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Modeling Hydrological Responses of Watershed Under Climate Change Scenarios Using Machine Learning Techniques

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Abstract

Climate change is the most important problem of the earth in the current century. In this study, the effects of climate change on precipitation, temperature, wind speed, relative humidity and surface runoff in Saghez watershed in Iran investigated. The main methods were using the Coupled Model Intercomparison Project phase 6 (CMIP6), the Soil and Water Assessment Tool (SWAT) and the Artificial Neural Network (ANN) model under the Shared Socio-economic Pathway scenarios (SSPs) using the Linear Scaling Bias Correction (LSBC) for the future period (2021–2050) compared to the base period (1985–2014). Additionally, MAE, MSE, RMSE and R^2 indices used for model calibration and validation. The average projected precipitation was forecasted to decrease by 6.1%. In terms of the temperature, 1.4 C°, and 1.6 C° increases were predicted for minimum and maximum temperatures, respectively. Prediction of surface runoff using the SWAT model also illustrated that based on SSP1-2.6, SSP3-7.0 and SSP5-8.5 scenarios, runoff will decrease in the future period, which based on three mentioned scenarios is equals to 17.5%, 23.7% and 26.3% decrease, respectively. Furthermore, the assessment using the artificial neural network (ANN) also showed that the parameters of precipitation in the previous two days, wind speed and maximum relative humidity have the greatest effect on the watershed runoff. These findings may be helpful to reduce the impacts of climate change, and make the suitable long-term plans for management of the watersheds and water resources in the region.

Keywords Climate change · Saghez watershed · CMIP6 · SSPs · SWAT and machine learning

1 Introduction

Among atmospheric and hydrological variables, precipitation is the most important one. Hence, prediction of this parameter in different areas is necessary (Goudarzi et al. 2016). Asif et al. (2023) investigated the effects of climate change on water resources and water management in North America. The results represented that, unpleasant

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events such as destructive floods, excruciating droughts, changing in precipitation, which happening in many parts of North America due to the climate change cause the serious problems in water supplying and affecting water flows and water quality in the Southwestern United States and flat places in Canada and Mexico.

Global circulation models (GCMs) are the strongest models for assessment of the climate change influence and simulating the different atmospheric systems, land, the level of ice-sea, and ocean (Fowler et al. 2007). Zhu et al. (2020) to simulate climate extremes over China evaluated the importance of CMIP6 and CMIP5 models. The results illustrated the progress of CMIP6 models in assessment of climate extremes over China. Palmer et al. (2023) used CMIP6 models for evaluation in Europe. Their research demonstrated that the individual models are suitable and have good abilities for large-scale processes, which representing the Europe's current climate. Majdi et al. (2022) used CMIP6 models and SSP scenarios to predict precipitation and temperature changes in Middle East and North Africa (MENA). According to the results of this study, temperature will increase, while precipitation will decrease in the future.

Malmir et al. (2016) evaluated the effects of climate change on temperature, precipitation, and flow of the Qarasu River in Kermanshah province in Iran. In this study, the Statistical Downscaling Models (SDSM), Hadley Centre Coupled Model, version 3 (HadCM3), and ANN model were used. The results showed an increase in temperature and a decrease in rainfall and runoff in the future period. Heydari et al. (2019) investigated the effects of temperature and precipitation changes on the flow rate in the Urmia Lake catchment. For this purpose, the Hadley Centre Global Environment Model version 2 (HadGEM2) and the Representative Concentration Pathway (RCP) scenarios were used. The results showed that precipitation will decrease by 4.5% in the future period (2041–2060), while the minimum and maximum temperature will decrease 2.6 ºC and 1.3 ºC, respectively. Hejazizadeh et al. (2022) assessed the changes trend in precipitation extremes over MENA in a future period (2021–2050). The results demonstrated that the amount of precipitation will decrease, but the precipitation extremes and their intensities will have an increase trend. Alehu and Bitana (2023) evaluated the effect of climate change on the water balance of the Lake Hawassa basin in southern Ethiopia using Hadley Global Environment Model 2-Earth System (HadGEM2-ES) and SWAT model under the RCP scenarios. According to the results, precipitation, temperature and evapotranspiration will increase, but water balance, surface runoff and water yield will decrease in the coming decades. Liu et al. (2023) studied the influence of climate change on the shortage of water and hydrological extremes in the Yellow River Watershed. The used methods in this research were SSPs and Representative Concentration Pathways (RCPs). The findings of this research illustrated that the Yellow River will expose the lack of water, and more flash floods and extreme droughts will happen in the 20st century.

