration relationship (Equation 2) (Tolson and Shoemaker, 2004), the components of which are described below:

$$Q_{surf} = \frac{\left(R_{day} - I_n\right)^2}{\left(R_{day} - I_a - S\right)} \quad (2)$$

in which

Q_{surf}: Daily surface runoff *(mm),*

R_{day}: Daily rainfall depth *(mm),*

S: Humidity retention parameter in SCS curve number *(mm),*

I_a: Initial maintenance or initial amount of water uptake, which includes surface storage, uptake by vegetation, and infiltration before runoff *(mm),*

In the Green-Ampt formula, or Equation (2), the Infiltration velocity is calculated by Equation (3) (Green and Ampt, 1911).

$$f_{inf,t} = K_e.\left(1 + \frac{\psi_{wf}.\Delta\theta_v}{F_{inf,t}}\right) \quad (3)$$

in which

$f_{inf,t}$: Infiltration rate at time t (mm/hr^{-1}),

K_e: Effective hydraulic conductivity (mm/hr^{-1}),

ψ_{wf}: Wetting front matric potential *(mm),*

$v_{\Delta\theta}$:Volume changes in soil moisture in the wetting front (mm/mm^{-1})

$F_{inf,t}$: Cumolative infiltration at time *t (mm)*

2.5. Potential evapotranspiration

In the SWAT model, there are three methods for calculating evapotranspiration: (a) Penman-Monteith method (Monteith, 1965), (b) Priestley-Taylor method, and (c) Hargreaves-Samani method. The parameter requirements of the Penman-Monteith method include air temperature, solar radiation, and relative humidity (Priestly and Taylor, 1972) and the Hargreaves-Samani method requires only air temperature (Hargreaves and Samani, 1985).

The SWAT model estimates soil evaporation and plant evaporation separately based on Ritchie's (1972) method. Evaporation from the soil surface is estimated by an exponential function of soil depth and the amount of water in the soil. Evaporation from plants is also obtained using a linear function with the help of potential evapotranspiration, leaf area index, root depth, and the amount of water in the soil. The moisture content of different soil layers at any time and place is calculated and estimated taking into account the sum of the above factors.

Finally, after determining the surface runoff by the curve number or the Green-Ampt method, the amount of runoff that is to enter the main waterway is calculated. The Manning equation is used to determine the flow velocity and the variable storage method, or the Muskingum method to routing the flow of water in larger channels. However, it should be noted that the amount of water transfer losses over the flow path and the time delay of surface runoff are also considered for large watersheds, such as Sarbaz, whose concentration time lasts more than one day depending on the intensity of storms.

More details on water balance equations, and in particular the estimation of all components of the water balance equation, are available in Neitsch et al. (2005).

2.6. Data used by the SWAT model in the study

The data required by the model include the basic maps and meteorological variables. The maps include topographic, land use, and soil information layers. Daily statistics of temperature and precipitation of the stations and daily discharge statistics of the stations in the region, especially the runoff discharge of the Pishin sation (located just before outlet), were used and analyzed. Meteorological statistics were received from the Meteorological Organization and hydrometric statistics from the General Directorate of Regional Water of Sistan-va-Baluchestan Province. The time series of statistical data in both meteorological and hydrometric types were collected and used for the period of 1970-2010. The meteorological data included precipitation, minimum and maximum temperatures, wind speed, solar radiation, and relative humidity of Sarbaz and Bahouklat synoptic stations, and the hydrometric data included monthly discharges of the Pishin station in the statistical period of 1997-2010. The types and specifications of the studied stations whose information is used are shown in Table (1).

2.7. Hydrological modeling using the SWAT model

To simulate runoff using the SWAT model, the Sarbaz watershed was first divided into a number of sub-watersheds based on the Digital Elevation Model (DEM with 30-m resolution). Then, according to the uniformity and homogeneity of the soil and land-use maps, hydrological response units (HRU) were obtained using DEM. Physiographic characteristics of all hydrological units including slope and waterway dimensions for sub-watersheds were calculated and simulated internally by the model based on DEM. This watershed segmentation enables the SWAT model to reflect differences in evapotranspiration for different land and soil uses, increases computational accuracy, and provides a better physical description of the water balance (Judi Hamzehabad et al., 2016).

