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## Simulation of the monthly runoff in Neyshabur Watershed considering the maximum monitoring stations in SWAT model

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Article Info	Abstract
<p><b>Article type:</b> Research Article</p> <p><b>Article history:</b> Received: February 2023 Accepted: May 2023</p> <p><b>Corresponding author:</b> emahjoobi@shahroodut.ac.ir</p> <p><b>Keywords:</b> Calibration KGE NSE SUF2 SWAT-CUP</p>	<p>Runoff is a crucial hydrological variable that provides vital information for water resource management and planning. In this study, we used Soil and Water Assessment Tool (SWAT) to simulate monthly runoff in Neyshabur Watershed, Khorasan Razavi Province, for a ten-year period from 2000 to 2009. We considered all available rain gauges, synoptic, and evapotranspiration stations within and around the watershed. We calibrated the model parameters and coefficients using the SUFI2 algorithm in SWAT-CUP software package. We found that the parameters related to the infiltration process, such as CH_K2, CN2, SOL_AWC, and REVAPMN, had the most significant impact on the runoff. We evaluated the model's performance during the calibration and validation periods using parameters such as P-factor, R-factor, Kling-Gupta efficiency (KGE), Nash-Sutcliffe efficiency (NSE), and coefficient of determination (<math>R^2</math>). The simulation results showed good agreement with the observed monthly runoff for both the calibration and validation periods. The NSE and <math>R^2</math> values were 0.84 and 0.87, respectively, at Zarande Andarab station for the calibration period, and 0.74 and 0.78, respectively, for the validation period. The Hosseinabad Jangal station showed even better performance, with NSE and <math>R^2</math> values of 0.93 and 0.93, respectively, for the calibration period, and 0.90 and 0.90, respectively, for the validation period. Comparing our results with previous studies in the same watershed, we found that utilizing a more comprehensive monitoring network and increasing the statistical period of the study can significantly enhance model's performance and reduce uncertainties in the calibration and validation stages.</p>

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## Introduction

"Runoff" is a crucial hydrological variable for water resource development, planning, and management, and runoff modeling provides useful information for hydrology management. Predicting and estimating runoff is crucial for proper watershed management and operation, as well as minimizing flood and drought damages (Yuan et al., 2017). Floods and droughts can negatively impact natural water supply, irrigation, and hydroelectric systems, causing significant economic, social, and environmental impacts worldwide (Orellana-Alvear et al., 2020). Therefore, it is essential to establish flood warning systems that rely on accurate rainfall estimation, which is highly dependent on the accuracy of runoff prediction (Nikolopoulos et al., 2013).

Accurate estimation of runoff in a watershed is challenging due to various influential parameters such as soil, vegetation cover, and slope. Simulating hydrological processes is critical due to the high cost of measurement and limited data availability. However, lack of statistics, resources, and widely accepted methods is a significant barrier to achieving this goal (Teimoory et al., 2019). Experts have proposed various models for simulating watershed processes, with the SWAT being one of the most widely used in watershed management research worldwide (Mokhtari et al., 2020).

The Soil and Water Assessment Tool (SWAT) model is a physics-based hydrological model developed by Arnold et al. (1998) for predicting the impact of land management operations on flow, sediment, and agricultural chemical materials in complex watersheds with variable soils, land use, and management operations for long periods. The model uses soil, land use, topography, and weather data to simulate hydrological processes daily and at higher time steps (Neitsch et al., 2011). Its primary components include hydrology, climate, erosion, plant growth, nutrient elements, pesticides, and land management. The SWAT model can be used in watersheds that lack regular monitoring data.

Several studies have used the SWAT model to simulate runoff in various watersheds worldwide. For instance, Vilaysane et al. (2015) used the SWAT model to simulate the flow in Xedone watershed and showed that the calibrated model could be used for further analysis to study the impacts of weather and land use changes, water quality, and sediment yield. Similarly, Goodarzi et al. (2016) used the SWAT model to simulate rainfall-runoff in the Gharehsou watershed and optimized the parameters using SWAT-CUP. Swami et al. (2016) used the SWAT model to simulate runoff and sediment yield in the Kaneri watershed. They calibrated the model for annual and monthly runoff and sediment yield from 1979 to 2000 and validated it for the years 2001 to 2013. In the calibration, the Coefficient of Determination ( $R^2$ ) for monthly and annual runoff was 0.849 and 0.951, respectively, and for the validation period, it was 0.801 and 0.950, respectively. Mohammadi et al. (2017) used the SWAT model to analyze the sensitivity of flow and nitrate concentration in the Talar watershed. The results showed that the SWAT model successfully simulated both the quantity and quality of water in the watershed, making it a useful tool for water resources management and planning. Habibi and Goodarzi (2018) investigated the performance of the SWAT model in simulating the runoff of the Hableroud watershed over 30 years. They used  $R^2$  and the Nash-Sutcliffe efficiency (NSE) to evaluate the model. In addition, Moazenzadeh et al. (2019) simulated the annual runoff in the Neyshabur watershed using the SWAT model and demonstrated its ability to successfully simulate continuous and long-term runoff in the study area. They used the SUFI2 algorithm for validation, uncertainty analysis, and sensitivity analysis of the model. The model validation at the Andarab, Kharv, and Hosseinabad Jangal stations was evaluated based on NSE values of 0.84, 0.77, and 0.92, respectively, which were acceptable, despite some underestimation of the peak flows. The NSE values for the verification period at these stations were 0.71, 0.66, and 0.92, respectively. Haixia et