Maurya et al. (2023) assessed the effects of climate change on the streamflow in the near future (2011–2040).The methods, which used in this study, were the bias corrected, statistically downscale models of NASA, Earth Exchange Global Daily Downscaled Projections–Coupled Model Intercomparison Project Phase 5 (NEX-GDDP-CMIP5). The results demonstrated that the streamflow will increase in the future period.

According to many previous researches, climate change effects will be stronger in the future and will threaten the water resources, environment, industry, human health, agriculture, etc. Hence, doing projects in different regions in order to predict and reduce the impact of climate change in the future is necessary. Therefore, in this study the climatic parameters and surface runoff changes using CMIP6, SWAT and ANN models under different SSP scenarios, were predicted in Saghez watershed in Iran for the future period (2021–2050). Based on the results of this study, despite the decrease of the precipitation and runoff in the future period, the runoff flow, loss of soil moisture and torrential rains which caused by the increase in temperature will increase and the flash floods will happen. The results of this research would help to develop the required strategies in order to reduction of climate change impacts, and making serious decisions, and work out long-term plans for management of the watersheds and water resources to control the floods, improve water supply and water quality, soil and vegetation management, reduce the air, soil and water pollution, etc.

2 Data and Methodology

2.1 Study Area

The study area is Saqez watershed in the north of Saghez city in Iran. The geographic location of this area is between 35º 40′ 45" to 36º25′ 46" north latitudes and 45º.46′ 28" to 46º 46′ 55" east longitude. This watershed, which covers an area of about 4550 square kilometers, is one of the important sub-basins of the Urmia Lake in Iran. The average annual rainfall of the watershed is 430.5 mm and the region has a temperate mountain climate. The geographic location of the study area and the investigated stations are shown in Fig. 1, and their geographic characteristics are presented in Table 1. Also, Fig. 2 shows the flowchart of the process in this study.

2.2 GCM Models

Different CMIP6 models to check the daily temperature and precipitation data were used. Due to the different accuracy of the models in different regions and various parameters, the different models that were available for all three our investigated scenarios evaluated and the best model used for forecasting each parameter. The investigated models are given in Table 2.

Daily data of CMIP6 models for both the historical (1985–2014) and the future (2021–2050) periods downloaded from the Earth System Grid Federation (ESGF) center (https://esgf-node.llnl.gov/search/cmip6/).

After obtaining the data, the observed and historical parameter values for the study stations extracted by preparing a program in MATLAB using the GCMs data in the base period (1985–2014). The linear downscaling method used for data downscaling. The difference between the values of observed and historical parameters evaluated using four indices. The temperature, precipitation, wind speed, relative humidity and surface runoff changes predicted under three different scenarios using the best models for the future period (2021–2050), and their changes compared to the historical period (1985–2014). The reason for choosing the used models from the set of CMIP6 models is the validity, accuracy and availability of parameters and required scenarios for the study.

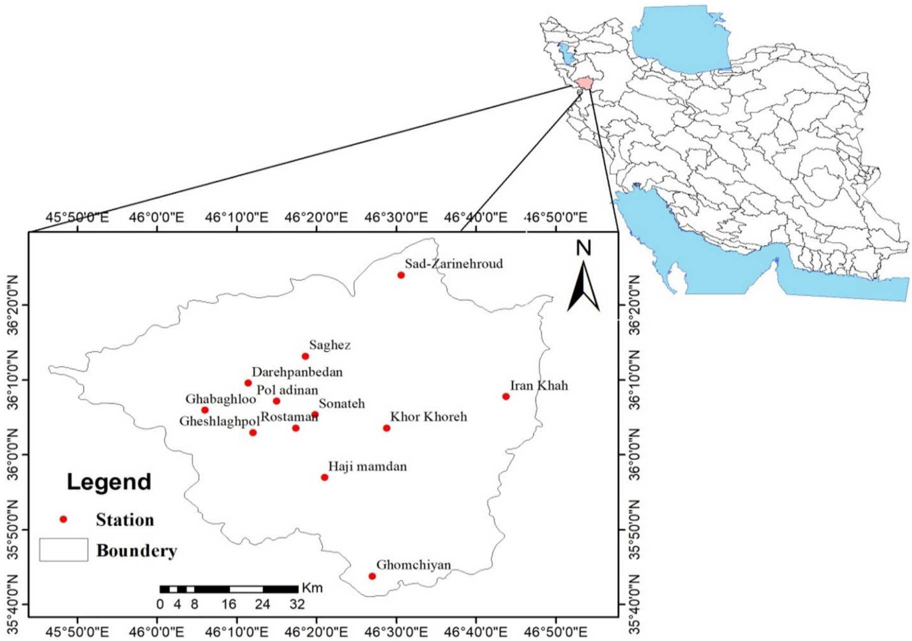


Fig. 1 The geographic location of the Saghez watershed and the meteorological and hydrometric stations