Two methods can be used to enter or introduce the watershed boundary, sub-watersheds, and hydrographic network to the SWAT model. In the first method, a software package is used in which the format of the prepared maps can be entered into the model, and in the second method, the SWAT model is internally produced by its own algorithms using DEM. In this study, the second method was used to extract watershed divisions, but after applying improvements (removal of depressions & spikes) which was done on the DEM map. Considering the threshold of 1000 ha as the minimum acceptable area for drainage area, in the end, the Sarbaz watershed was divided into 353 sub-watersheds. In the next step, the homogeneous units of HRU were extracted using the overlay technique or superimposing soil maps, land-use, and slope classes (resulting from DEM). In the Sarbaz watershed, some land -uses, e.g., rangeland (53% of the watershed area), slope classes from 0 to 21 degrees (58% of the watershed area), and loamy soil category (82% of the watershed area), have the largest area in the watershed. Considering the amount of area and predominance of rangeland land-use, slope classes, and soil type in each sub-watershed, 1131 units of almost homogeneous HRU were extracted. The map of the sub-watersheds and the drainage network of the Sarbaz watershed are shown in Figure 2.

Table 1. Details of stations used in Great Sarbaz watershed

Height	**Statistical period**	**Latitude**	**Longitude**	**Station type**	**Station name**
880	1997-2010	26°37'59"	61°16'00"	Automatic rain gauge	Sarbaz
120	1997-2010	25°41'59"	61°24'35"	Evaporation measurement	Bahoukalat
257	1997-2010	26°07'00"	61°37'00"	Hydrometric	Pishin

After mapping the HRUs, the meteorological data on daily precipitation and minimum and maximum daily temperatures of the Sarbaz and Bahouklat stations were entered into the model. To compare the measured and simulated results through the model and evaluate the SWAT model in runoff simulation, the monthly discharge data of the Pishin hydrometric station for the period of 1997-2010 were used. Also, to calibrate, validate, and analyze the uncertainty of the model parameters, the SUFI-2 algorithm was used in the SWAT-CUP software. Finally, the correlation coefficient (R^2), efficiency coefficient of Nash-Sutcliffe (ENS), p-factor, and R-factor indices were used to evaluate the model's capability of simulating the flow of observational data from the Pishin station and to identify and analyze the uncertainty of the model parameters.

2.8. Validation, calibration, and analysis of the uncertainty of model parameters

In this study, the SUFI-2 algorithm in SWAT-CUP software was used as one of the optimized and successful algorithms to identify the parameters of the SWAT model. The reason for choosing the SUFI-2 program was its capability of managing a large number of parameters, simultaneity of sensitivity and uncertainty analyses, calibration, and model validation. Since the selection of appropriate values for model calibration is a time-consuming and costly process, reverse modeling was used as a suitable method for calibration and uncertainty analysis. The SUFI-2 model actually is the opposite of the SWAT model. That is, it takes observational data and the allowable range of model parameters involved in calibration (Abbaspour et al., 2007).

2.9. Criteria for uncertainty analysis by the SUFI-2 algorithm

The SUFI-2 method considers all uncertainties, including input uncertainties (such as rainfall), conceptual model, parameters, and measured data in modeling. The uncertainty, which includes all the above, is measured by an index called the p-factor, which represents the percentage of measured data that falls within the 95% uncertainty band (95_{PPU}). The 95_{PPU} criterion is obtained by calculating the corresponding values of 2.5% probability as low limit and 97.5% as high limit using 5% omission of very bad simulations. Since the effect of all uncertainty factors is reflected in the measured variable, the p-factor is a good measure of the strength of the uncertainty analysis performed. The R-factor is another parameter that determines the uncertainty analysis in the SUFI-2 program, which is the average 95% confidence bandwidth obtained by dividing the standard deviation of the simulation data by the actual data. Theoretically, the numerical values of r-factor and p-factor are in the range of 0-100% and zero to infinity, respectively. But in practice, it is not possible to reach such figures (Abbaspour, 2015). Now, the details of the steps in the SUFI-2 method are provided:

1- In the first step, the objective function g(ϴ) and the factors range {ϴabs min ∗ ϴabs max} are defined.