al. (2019) also studied and simulated runoff in the upper Zhanghe watershed using the SWAT model, showing that it could be used for further analysis of the effects of climate and land use changes on water quality. Hu et al. (2020) used SWAT model to consummate watershed data and better quantify the impact of climate changes and human activities on Min-Tuo River basin runoff in 1980, 1990, 1995, 2000, 2005, 2010 and 2015 under different land-use conditions. The results suggested that the reduced precipitation was the main cause of runoff reduction and the runoff alteration was most sensitive to changes of landscape parameters. The graphs show the correspondence between simulated and observed monthly runoff, so that  $R^2$  and NSE of Gaochang station in the calibration and validation periods were 0.76, 0.76, 0.90, and 0.89, respectively. Al-Kakey et al. (2023) evaluated the accuracy of the Climate Forecast System Reanalysis (CFSR) product and observational precipitation data for streamflow simulation using the SWAT model in the northeastern part of the Little Zab River Basin. Results showed that the CFSR precipitation had a satisfactory correlation with rain gauge data ranging from 0.55 to 0.81. The performance of SWAT-based streamflow simulation achieved a 'very good' rating in calibration (2006–2010) and validation (2011–2013). Su et al. (2023) used the SWAT model to simulate the runoff in the Hulan River basin. The runoff data collected from Lanxi Hydrological Station from 2008 to 2020 were used to validate the model. Their results showed that NSE and  $R^2$  were 0.77 and 0.93, respectively, for the calibration period from 2010 to 2013, while they were 0.75 and 0.84, respectively, for the validation period from 2014 to 2016.

In summary, the SWAT model is a reliable and widely used tool for simulating hydrological processes in watersheds

worldwide, and its ability to accurately predict runoff makes it an essential tool for water resource management and planning. A notable point to consider when reviewing previous studies is the potential use of the SWAT model under conditions where there are limited statistical gauge stations. However, in our study, we simulated the runoff of the Neyshabur Watershed based on the maximum available gauge stations that were located inside and near the watershed, over a period of 10 years.

## Materials and Methods

### Study Area

The Neyshabur Watershed is a region within the Central Persian Desert Basins. Its boundaries are situated between 35°40' to 36°39' latitudes and 58°13' to 59°30' longitudes. The watershed comprises an area of approximately 9500 square kilometers and spans from the Binalud Mountains with a maximum altitude of 3316 meters to the outlet of the main river, where the minimum altitude is 1049 meters. The Neyshabur Watershed is adjacent to the Binalud Mountains in the north, the Lalehjuq and Yalpalang hills in the east, the Neizehband hill and the Kuhenamak mountains in the south, and the Sabzevar watershed in the west. Nearly half of the watershed is covered by irrigated and rainfed agriculture and orchards. The rainfall in this region is short-term and torrential, mainly in the cold and rainy season, and it is about a quarter of the average global rainfall (870 mm). In terms of temperature, the area also has hot summers and relatively cold winters. Table 1 shows the meteorological and hydrological conditions and related details. Figure 1 displays the watershed's location within Iran and Khorasan Razavi Province, highlighting the topographic map, river network, and distribution of measurement stations.

**Table 1.** Meteorological and hydrological features of Neyshabur

Climate	Precipitation	Temperature	Number of Frost days	Absolute Humidity	Evaporation	Maximum Wind Speed
Dry and semi-dry	230 mm	13 °C	90 days	49%	2100 mm	30 m/s