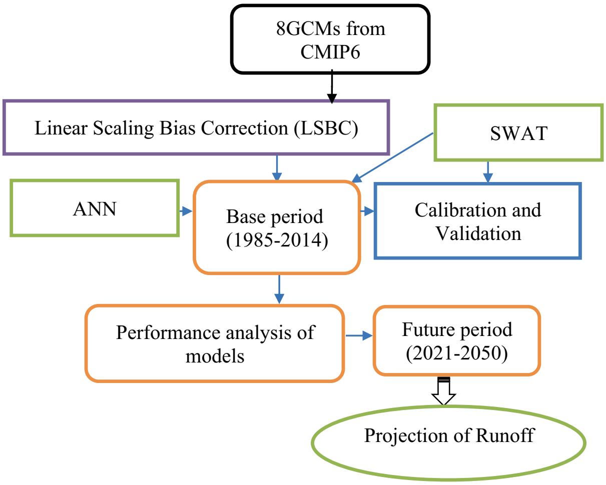
2.3 Scenarios

The scenarios related to CMIP6 have been presented under the title of Shared Socio-economic Pathway scenarios (SSPs). The SSP quantities are a common effort between the IAV and the IAM associations, which held in a series of meetings and have defined a limited set of five SSP story lines. The story lines describe the main features of the future development paths of the SSP. There are five SSP scenarios from SSP1 to SSP5,

Table 1 Geographic characteristics of the studied stations

Row	Station	Station type	Lon	Lat	Alt
1	Saghez	Synoptic	46.16	36.15	1522.8
2	Ghabaghloo	Rain gauge/Hydrometric	46.1	36.1	1500
3	Darehpanbedan	Rain gauge/Hydrometric	46.19	36.16	1470
4	Sonateh	Rain gauge/Hydrometric	46.33	36.09	1434
5	Gheshlaghpol	Rain gauge/Hydrometric	46.2	36.05	1436
6	Poladinan	Rain gauge/Hydrometric	46.25	36.12	1460
7	Rostaman	Rain gauge	46.29	36.06	1900
8	Ghomchiyan	Rain gauge	46.45	35.33	1650
9	Khor Khoreh	Rain gauge	46.48	36.06	1570
10	Iran Khah	Rain gauge	46.73	36.13	1600
11	Sad-Zarinehroud	Rain gauge	46.51	36.4	1383
12	Hajimamdan	Rain gauge	46.35	35.55	1920

Fig. 2 The flowchart of the process in this study



which respectively represent passing through the green road, the middle of the road, the stone road, the divided road, and the completion of the highway (Zahraei and Hosseini 2020). The study scenarios in this research are SSP1-2.6, SSP3-7.0 and SSP5-8.5.

2.4 Downscaling

Using the raw data of the models creates many errors; on the other hand, these data are grid. Therefore, in order to use these data for a station point it is necessary to do downscaling, evaluate and correct them based on the observation data. In this research the linear downscaling method used for downscaling the GCMs data. The downscaling is the mean difference between the observed monthly time series and the time series of the historical period of GCM/RCM over the same period of the observed time series. Then these differences applied to the simulated climate data to obtain the climate variables with corrected bias (Shrestha et al. 2016). The linear scaling approach (LSBC), which works with the corrected monthly values, based on the difference between observed and simulated values was used in this study. By applying the downscaling method on the simulated data, the performance of the model in the long-term simulation of precipitation and temperature variables increases a lot.

Table 2 The investigated CMIP6 models

Row	Model
1	BCC-CSM2-MR
2	CanESM5
3	CESM2
4	FGOALS-g3
5	GFDL-ESM4
6	MIROC6
7	MPI-ESM1-2-LR
8	MRI-ESM2-0

2.5 Performance Criteria of GCM Models

One of the criteria for evaluating the success of this research is using GCM models and new scenarios called SSP, which are currently the most accurate and up-to-dated global scenarios and models that have been using globally. In addition, in order to evaluate and analyze the performance of the investigated models, there are various performance indicators. The used indicators in this research are explained briefly in the following part.