2- The Latin cube sampling method in the range defined in the previous stage is used to generate a set of factors and the value of the objective function for each set of factors. The values of the objective function are evaluated using the Jacobin matrix *j* and the matrix and covariance of factors *c* according to Equation 4. (S_g^2 is the variance of the values of

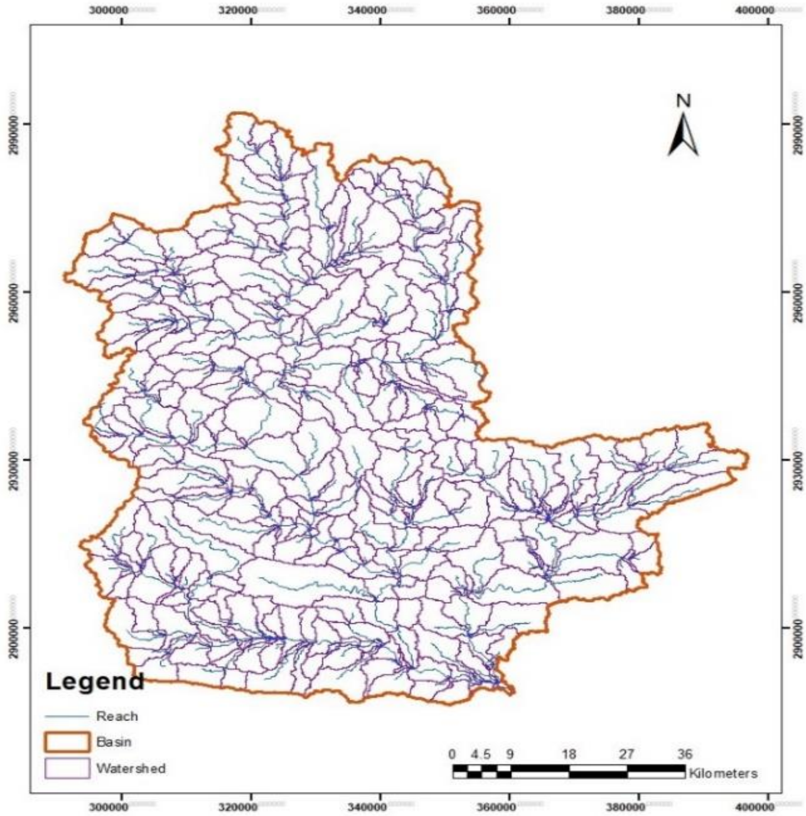

Fig. 2. Hydrographic map and boundary of hydrological response units of the great Sarbaz watershed

the objective function, obtained from running the model m times using *n* numbers of factors.)

$$J_{ij} = \frac{\Delta_{gi}}{\Delta\theta_j} \,.\, i = 1.\cdots.c_2^m \,.= 1.\cdots n \qquad c = S_g^2 (J^T J)^{-1} \tag{4}$$

where Ɵj* is the value of the Ɵj parameter in the optimal objective function and *v* is the degree of freedom or m-n.

3- The 95_{PPU} interval is calculated. Then, the p-factor and the r-factor indices (the percentage of observed data that fall into the 95_{PPU} interval) are determined by Equation 5:

$$r - factor = \frac{\frac{1}{n}\sum_{tj=1}^{n}\left(Y_{tj.97.5\%}^{M} - Y_{tj.2.5\%}^{M}\right)}{Q_{obs}} \tag{5}$$

where $Y_{tj.2.5\%}^{M}$ and $Y_{tj.97.5\%}^{M}$ represent the upper and lower boundaries of the uncertainty of 95_{PPU} and Q_{obs} is the deviation criterion from the observed data. The best results are obtained when 100% of the measured data overlap with 95_{PPU}. In other words, the p-factor is equal to 1 and the r-factor is less than zero. If the values of these two indices are satisfactory, the defined interval of factors will be a subsequent probability distribution; otherwise, the new interval of factors will be calculated based on Equations (6) and (7), and steps 1 to 4 will be repeated.

$$\theta_{j.min.new} = \theta_{j.lower} - max\left(\frac{\theta_{j.lower} - \theta_{j.min}}{2}.\frac{\theta_{j.max} - \theta_{j.upper}}{2}\right) \tag{6}$$

$$\theta_{j.max.new} = \theta_{j.upper} + max\left(\frac{\theta_{j.lower} - \theta_{j.min}}{2}.\frac{\theta_{j.max} - \theta_{j.upper}}{2}\right) \tag{7}$$

2.10. Evaluation criteria of model performance

Other evaluation indices of the model performance are correlation coefficient (R^2) and Nash-Sutcliffe efficiency coefficient (NSE), which were used in this study to measure the accuracy of the model at the validation and calibration stages. R^2 (coefficient of explanation or determination) indicates the correlation between the observed and simulated values using the regression analysis method, and its value varies between 0 and 1. If all predicted and measured values are equal, the value of the coefficient of determination will be equal to 1 (Equation 8).