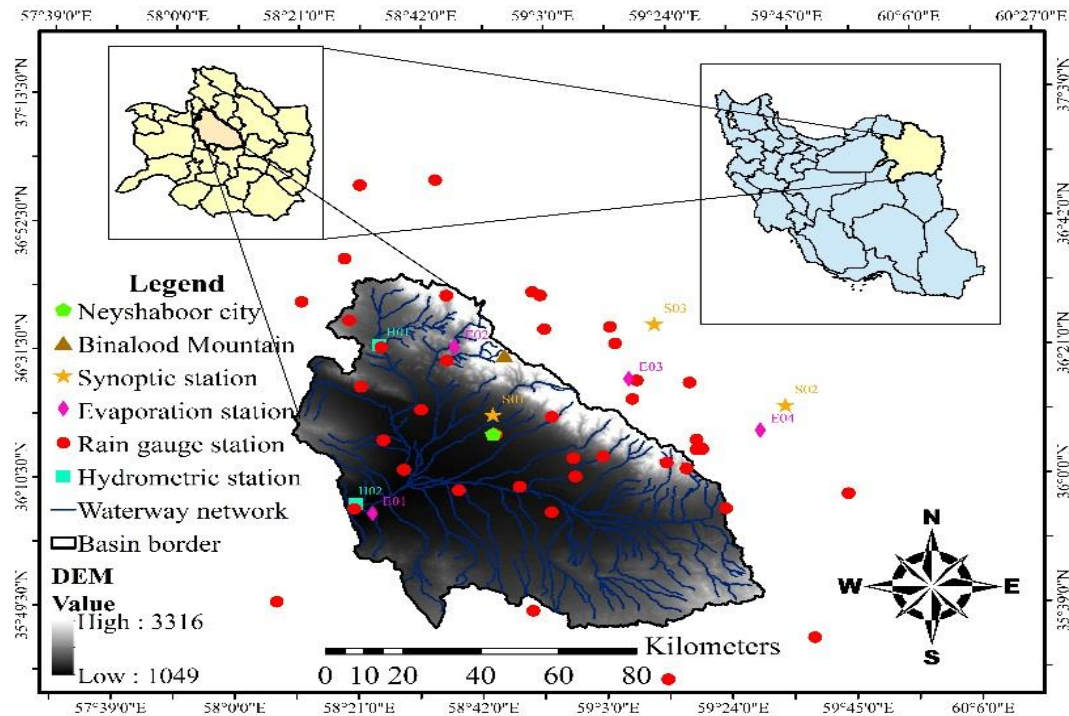


Figure 1. The location of the Neyshabur Watershed and meteorological stations

### SWAT model

The SWAT uses the water balance equation to simulate the hydrological cycle. Firstly, the watershed is divided into several sub-basins based on the surface topography and the structure of the river network. Then, sub-basins are partitioned into unique HRUs (Hydrological Response Units) that have distinct soil, topography, land use, and land management attributes (Neitsch et al., 2011).

The water balance equation for each HRU involves accumulation and storage of water in vegetation, precipitation and snowmelt, exchanging water between surface runoff and soil layers, infiltrating water into deeper layers, evapotranspiration, and subsurface and groundwater flow and storage.  $SW_t$  represents the current soil moisture content in millimeters,  $SW_o$  represents the initial soil moisture content in millimeters,  $t$  represents time in days,  $R_{day}$  represents the amount of precipitation on the  $i$ -th day in millimeters,  $Q_{surf}$  represents the amount of surface runoff on the  $i$ -th day in

millimeters,  $W_{seep}$  represents the amount of water entering the unsaturated zone of the soil profile on the  $i$ -th day in millimeters,  $E_a$  represents the amount of evapotranspiration on the  $i$ -th day in millimeters, and  $Q_{gw}$  represents the amount of groundwater flow on the  $i$ -th day in millimeters (Neitsch et al., 2011). Simulation of surface runoff is carried out using the United States Department of Agriculture (USDA) Soil Conservation Service curve number method according to the following equation. The parameter  $S$  is spatially dependent on changes in soil, land use, and slope, and temporally dependent on changes in soil moisture.

$$(2) \quad Q_{surf} = (R_{day} - 0.2S)^2 / (R_{day} + 0.8S)$$

$$(3) \quad S = 25.4(1000/CN) - 10$$

The  $CN$  parameter that describes the permeability properties of the watershed, is dimensionless and a function of the soil type, vegetation cover, and soil moisture. The Hargreaves–Samani method is used to calculate potential evapotranspiration, which only requires air temperature and solar radiation.

**Table 2.** Specifications of the stations within and near the Neyshabur watershed

Station Type	Latitude	Longitude	Elevation (m)	Station Type	Latitude	Longitude	Elevation (m)
Rain Gauge	36.26	58.80	12v13	Rain Gauge	35.99	58.94	1120
Rain Gauge	36.23	59.63	999.2	Rain Gauge	35.98	59.78	1500
Rain Gauge	36.48	59.28	1176	Rain Gauge	36.31	59.36	1360
Rain Gauge	35.96	59.43	1305	Rain Gauge	36.58	58.96	1350
Rain Gauge	36.08	59.33	1704	Rain Gauge	36.21	58.80	1210
Rain Gauge	36.13	59.1	1445	Rain Gauge	36.03	58.38	1072
Rain Gauge	36.13	59.36	1900	Rain Gauge	36.13	59.37	1788
Rain Gauge	36.36	58.43	1290	Rain Gauge	36.60	58.28	1510
Rain Gauge	36.25	58.96	1555	Rain Gauge	36.06	58.85	1138
Rain Gauge	36.21	58.48	1480	Rain Gauge	36.71	58.41	1352
Rain Gauge	36.91	58.48	1660	Rain Gauge	36.10	59.27	1988
Rain Gauge	36.08	59.01	1230	Rain Gauge	36.29	58.59	1207
Rain Gauge	36.91	58.7	1250	Rain Gauge	36.49	58.96	1390
Rain Gauge	36.6	58.7	2035	Rain Gauge	36.42	58.68	1503
Rain Gauge	36.28	59.2	2000	Rain Gauge	35.59	59.64	1798
Rain Gauge	36.33	59.21	1830	Rain Gauge	35.79	58.14	1291
Rain Gauge	36.13	58.53	1090	Rain Gauge	36.59	58.94	1467
Rain Gauge	36.16	59.37	980	Rain Gauge	36.43	59.16	1575
Rain Gauge	36.13	59.01	1200	Rain Gauge	35.51	59.22	1892
Rain Gauge	36.06	58.68	1170	Rain Gauge	36.47	58.50	1403
Rain Gauge	36.55	58.41	1635	Rain Gauge	35.72	58.86	1496
Rain Gauge	36.13	59.38	1480	Rain Gauge	36.48	59.15	1440
Evaporation	36.01	58.43	1086	Evaporation	36.45	58.70	1599
Evaporation	36.33	59.19	1832	Evaporation	36.17	59.55	1242
Hydrometric	36.47	58.49	1402	Hydrometric	36.04	58.38	1068
Synoptic	36.26	58.8	1213	Synoptic	36.23	59.63	999.2
Synoptic	36.48	59.28	1176				