The coefficient of determination (R^2) is a dimensionless standard and its best value is equals to one. Equation (1) shows how to calculate R^2 (Sedaghatkerdar and Fatahi 2008). Mean Square Error (MSE), which can vary from zero in high performance to infinity, which defined as relation (2) (Karamooz et al. 2006). The Root Mean Square Error (RMSE) is used as an analogy to show the difference between the simulated values and the measured values, which is defined as the Eq. (3) and it is used as the most common error index (Lin et al. 2006). The Mean Absolute Error (MAE) is used to compare the relative error of the simulated values with respect to the measured values, which is presented in the form of Eq. (4) (Hu et al. 2001).

$$R^2 = \frac{\sum_{i=1}^{N} X_o X_s}{\sqrt{\sum_{i=1}^{N} X_o^2 \sum X_s^2}} \tag{1}$$

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (X_o - X_s)^2 \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (X_o - X_s)^2}{N}} \tag{3}$$

$$MAE = \frac{\sum_{i=1}^{N} |X_o - X_s|}{N} \tag{4}$$

In the above relationships, X_o is the observation data, X_s is the simulated data and N is the number of data.

2.6 ANN

Artificial neural networks are one of the most efficient and broad types of intelligent systems (Amjadi 2002). The normal structure of an artificial neural network usually consists of an input layer, hidden layers, and an output layer. The input layer is a transmission layer and a means of providing the data. The output layer contains the values predicted by the network and the hidden layer is the place of data processing (Moghadam et al. 2008). In terms of the type of network, neural networks divided into two groups of feedforward and feedback networks, and in this study, feedforward networks and Multi-Layer Perceptron structures (MLP) used due to their more application in climate problems (Hosseini 2009).

For this purpose, the meteorological statistics of meteorological and hydrometric stations of Saghez watershed was used. The inputs of the multi-layer perceptron neural network were precipitation, minimum and maximum relative humidity, average wind speed and average, minimum and maximum temperatures on a daily basis and in different delays of several days. The output of the network was the amount of runoff from the total available meteorological and hydrometric data, 75% of the data used for network training and 25% used for network testing phase. In order to increase the speed of the network, the data standardized in the range of 0.1 and 0.9, and after determining the network structure, the network continued using Levenberg–Marquardt training algorithm and starting with the smallest number of neurons in the hidden layer and epoch until the network converges to the desired solution. When the network with any number of input layers, hidden neurons and epoch reached the desired result, that network selected as the optimal network. All these steps were done using MATLAB 2018 and SPSS 2023.

2.7 SWAT

SWAT is the semi-distributed hydrological model, which developed by Jeff Arnold for the United States Agricultural Research Service and since its creation in the early 1990s; its capabilities have been continuously developed. This model developed to predict the effects of land management activities on water, sedimentation and agricultural chemical factors at the watershed scale with soil diversity, land use and management conditions in a long time in the complex and vast watersheds. Furthermore, this model is more suitable for prediction of future climate change based on scenarios. The smallest working unit in this model is the hydrological response unit (HRU2), which is obtained from combining the slope classes, soil and land use maps (Goudarzi et al. 2016).

The model input data are meteorological data, watershed topography, soil characteristics, vegetation and land management. Other comprehensive meteorological data include effective factors on surface flow and channel, underground water, water harvesting, land management, reservoirs and lakes and water quality (Neitsch et al. 2011). The water in the soil, surface runoff, sediment and chemical elements are calculated first for each HRU and then for each sub-basin and finally for the entire watershed.

2.7.1 Simulation of Hydrological Features of the Study Watershed

In order to simulate the hydrological features with the SWAT model, first the digital height model with the separation of 30 m and the map of the waterway network of the study watershed added into the model. In the next step, using land use and soil maps and slope classes, hydrological response units defined. In this step, the watershed divided into 12 sub-basins and 412 hydrological response units. Daily data of the synoptic meteorological station of the watershed used to run the model. The used data include precipitation, daily minimum and maximum temperature, daily relative humidity and evaporation. In order to run this model for the study period, the climatic data separated into two separate periods for the calibration and validation of the model.

2.7.2 Calibration and Analysis of Uncertainty of the Model

In order to compare the simulated outputs of SWAT model with real data and calibration and validation of the model, the river flow data of the hydrometric stations near the outlet of the watershed used.