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(Q_i^{sim} - \bar{Q}_i^{sim}\right)\left(Q_i^{obs} - \bar{Q}_i^{obs}\right)\right]^2}{\sum_{i=1}^{n}\left(Q_i^{sim} - \bar{Q}_i^{sim}\right)^2 \sum_{i=1}^{n}\left(Q_i^{obs} - \bar{Q}_i^{obs}\right)^2} \quad (8)$$

where, Q_i^{sim} and Q_i^{obs} represent simulated and observed values and $\bar{Q}_i^{sim}$ and $\bar{Q}_i^{obs}$ show mean simulated and mean observed values, respectively.

The Nash-Sutcliffe coefficient is another index that explains the relative difference between simulated and observed values, which is expressed as Equation 9 (Moriasi et al., 2007).

$$NS = 1 - \frac{\sum_{i=1}^{n}(Q_{mi} - Q_{si})^2}{\sum_{i=1}^{n}(Q_{mi} - \bar{Q}_m)^2} \quad (9)$$

where Q_{si}, Q_{mi}, and $\bar{Q}_m$ represent simulated discharge, measured discharge, and mean measured values, respectively.

3. Results and Discussion

3.1. Calibration and uncertainty analysis

The relative importance of the input parameters in the calibration phase is evaluated according to its output type, and typically using the sensitivity analysis. Due to the fact that many parameters in the SWAT model are involved in simulating the monthly runoff, it is important to understand the watershed characteristics and hydrological processes based on data availability and before running the model in the calibration phase. Therefore, eliminating the parameters that had less impact on the monthly discharge of the Sarbaz watershed was one of the most important tasks in this study. However, before the calibration and validation of the model using SWAT-CUP software, the parameters that had a greater impact on the average monthly discharge of the watershed were identified. To perform the sensitivity analysis, different parameters with different minimum and maximum ranges were tested. Finally, 20 parameters were selected based on personal experience and the literature review. But, because, unlike the previously selected hydrological parameters, the parameters of this research had different ranges relative to the final selected parameters, it was once again implemented in SWAT-CUP software to obtain better results. In summary, to perform uncertainty analysis, we tried to pay attention to various parameters and processes that were more effective in simulating the monthly runoff. Finally, 10 parameters were selected out of the 20 parameters for sensitivity analysis in this study (Table 2) based on the personal experience and literature review (Nasserabadi et al., 2016; Akhavan and Judy Hamzehabad, 2015; Jalalvand et al., 2016; Kavian et al., 2017; Aalami et al., 2018; Salimirad et al., 2020).

In this study, the general sensitivity analysis was used to identify sensitive parameters to perform the calibration step. As shown in Table (2), the most important parameters in terms of the degree of sensitivity are the SCS curve number for medium humidity conditions, baseflow alpha-factor (alpha parameter in return flow), effective hydraulic conductivity of the bed in the main channel, the average available water capacity of the soil layer, and so on. The parameters with higher t-stat and lower p-value are ranked in Table 2 in terms of importance, sensitivity, and impact on the average monthly flow rate, respectively. Finally, after several times of model execution, the SUFI-2 algorithm determined the sensitivity of the parameters using the p-value and t-stat criteria. Accordingly, any parameter that has a higher t-stat value and a lower p-value (close to zero) was introduced as a sensitive parameter. Since the selected parameters had both higher t-stat and lower p-value, they were classified in Table 2 according to their importance and sensitivity to the average monthly flow rate.