To develop the model, we utilized climatic data from 41 rain gauges, four evaporation gauges, and three synoptic stations located within and near the watershed (Table 2). We validated the model using monthly data from two hydrometric stations located upstream and downstream of the watershed. We obtained the topographic surface map (Digital Elevation Model) at a resolution of 30 meters from USGS and the soil map from FAO. Additionally, we acquired the land use map from the Forests and Natural Resources Organization. The daily rainfall, maximum and minimum temperature were incorporated into the model. We identified synoptic stations in Mashhad, Gonabad, and Neyshabur as reference stations in the model to estimate missing data and simulate solar radiation, relative humidity, and wind speed. Lastly, we ran the model monthly, with the years 2000 and 2001 designated as the model's warm-up period. We calibrated the model using the SUFI2 algorithm and monthly flow data from 2002 to 2006. The Nash-Sutcliffe efficiency is used as the objective function of calibration.

The main goal of sensitivity analysis is to determine the inputs that have the greatest impact on changes in outputs. In this article, the Global Sensitivity Analysis method was used and the most sensitive parameters were identified at each modeling step based on P-Value and T-Stat. Specifically, the higher the T-Stat and the lower the P-Value, the more sensitive the model is to changes in that parameter (Abbaspour and Srinivasan, 2014). For uncertainty analysis, two factors of P-Factor and R-Factor were used. P-Factor represents the percentage of observed data falling within the 95% confidence interval, with a range of values between zero and one. The closer it is to one, the better the simulation data matches the observed data. In contrast, R-Factor indicates the width of the 95% confidence interval. Lower values indicate less uncertainty in the model (Abbaspour and Srinivasan, 2014). Finally, the model performance was evaluated at different stages based on the Kling-Gupta Efficiency (KGE), Nash-Sutcliffe Efficiency (NSE), Coefficient of Determination ( $R^2$ ), P-Factor, and R-Factor (Table 3). Gupta et al. (2009) presented the

KGE function based on the decomposition of NSE and Mean Squared Error (MSE) statistics. KGE can be divided into three terms indicating the correlation, deviation,

and relative variability between the observed and simulated values. Like NSE, KGE values range from negative infinity to one, with an optimal value of one.

**Table 3.** Statistical indicators used in evaluation and comparison

No	Statistical Index	Formula
(4)	Coefficient of Determination ( $R^2$ )	$R^2 = \frac{\sum_{i=1}^N ((S_i - \bar{S})(O_i - \bar{O}))^2}{\sum_{i=1}^N (S_i - \bar{S})^2 \sum_{i=1}^N (O_i - \bar{O})^2}$
(5)	Nash-Sutcliffe Efficiency (NSE)	$NSE = 1 - \frac{\sum_{i=1}^N (O_i - S_i)^2}{\sum_{i=1}^N (O_i - \bar{O})^2}$
(6)	Kling-Gupta Efficiency (KGE)	$KGE = 1 - \sqrt{(R - 1)^2 + \left(\frac{\bar{S}}{\bar{O}} - 1\right)^2 + \left(\frac{\sigma_s}{\sigma_m} - 1\right)^2}$

In the above equations,  $S_i$  is the amount of the simulated runoff for the  $i$ -th month,  $\bar{S}$  is the average of the simulated runoff,  $O_i$  is the amount of the observed runoff for the  $i$ -th month,  $\bar{O}$  is the average of the observed runoff,  $N$  is the number of samples,  $R$  is the correlation coefficient between observed and simulated data,  $\sigma_m$  and  $\sigma_s$  are respectively the standard deviation of observed and simulated runoff.

### Result and Discussion

To calibrate the model, we selected a preliminary list of parameters based on previous studies (Alizadeh et al., 2013; Shafiei et al., 2013; Moazen-zadeh et al., 2019). After conducting a sensitivity analysis using SWAT-CUP, we identified 15 sensitive parameters that affected the watershed runoff based on P-Value and T-Stat coefficients (Table 4).