One of the issues, which occurs while calibrating this model, is the uncertainty in the simulation, which caused by the uncertainty in the model inputs and causes the uncertainty in the conceptual model and model parameters. In these models, due to the multiplicity of model parameters and the compensatory or intensifying effect of parameters on each other, often several sets of completely different parameters can lead to similar and acceptable results (Abbaspour 2013). In this research, SWAT Calibration and Uncertainty Programs (SWAT-CUP) and SUFI-2 Algorithm used for accurate calibration. SWAT-CUP is a program for calibration of SWAT model. This program also used for calibration, validation, uncertainty analysis, and sensitivity analysis.

SUFI-2 Algorithm SURF-2 is a semi-automatic inverse modeling algorithm. In this method, the uncertainty that includes all sources of uncertainty evaluated and expressed quantitatively. In the SURF-2 method, the degree of uncertainty calculated by two criteria: P-factor and R-factor. P-factor is the percentage of observed data that are in the uncertainty estimation band of 12%. This band calculated at the levels of 2.5% and 97.5% of the cumulative distribution function of the output variable obtained by Latin Hypercube Sampling (LHS), which is a statistical method for generating a near-random sample of parameter values from a multidimensional distribution. Since the effect of all sources of uncertainty is reflected in the output variables, in this method all uncertainties are considered.

2.7.3 SWAT Model Performance Evaluation

The SWAT model efficiency evaluation process is done by R^2, NSE, P-FACTOR and R-FACTOR criteria. The coefficient of determination (R^2) shows the dispersion ratio between the predicted and measured values and its value is variable between zero and one, if the predicted and measured values are equal, the value of R^2 is equals to one, which is the best amount of it. R-factor is equals to the thickness of the 95ppu band divided by the standard deviation of the measured data, the closer value to zero represents the better simulation. P-factor indicates how many of the observed data are in the range of uncertainty, and the closer number to one shows the better result. The NSE coefficient shows the relative difference between the observed and simulated values. The value of this coefficient varies between one and negative infinity. The closer number to one represents the better simulation of the model. NSE and R^2 coefficients calculated using the following relationships (Goudarzi et al. 2016):

$$\mathrm{NSE} = 1 - \frac{\sum_i \left(Q_{m,i} - Q_s\right)_i^2}{\sum_i \left(Q_{m,i} - \overline{Q_m}\right)_i^2} \tag{5}$$

$$R^2 = \frac{\left[\sum_i \left(Q_{m,i} - \overline{Q_m}\right)\left(Q_{s,i} - \overline{Q_s}\right)\right]^2}{\sum_i \left(Q_{m,i} - \overline{Q_m}\right)^2 \sum_i \left(Q_{s,i} - \overline{Q_s}\right)^2} \tag{6}$$

Q_m The average observed discharge (m^3/s)
Q_s The average simulated discharge (m^3/s)
$Q_{m,i}$ The observed discharge (m^3/s)
$Q_{s,i}$ The simulated discharge (m^3/s)

3 Results and Discussion

3.1 Evaluation of the Performance of CMIP6 Models Based on the Linear Scaling Bias Correction (LSBC) Method

In this research, some GCM models from CMIP6 evaluated according to their high resolution and available meteorological data. After the bias correcting using the LSBC method, the performance of these models evaluated in simulating of the investigated parameters in the historical period (1985–2014) of these models. An example of the bias correction on the precipitation and temperature data of the study synoptic station is shown in Figs. 3 and 4, respectively. The data corrected by LSBC method compared to the raw data are much closer to the observed data and it has caused accuracy in the simulation of the mentioned parameters.

The results of evaluating the observed and simulated rainfall data by LSBC showed that the accuracy of the models is different. Based on the RMSE values, the BCC_CSM2_MR model and then the MPI-ESM1-2-LR model have higher accuracy than other models for simulating the precipitation of Saghez synoptic station. The RMSE of these models using the observed rainfall data is equals to 4.3 and 4.9, respectively. In general, based on various indices, BCC_CSM2_MR model is suitable for simulating rainfall in the study area, and its coefficient of determination is equals to 0.99. The performance results of the investigated models in simulating the rainfall of the study area are given in Table 3.

The comparison of observed and simulated rainfall values during the base period (1985–2014) based on BCC_CSM2_MR model and the Linear Scaling Bias Correction (LSBC) in the study stations is given in Fig. 5. The results indicated the appropriate accuracy of the selected model in simulating the rainfall of the study area.