According to Table 2, the parameter "curve number for medium humidity conditions (r-CN2.mgt)" has the highest and the parameter "percentage of deep aquifer feeding from the shallow or non-enclosed aquifer (v_RCHRG_DP.gw)" has the lowest effect on the monthly discharge of the watershed. In other words, the parameter with the lowest p-value index and the highest t-stat value was recognized as the highly sensitive parameter and the parameter with the highest p-value and the lowest t-stat value was recognized as the less sensitive parameter among these 10 parameters, respectively. Nasserabadi et al. (2016), Akhavan and Judy Hamzehabad (2017), Kavian et al. (2017), Aalami et al. (2018), Rezaei Moghadam et al. (2019), and Salimirad et al. (2020) reported similar results as explained in this study. This conclusion shows that in most watersheds where the SWAT model is used to estimate the monthly flow, almost most of the selected parameters in calibration stage represent the environmental and geographical similarities within these areas, and there is a large percentage of commonality between these parameters in terms of parameter range and type.

After preparing the necessary information, the SWAT hydrological model was calibrated using the observed data from 1997 to 2005 for 9 years including 2 years as the warm-up (1997–1998) and the average monthly flow measured at the Pishin hydrometric station. In the calibration stage, an attempt was made to make the model compatible as much as possible in the study area by improving the parameters and reducing the model errors. In fact, calibration involves changing the values of the model parameters in such a way that when comparing the values predicted by the model with the observed (measured) data, the difference between them is minimized.

To optimize the initial range of input parameters, it was assumed that the statistical distribution of the parameters in those ranges was uniform, so using the general sensitivity analysis, 485 samples were selected from each interval. Then, by combining 485 samples from each of the 10 parameters, the SWAT model was implemented and calibration indices were calculated. Finally, this process achieved the desired results, shown in Table (3), after 6 steps and performing 485 repetitions in each step.

Table 2 - Selected parameters after sensitivity analysis for the calibration stage

t-Stat	P-Value	Description	Parameter name	Sensitivity rank
24.08	0	SCS runoff curve number for medium moisture condition (II)	r-CN2.mgt	1
15.13	0	Baseflow alpha factor (days)	v_ALPHA_BF.gw	2
-10.27	0	Effective hydraulic conductivity of the bed in the main channel (mm / h)	v_CH_K2.rte	3
-2.38	0.01	Available water capacity of the soil layer (mm/mm)	r_SOL_AWC(1).sol	4
-1.40	0.16	Time delay for aquifer recharge (day)	v_GW_DELAY.gw	5
-1.01	0.31	Average slope gradient in HRU	r_HRU_SLP.hru	6
0.94	0.34	Water absorption factor by plants	v_EPCO.hru	7
-0.77	0.43	Infiltration rate in deep aquifer or capillary rise from shallow aquifer	v_GW_REVAP.gw	8
0.76	0.29	Minimum amount of water storage in the shallow aquifer that is required to start the evaporation of groundwater through capillary or deep aquifer feeding (mm)	v-REVAPMN.gw	9
0.99	0	Deep aquifer recharge from shallow or un-confined aquifer (%)	v_RCHRG_DP.gw	10

Table 3. Performance evaluations for the monthly discharge simulation

Validation	Calibration	Index
0.53	0.80	Nash-Sutcliffe
0.38	0.83	Explanation coefficient (R^2)
0.72	0.76	p-factor
1.23	1.53	r-factor

Figure (3) shows the two hydrographs (monthly average flow diagram) of the observed and predicted flow at the selected station after the final calibration, and Table (3) show the performance evaluations for the monthly discharge simulation that is related to indices of determining the uncertainty and the objective function used to evaluate the model performance. It can be concluded that the index of coefficient of determination (R^2) and Nash-Sutcliffe Efficiency (NSE) are relatively high, and this implies that the correlation between observational and simulated data are strong in calibration stage. Based on the results of Nash and Sutcliffe (1970) and Zuo et al. (2014), if R^2 and NSE are greater than 0.75, the performance of the model is interpreted as excellent and satisfactory. Also, since the value of the objective function (R^2) is 0.83 and exactly between the range of 0.75 to 1 (0.83) according to its performance ranking provided by Moriasi et al. (2007), so it can be stated with certainty that the simulation results in the calibration phase are satisfactory. Also, based on the value of R^2 obtained after 6 steps with 485 repetitions in each step, the model can be used for hydrological modeling by the users.

Finally, the p-factor and r-factor uncertainty indices for the calibration period were 0.76 and 1.53, respectively. The r-factor is a statistic that shows the average bandwidth of uncertainty at 95_{PPU}, and the closer it is to zero, the more accurate the model is. According to the classification presented by Abbaspour et al. (2015), the p-factor of 1 and r-factor of 0 indicate the complete conformity of the values predicted by the model and measured in the hydrometric station, and the farther the values of these two indicators are from these two values, the lower the simulation accuracy is. The value of p-factor statistic calculated in this study was 0.76. The p-factor index shows that more than 75% of the observational data are within the 95% uncertainty band (95_{PPU}), which indicates a very good calibration of the model based on this index.