**Table 4.** Sensitive parameters in the model calibration.

No	Parameter	Description	Min	Max	T-Stat	P-Value
1	CH_K2	Effective hydraulic conductivity in main channel (mm/hr)	0	79.14	4.28	0
2	CN2	Initial SCS runoff curve number for moisture condition II	-0.3	0.06	3.22	0
3	SOL_AWC	Available water capacity (mm water/ mm soil)	-0.38	0.20	1.95	0.05
4	REVAPMN	Threshold water level in shallow aquifer for revap (mm)	55.20	351.79	1.91	0.05
5	SURLAG	Surface runoff lag coefficient	1	14.81	1.86	0.06
6	SMTMP	Snow melt base temperature (°C)	-0.67	5	1.69	0.09
7	GW_DELAY	Groundwater delay time (days)	207.2	500	1.33	0.18
8	PLAPS	Precipitation lapse rate (mm H <sub>2</sub> O/km)	0	64.15	1.19	0.23
9	TRNSRCH	Fraction of transmission losses from main channel that enter deep aquifer	0.25	0.76	1.16	0.24
10	SFTMP	Snowfall temperature (°C)	-1.20	5	1.11	0.26
11	GWQMN	Threshold water level in shallow aquifer for baseflow (mm)	462.01	3487.98	0.69	0.48
12	SMFMN	Melt factor for snow on December 21 (mm H <sub>2</sub> O/°C-day)	2.03	7.34	0.61	0.53
13	ESCO	Soil evaporation compensation factor	0.58	0.95	0.59	0.55
14	CH_N2	Manning's roughness value for the main channel	0.13	0.3	0.58	0.55
15	SMFMX	Melt factor for snow on June 21 (mm H <sub>2</sub> O/°C-day)	3.41	10	0.47	0.63

The most effective parameters in determining runoff were CH\_K2, which represents effective hydraulic conductivity in the main channel, CN2, which indicates

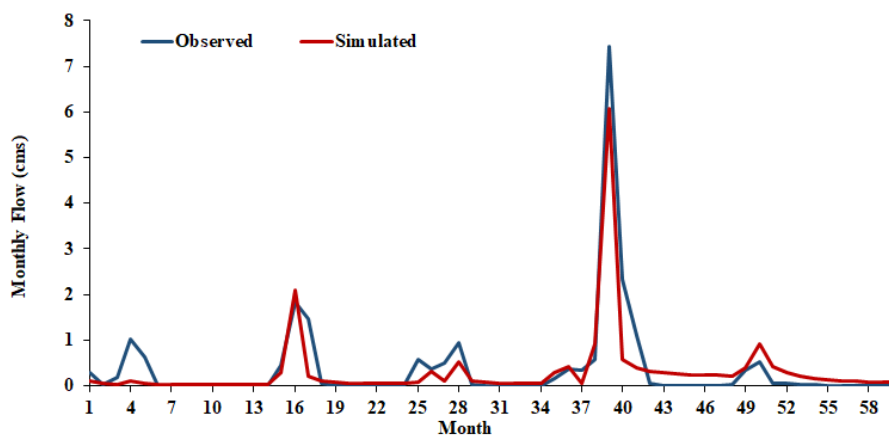
soil permeability, land use, and antecedent soil water, SOL\_AWC, which shows initial soil moisture content, and REVAPMN, which represents the threshold depth of

shallow aquifers for infiltration into deep aquifers. The model's sensitivity to snow parameters, including SMTMP, SFTMP, SMFMN, SMFMX, and TIMP, can also be expected due to the mountains in the northern and eastern regions.

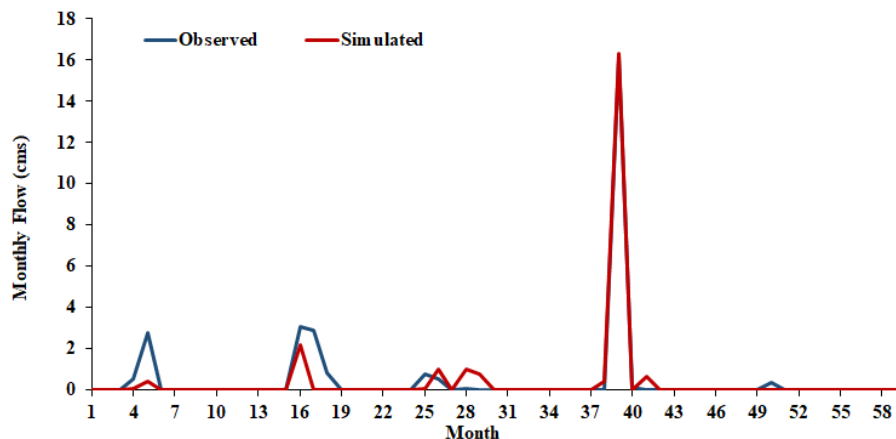
Alizadeh et al. (2013) and Moazen-zadeh et al. (2019) have also identified these parameters as the most sensitive ones in estimating runoff, evapotranspiration, and infiltration in this watershed. However, the

number of identified sensitive parameters in this study is significantly less than in previous studies. This may be due to the reduction in uncertainties resulting from the use of the most comprehensive monitoring network inside and around the watershed.

The results of the runoff simulation at Zarande Andarab and Hosseinabad Jangal stations in the upper stream and the outlet of the watershed during the calibration are shown in Figures 2 and 3.



**Figure 2.** Monthly runoff observation data and simulation results at Zarande Andarab hydrometric station in calibration.