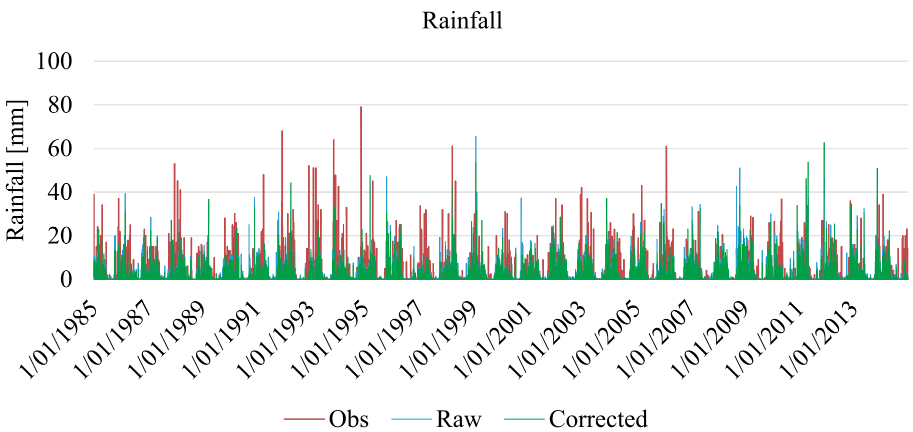


Fig. 3 Observed, raw and modified values of precipitation by LSBC method for Saghez synoptic station in the base period (1985–2014)

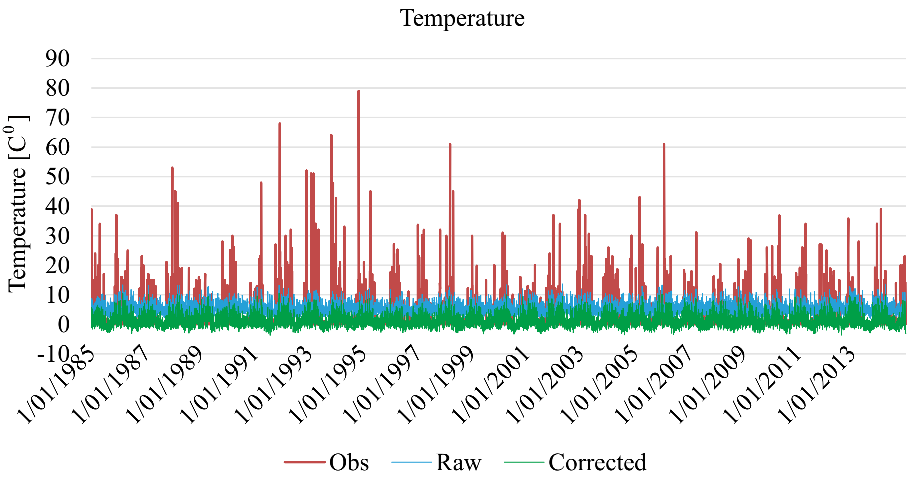


Fig. 4 Observed, raw and modified values of temperature by LSBC method for Saghez synoptic station in the base period (1985–2014)

In general, the results of evaluating the performance of CMIP6 models and downscaling of LSBC indicated that there is no significant difference between the simulated and observed values of the meteorological parameters with a critical error of 0.05. The results of various error measurement indices also indicated that the LSBC method has a suitable accuracy for the downscaling of the investigated parameters in the study area and the performance of this method evaluated for the study models. In sum, the evaluation of different models showed that BCC_CSM2_MR model for precipitation and wind speed simulation and MRI-ESM2-0 and CanESM5 models for temperature and relative humidity simulation, respectively, are more accurate than other models.

3.2 Forecasting the Climate Change in the Future

In order to investigate and analyze the climate change, the climate variables, which obtained from the global models using the selected models and applying the LSBC method were predicted in the future period (2021–2050). Then the changes in the study climate parameters using three Shared Socio-economic Pathway scenarios (SSPs) in the study area in the future period (2021–2050) compared to the base period (1985–2014) investigated.