The r-factor index, which represents the bandwidth of calibration uncertainty in calibration, is relatively high – about 1.53. According to Abbaspour et al. (2007), when accessing and using high quality measured data, an r-factor of ≤ 1 indicates relatively low uncertainty and a desirable calibration. The simulation results of the model with the discharge data of the Pishin station from 1997 to 2010 showed that based on the value of indicators uncertainty analysis is within the desired range. In other words, according to the value of the objective function R^2 (0.83), it was found that there was 83% correlation between observational and simulated data within the uncertainty bandwidth.

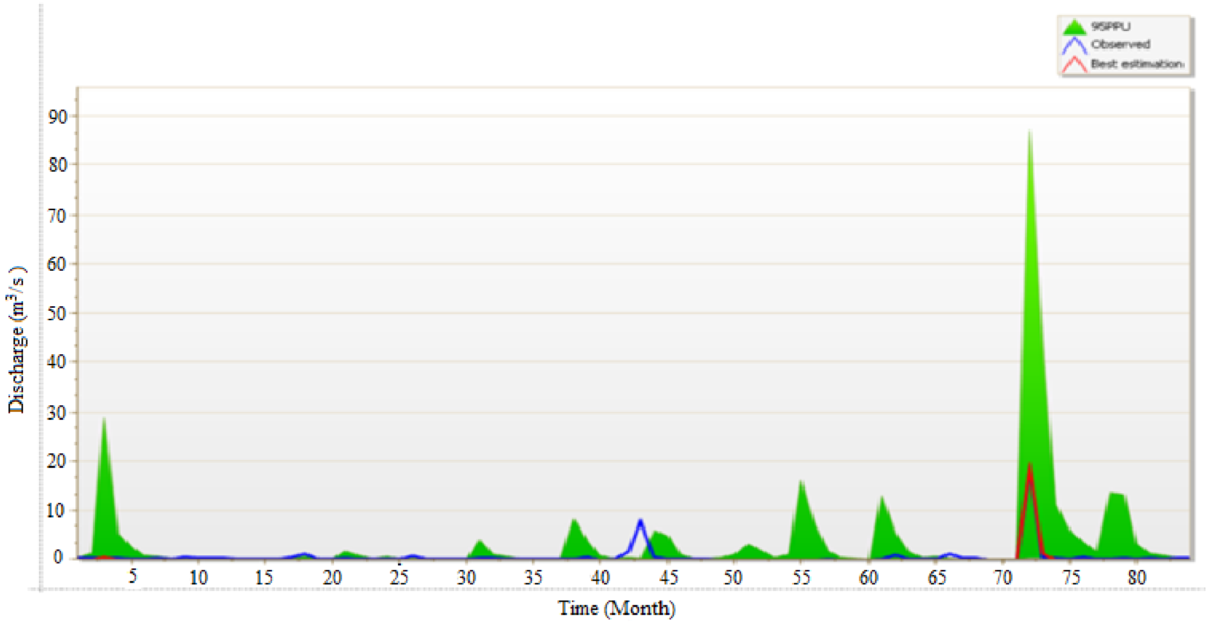

Fig. 3. Monthly simulated and calibrated discharges of different objective functions compared with observed data of Sarbaz watershed

The observational and best-simulated hydrographs (Figure 3) and the performance evaluation indicators of the model (Table 3) imply that, in general, the time matching of the hydrograph peak and trough points show good fit. This is the reason why the objective function value was calculated to be good and the coefficient of determination (R^2) is relatively high (0.83). However, despite the fact that the Sarbaz River is mainly seasonal and non-permanent, and the studied watershed is facing a lack of relatively accurate hydrometric data, the coefficient of determination in the calibration phase in this 9-year period clearly shows that there is a strong correlation between the observational data and the data estimated by the model. The monthly flow rate (discharge) in the two hydrographs (observed and estimated) during the period is also relatively well fitted in most cases, and in general, the flow rate as shown in Figure 3 is slightly higher than the actual observed values in some months of the year. In other words, it has been over-estimated. In general, the results of the SWAT running model in the calibration stage and the review of model performance indicators show that the model with the default values of the specified parameters has been capable of well simulating the time and amount of monthly peak flows. As a result, considering the quantity of evaluation indicators, it can be stated that the SWAT model has acceptable and desirable accuracy for the simulation of runoff in the Sarbaz watershed.