**Figure 3.** Monthly runoff observation data and simulation results at Hosseinabad Jangal hydrometric station in calibration.

The simulation results indicate that the peak flows of runoff are underestimated in some months, particularly at Zarnadeh Andarab station, which was also observed in Moazen-zadeh et al. (2019) study. This could be attributed to SWAT correcting the infiltration curve based on the water available in the entire soil profile instead of modifying the curve based on the moisture

condition of the upper layers of soil, which play a more dominant role in surface saturation during heavy rainfalls. Modifying the curve based on such conditions and considering processes such as swelling of surface soil layers that affect the reduction of infiltration capacity could lead to improve accuracy of runoff

estimation, especially at the peak points of the hydrograph.

Comparing the performance of the developed model with Shafiei et al.'s (2013) model, the simulation of low flows at the watershed outlet is better. However, due to the simplification of complex interactions between runoff and subsurface flow in low precipitation, simulation models generally have weaker performance in estimating low flows (Hantush and Kalin, 2005). Additionally, the lack of groundwater flow, particularly in arid and semi-arid regions, results in rapid flow into the river (Sun and Cornish, 2005), especially in the presence of considerable upstream withdrawals.

Table 5 displays the performance criteria for validation. Moriasi et al. (2007) categorized model performance into four groups by evaluating the PBIAS and NSE simultaneously (Table 6). The model demonstrated acceptable NSE and PBIAS coefficients at both the Zarnadeh Andarab

and Hosseinabad Jangal stations, indicating good overall performance in simulating runoff in the Neyshabur watershed. Moreover, the  $R^2$  coefficient is also acceptable, and the KGE value is above 0.7 at both stations. However, the Zarnadeh Andarab station, located in the northern heights of the watershed with significant changes in altitude, may affect the model's behavior. Additionally, management practices applied in the watershed, while improving water resource management, can have long-term effects on the area's hydrology, resulting in changes in the natural flow regime. Two artificial water supply reservoirs located upstream of the Zarnadeh Andarab hydrometric station can also impact the natural flow regime (Abbaspour et al., 2015). Although these factors may explain the model's behavior, especially in peak flows, underestimating peak flows can lead to destruction caused by floods.

**Table 5.** Model performance evaluation criteria in runoff simulation (calibration)

Hydrometric Station	R-Factor	P-Factor	PBIAS	$R^2$	NSE	KGE
Zarande Andarab (Upstream)	0.95	0.62	15.8	0.87	0.84	0.72
Hosseinabad Jangal (Downstream)	1.05	0.15	18	0.93	0.93	0.82

**Table 6.** Performance classification of models based on the Nash-Sutcliffe and deviation coefficient (Moriasi et al., 2007)

Performance	Criteria #1	Criteria #2
Very Good	$NSE > 0.75$	$PBIAS < \pm 10$
Good	$0.65 < NSE < 0.75$	$\pm 10 < PBIAS < \pm 15$
Satisfactory	$0.5 < NSE < 0.65$	$\pm 15 < PBIAS < \pm 25$
Unsatisfactory	$NSE < 0.5$	$PBIAS > \pm 25$

Around 62% of the observed data in the upstream area falls within the 95% uncertainty band, which has a width of approximately 0.95. However, as we move towards the downstream, the percentage of observed data that falls within the 95% uncertainty band decreases. This change in behavior from upstream to downstream may be due to several factors, including the presence of multiple artificial reservoirs in the watershed, particularly in its tributaries, significant land subsidence in the western part of the watershed, and a significant percentage of irrigated agriculture and orchards with high evapotranspiration.

Studies have shown that modeling runoff using the SWAT model in humid

climates generally performs better compared to dry and semi-arid climates (Abbaspour et al., 2007) due to the low and discontinuous flow regime. The flow regime in the Neyshabur Watershed is also discontinuous, and runoff occurs only during intense rainfall events (Alizadeh et al., 2013). Although runoff is low in many cases, simulation results in both stations, especially in Hosseinabad Jangal, are still considered suitable due to an adequate number of rainfall gauges with a desirable distribution throughout the watershed, especially in mountainous areas.

After model validation and sensitivity analysis, the performance of the model in predicting the flow from 2007 to 2009 was

investigated. Table 7 shows the results of the performance evaluation criteria for validation. The NSE and PBIAS coefficients of the Zarnadeh-Andarab station fall in the ranges of good and unsatisfactory, respectively, and the NSE and PBIAS coefficients of the Hosseinabad Jangal station fall in the ranges of very good and satisfactory, respectively.