Table 3 The performance evaluation of CMIP6 models based on LSBC in simulating of precipitation

Row	Model	MSE	RMSE	MAE	R^2
1	BCC_CSM2_MR	18.6	4.3	3.8	0.99
2	MPI-ESM1-2-LR	24.2	4.9	4.2	0.99
3	MRI-ESM2-0	98.9	9.9	8.1	0.97
4	MIROC6	144.8	12	9.2	0.88
5	FGOALS-g3	64.8	8.1	6.7	0.99
6	CanESM5	74.4	8.6	6.8	0.98
7	CESM2	85.4	9.2	7.5	0.97
8	GFDL-ESM4	143.7	12	7.8	0.92

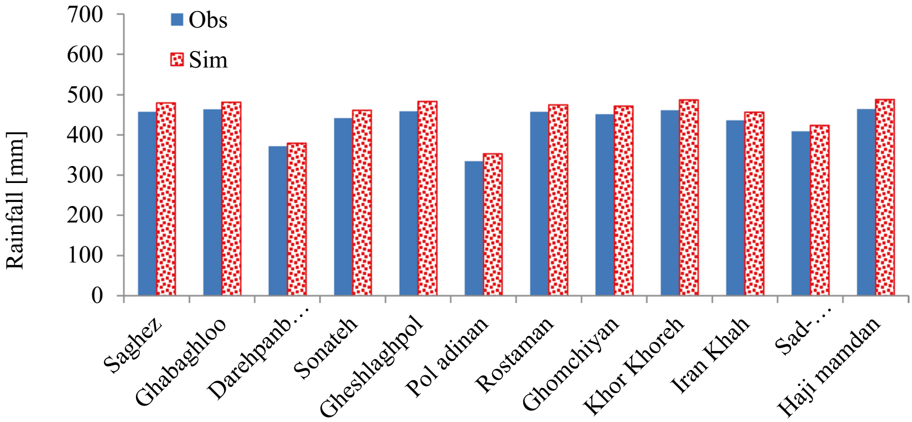


Fig. 5 Observed and simulated precipitation of the study meteorological stations in Saghez watershed during the base period (1985–2014)

The long-term average changes of climatic parameters in the base and future statistical periods based on the studied scenarios are presented in Table 4. The results showed that the amount of precipitation decreases by 6.1% in the future period. Average relative humidity and wind speed will increase 1.2% and 2.4%, respectively. In terms of the minimum temperature parameter, the results indicated an increase of 1.4 ºC in the minimum temperature in the future period. The maximum temperature will increase as well as the minimum temperature by 1.6 ºC.

3.3 Evaluation of Climatic Elements Affecting Runoff Using the ANN

A combination of study climatic elements (e.g., temperature, humidity, wind speed) and the amount of precipitation in different delays inputted the ANN model. The results showed that the runoff of the study area with six parameters of minimum temperature, maximum temperature, minimum relative humidity, maximum relative humidity, wind speed and precipitation in the previous two days had the greatest effect and correlation (Table 5).

Studying the different neural network structures showed that a three-layer perceptron model (MLP) with hyperbolic tangent active function (Tansig) in the hidden layer and identity active function in the output layer and Levenberg–Marquardt algorithm and 2000 rounds of training (EPOCH) has the best possible result. The neurons in the three-layer perceptron model include 6 neurons in the first layer or the input layer (precipitation in the previous two days, minimum temperature, maximum temperature, minimum humidity, maximum humidity and wind speed), 4 neurons in the hidden layer and 1 neuron in the output layer (runoff) which shown in Fig. 6.

The precipitation variable has the greatest effect on the network output (surface runoff). Wind speed, maximum relative humidity, maximum temperature, minimum temperature and minimum relative humidity, respectively, have the next greatest effect on runoff (Fig. 7). In Table 6, the weight and percentage of importance of the atmospheric variables affecting the surface runoff in the study area are presented.

Figure 8 shows the values of observed and estimated flow using the different structures of the artificial neural network. The observed and estimated parameters with a

Table 4 The climate parameters changes in the future period compared to the base period based on different scenarios

Parameter	The average in the base period	Future period(2021–2050)			The average in the future period	Changes rate	Percentage of changes
		SSP1-2.6	SSP3-7.0	SSP5-8.5			
Precipitation	434	401.7	415.5	410.3	409.2	-24.9	-6.1
Relative humidity	53.7	54.1	54.3	54.7	54.4	0.6	1.2
Wind speed	2.1	2.2	2.2	2.2	2.2	0.1	2.4
Maximum temperature	18.9	20.1	20.6	20.8	20.5	1.6	7.8
Average temperature	10.9	12.6	12.4	12.1	12.3	1.5	11.8
Minimum temperature	2.8	4.0	4.2	4.4	4.2	1.4	32.3

two-day rainfall delay (n-2), were closer to each other than other structures. Additionally, here n is the number of days of runoff delay. The neural network model did not have the necessary ability to simulate very high and low flow values and it does not have the appropriate accuracy in simulating the limit values.