However, it should not be forgotten that without calibration and analysis of the uncertainty of input parameters of the model, not every model can be recommended for simulation in the region; and certainly, the use of more accurate data with a longer time-base can improve the simulation results and effectively increase the performance accuracy of the model.

3.2. Validation of the average monthly flow rate

Model validation was performed by repeating the same process as calibration. The difference is that during this period, the input parameters were not optimized, but the optimized parameters of the calibration stage were used. After determining the optimal range for the model parameters in the calibration stage, the SUFI-2 method was run once again using the optimal range of the parameters and flow data for the validation period with a time-base of 4 years (2006 to 2010). Also, the monthly average flow rate of the measured data of the Pishin hydrometric station (from 2006 to 2010) was used to compare the results between observed and predicted values by the model.

Figure (4) shows the hydrographs of the monthly average flow rate between measured and predicted flows at the validation stage. The results of NSE, R^2, p-factor, and r-factor indices were obtained for the whole watershed, and these results are also shown in Table (3) for the selected

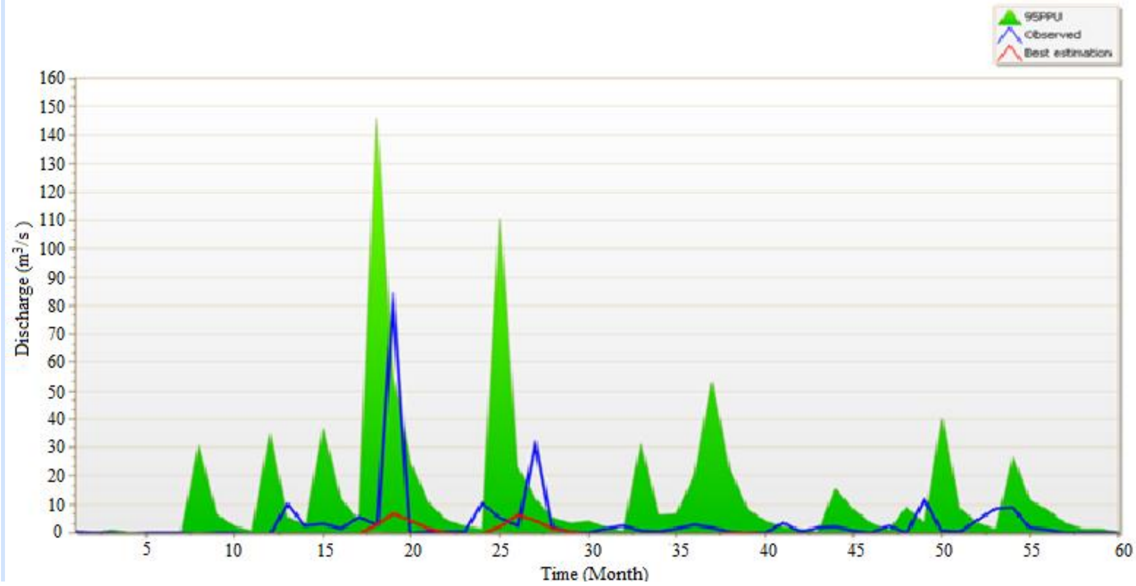

Fig. 4. Monthly simulated and validated discharges of different objective functions compared with the observed data of the Sarbaz watershed

In general, the appearance of the observed and simulated hydrographs and the performance evaluation indices of the model show that the overlap status of the hydrographs at the validation period is good and acceptable. The difference is that the values of p-factor and r-factor have decreased slightly at the validation stage towards zero. This indicates that the input parameters have appropriately been selected for the use at the validation step. But, the R^2 and NSE have drastically been decreased in contrast to the calibration stage. The reduction of the objective function R^2 and NSE used in the validation period compared to the calibration period shows that the correlation between the measured and simulated data is less than the calibration period. The lower objective function could be natural in such watersheds possibly due to the lower accuracy of the measured data while recording them at the Pishin hydrometric station during this period (2006 to 2010). However, R^2 and NSE in many studies (Raoof et al., 2007; Meamarian et al., 2019; Yuan and Forshay, 2020) show that somehow these values decrease at the validation stage. Another reason for the decrease in R^2 and NSE at the validation stage is that by comparing the observed data between calibration and validation stages, it was found that the amount and percentage of observational data that is within the 95% uncertainty bandwidth have also decreased by 4% during the validation period compared to the calibration period. This, in turn, reduces R^2 and NSE between the observed and estimated data at the validation stage.