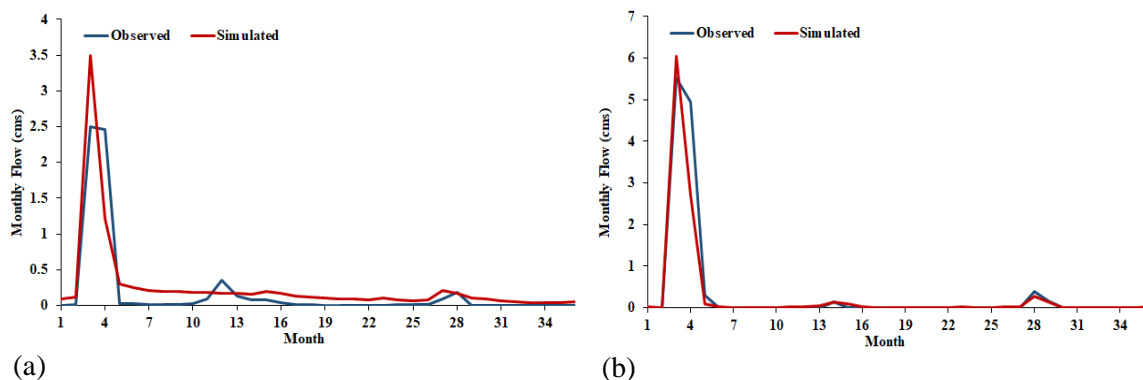
Furthermore, the  $R^2$  coefficients of Zarnadeh-Andarab and Hosseinabad Jangal stations are desirable and very desirable, respectively. The KGE value is reduced in the upstream but is very desirable in the outlet; therefore, overall, the model's performance is satisfactory in the upstream and good in the outlet.

**Table 7.** Model performance evaluation criteria in runoff simulation (verification)

Hydrometric Station	R-Factor	P-Factor	PBIAS	$R^2$	NSE	KGE
Zarande Andarab (Upstream)	0.5	0.61	-46.3	0.78	0.74	0.52
Hosseinabad Jangal (Downstream)	0.63	0.22	15.1	0.9	0.9	0.81

Figure 4 compares the time series of observed and simulated runoff at both stations during the validation. The model was very successful in simulating runoff behavior at the watershed outlet. However, at the upstream, the model simulated higher baseflow compared to the observed values,

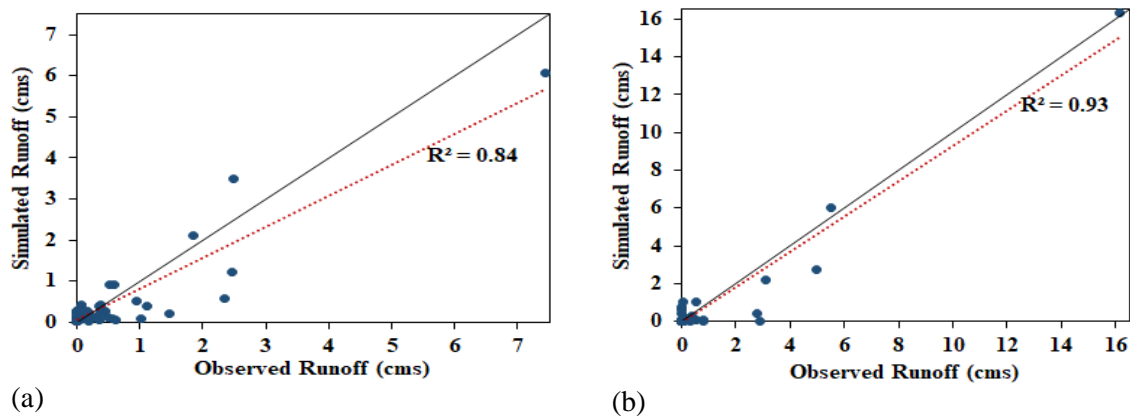
indicating a higher contribution of groundwater to river flow. The difference with observed flow may be due to multiple withdrawals by farmers. Nevertheless, it should be noted that there is always some uncertainty due to the model's imperfect fit with the watershed's conditions.



**Figure 4.** Comparison of observed and simulated monthly runoff time series of Zarande Andarab (a) and Hosseinabad Jangal (b) hydrometric station in validation

Figure 5 shows well-fitted hydrographs for both stations over the 10-year statistical period. The  $R^2$  coefficient for the entire statistical period was 0.84 for the Zarnadeh-Andarab station and 0.93 for the Hosseinabad Jangal station, indicating the model's good performance in simulating runoff in the Neyshabur Watershed.

Figure 6 illustrates the violin plots of the model's performance compared to observed flows at both stations over the entire statistical period. The model underestimates the flows in the upstream, but still has good performance and acceptable uncertainty in simulating the changes in the runoff at the watershed outlet.



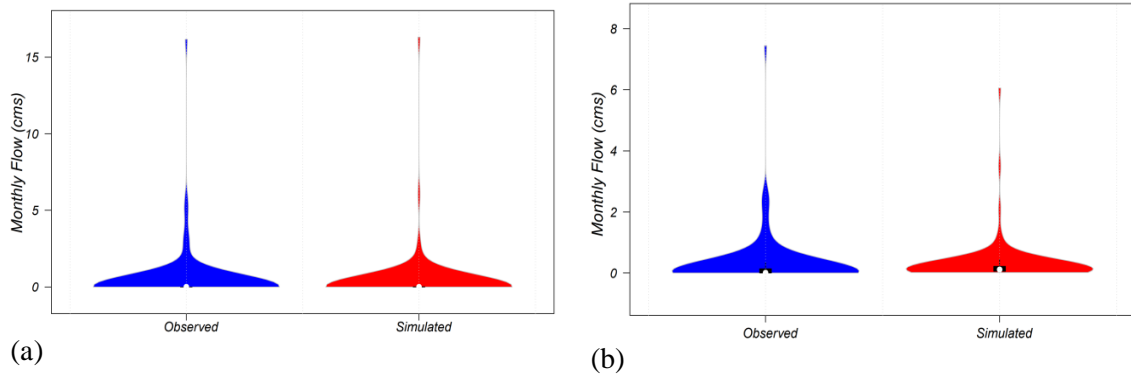
**Figure 5.**Correlation diagram between observed and simulated runoff at Hossein Abad Jangal station (a) and Zarande Andarab (b)