In these studies, the model performance is very important as not only does it justify the application of the model to the study area but it also validates the efficiency of the SWAT model in the Sarbaz watershed. Uncertainty bandwidth has also decreased during the validation period, which is due to the reduction in the value of the objective function used in this period. Reducing uncertainty and the approach of the values of uncertainty indices (p-factor and r-factor) to ideal values are very important in these studies. Since these watersheds are not equipped with automatic hydrometric stations, if water resources management or watershed management plans are implemented within these areas, it can affect the estimation of runoff with different return periods. Therefore, the dynamics of the model parameters in the specified uncertainty interval can affect the simulated runoff in future projects.

4.Conclusion

Nowadays, many hydrological models have been developed to simulate runoff at the watershed scale. Choosing a suitable model may not be easy due to their great variety and the need to calibrate the models. The literature review shows that physical and process-based models, such as SWAT, which use a number of parameters, are both user-friendly and more accurate than experimental and conceptual models. By implementing the SWAT model in the Sarbaz watershed, it was possible to simulate the average monthly flow of the river in this watershed. In principle, uncertainties in hydrological studies are undeniable and always exist, and it should be possible to reduce and minimize existing uncertainties. As a result, future studies in the Sarbaz watershed and the projects such as future dam construction, water master plans, etc. for flood control will usually be done more carefully. Since in large watersheds and arid areas like the Sarbaz watershed, wherever water resources management projects are implemented, the components of the water balance equation such as runoff are calculated more accurately and the programs such as allocating water resources to stakeholders are implemented more optimally. When using hydrological models, selecting the type and range of input parameters to the model is essential. Therefore, in this study, at the calibration stage, out of 20 input parameters that had high sensitivity, 10 parameters were first selected based on personal experience and the literature review. The choice of parameter type and range in addition to hydrological, geographical, and environmental characteristics of the watershed depends on their role, impact, and importance in creating the type of model output, which is specifically runoff (average monthly flow) in this study. Many of these input parameters, such as the SCS curve number for medium humidity conditions, baseflow alpha-factor (alpha parameter in return flow), effective hydraulic conductivity of the bed in the main channel, and the average available water capacity of the soil layer, had a significant effect on surface runoff (model output) in this study. They have also been used in many previous studies.

In this study, common evaluation indices such as p-factor, r-factor, NSE, and R^2 were used to evaluate the efficiency of the calibration phase; and the calibration results of the average monthly discharge of the Sarbaz watershed during the statistical period of 1997-2005 were satisfactorily obtained in an acceptable manner.

Also, comparing the results of the present study with other similar studies shows that despite the challenges related to the input data for the studied watershed, the simulation accuracy is acceptable, and almost similar results were obtained by the other researchers. This implies that the SWAT model can be used by the users as a candidate model in the Sarbaz watershed and similar basins to simulate monthly runoff.

The research results also indicate that the SWAT model can simulate runoff in relatively large watersheds, such as the Sarbaz, which have complex and relatively heterogeneous conditions with appropriate accuracy. However, if the input data are used with appropriate accuracy in modeling and also sufficient accuracy is achieved in calibrating the model, the model will be more representative of the real conditions of the watershed. Finally, it can be stated with certainty that at the SWAT Check Error stage, all watershed conditions can be simulated if the average values of the water balance components during the simulation period correspond to real values, but if the flow data, whether observed or recorded in performing the calibration and validation step entered in SWAT-CUP software, are not in accordance with the hydrological realities of the basin or being measured with low accuracy, after running in this software, even with a constant uncertainty related to the parameters, it will be clear that they will not be within the band of 95% uncertainty. According to the optimal simulation of the model in the initial implementation phase of the SWAT model, it was found that in some months of the mentioned years, the discharge data is not accurate enough and does not correspond to the hydrological realities of the watershed, and the monthly flow was slightly overestimated in very short periods of time.

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