**Table 8.** Summary of vital information from studies on Neyshabur Watershed

Description			Shafiei et al. (2013)	Alizadeh et al. (2013)	Moazenzadeh et al. (2019)	The present study
Number of rain gauge stations			6	23	18	41
Number of evaporation stations			2	4	4	4
Number of synoptic stations			0	3	2	3
Warm up period			01/01/1992 – 31/12/1992 (1 year)	01/10/1997 – 30/09/2000 (3 years)	01/10/1997 – 30/09/2000 (3 years)	01/01/2000 – 31/12/2001 (2 years)
Calibration period			01/01/1993 – 31/12/1996 (4 years)	01/10/2000 – 30/09/2007 (7 years)	01/10/2000 – 30/09/2007 (7 years)	01/01/2002 – 31/12/2006 (5 years)
Validation period			01/01/1997 – 31/12/1999 (3 years)	01/10/2007 – 30/09/2010 (3 years)	01/10/2007 – 30/09/2010 (3 years)	01/01/2007 – 31/12/2009 (3 years)
Number of effective parameters			20	21	18	15
Zarande Andarab	NSE	Calibration	-	0.84	0.84	0.84
		Validation	-	0.79	0.92	0.74
	R <sup>2</sup>	Calibration	-	0.85	0.85	0.87
		Validation	-	0.79	0.94	0.78
	P-Factor	Calibration	-	0.42	0.48	0.62
		Validation	-	0.36	0.36	0.61
	R-Factor	Calibration	-	0.35	0.35	0.95
		Validation	-	0.41	0.4	0.5
Hosseinabad Jangal	NSE	Calibration	-	0.79	0.92	0.93
		Validation	-	0.71	0.71	0.9
	R <sup>2</sup>	Calibration	0.74	0.82	0.97	0.93
		Validation	0.73	0.71	0.71	0.9
	P-Factor	Calibration	-	0.37	0.37	0.15
		Validation	-	0.42	0.42	0.22
	R-Factor	Calibration	-	0.68	0.68	1.05
		Validation	-	0.63	0.63	0.63

Table 8 summarizes vital information expressed in studies conducted on this watershed in the past decade. Utilizing a more comprehensive monitoring network and increasing the simulation period are effective in improving model performance

and reducing model uncertainties for calibration and validation. Additionally, water losses due to infiltration and other related parameters are recognized as effective factors in simulating runoff in various studies.



**Figure 6.** Violin plot of runoff simulation at Hosseinabad Jangal station (a) and Zarande Andarab(b)

### Conclusion

In this study, we simulated the runoff of the Neyshabur Watershed in Khorasan Razavi Province, using the SWAT model for a ten-year period (2000-2009). To estimate the effect of meteorological parameters in the model, we used the most comprehensive monitoring network, including 41 rain gauges, three synoptic stations, and four evapotranspiration stations. The SUFI2 algorithm was utilized to calibrate the model, and monthly flow at the upstream and watershed outlet was used for calibration and validation.

The first run results showed that the SWAT model can accurately simulate peak flows, matching the time of the rainy months and the actual peak flows, which is consistent with the findings of Moazenzadeh et al. (2019). In addition, the developed model had fewer sensitive parameters compared to previous studies, which is an important point. The calibration and validation indices and diagrams demonstrated that the SWAT model had acceptable accuracy and capability in simulating monthly runoff in the Neyshabur Watershed. The sensitivity analysis revealed that the infiltration rate from the

bed and channel bottom, capacity and permeability conditions, initial soil moisture, and threshold water level in shallow aquifer had the greatest impact on simulated runoff. CH\_K2 (infiltration rate from the bed and channel bottom) was identified as the most sensitive parameter. For the calibration period, the NSE and  $R^2$  values were higher at the Zarnadeh Andarab station, with values of 0.84 and 0.87, respectively, and at the Hosseinabad Jangal station, with values of 0.93 and 0.93, respectively, indicating desirable performance of the model. For the validation, the NSE and  $R^2$  values at the upstream were 0.74 and 0.78, respectively, and at the outlet were 0.90 and 0.90, indicating the high ability of the developed model in simulating and predicting runoff.

In conclusion, the use of the SWAT model is efficient and cost-effective, enabling the evaluation of various management programs and implementation of better decision-making processes. The developed model is recommended as an optimal tool for runoff simulation in the Neyshabur Watershed, with potential for use in climate studies and related fields.

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