3.4 Runoff Simulation Using the SWAT Model

3.4.1 Initial Implementation of the Model

The Digital Elevation Model (DEM), land use and soil maps and data, and climatic data of the study area were given as inputs of the model. From the combination of the mentioned maps, Saghez watershed divided into 12 sub-basins and 412 Hydrological Response Units (HRU), the results of that used as SWAT-CUP input.

3.4.2 Sensitivity Analysis, Calibration and Validation

Sensitivity Analysis The SUFI-2 program applied for sensitivity analysis. The relative sensitivity values evaluated in the parameter estimation process based on 25 effective parameters on runoff and 16 sensitive parameters identified as shown in Table 7.

Table 5 The formed structures by artificial neural network based on different climatic parameters

Model	Network structure	The number of neurons in the hidden layer	Relative percentage error
1	Q = Rain + Tmin + Tmax + RHmin + RHmax + Wind	2	0.76
2	Q = Rainn-1 + Tmin + Tmax + RHmin + RHmax + Wind	4	0.75
3	Q = Rainn-2 + Tmin + Tmax + RHmin + RHmax + Wind	4	0.71
4	Q = Rainn-3 + Tmin + Tmax + RHmin + RHmax + Wind	2	0.72
5	Q = Rainn-4 + Tmin + Tmax + RHmin + RHmax + Wind	6	0.74

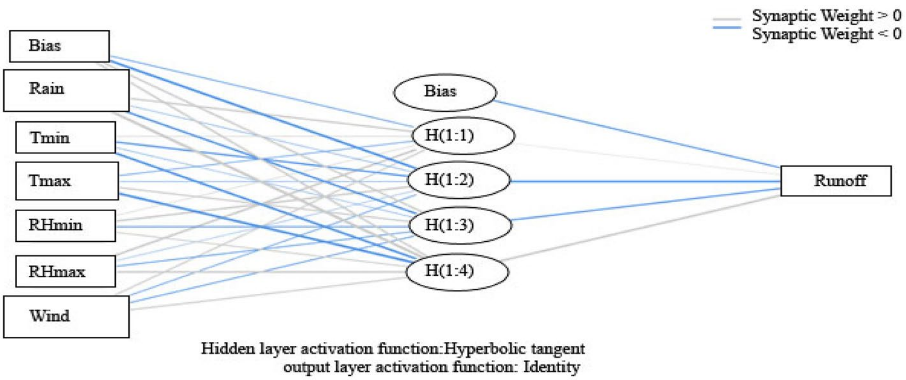


Fig. 6 The structure of the artificial neural network with the best performance in this research

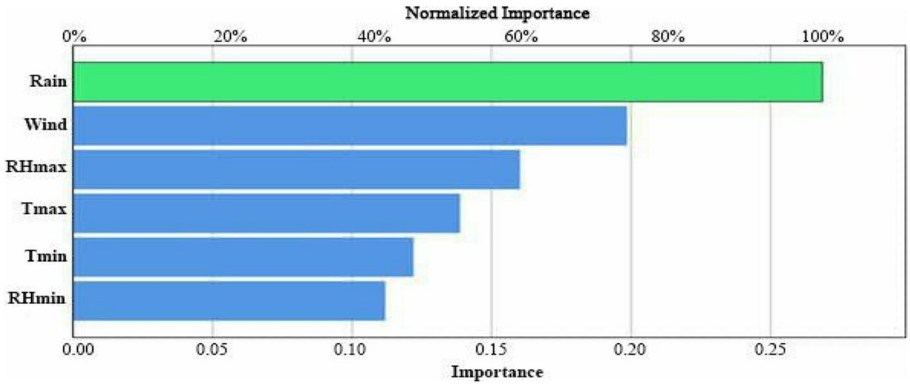


Fig. 7 Atmospheric variables affecting surface runoff on priority order in the study area

Calibration and Validation Calibration is the adjustment and correction of the input parameters of the model in such a way that it has the best fit with the observational data and in this way leads to the reduction of the uncertainty caused by the input parameters (Abbaspour et al. 2015). For this purpose, the SWAT-CUP software and SUFI-2 program were used. The data of Darehpanbedan hydrometric station was used at the outlet for the statistical period (1997–2014), which was chosen for the calibration of monthly

Table 6 Presenting the weight and percentage of importance of the atmospheric variables affecting the surface runoff in the studied area

Variable	Importance	Normalized Importance
Rain	.269	100.0%
Tmin	.122	45.4%
Tmax	.139	51.7%
RHmin	.112	41.7%
RHmax	.160	59.7%
Wind	.198	73.9%

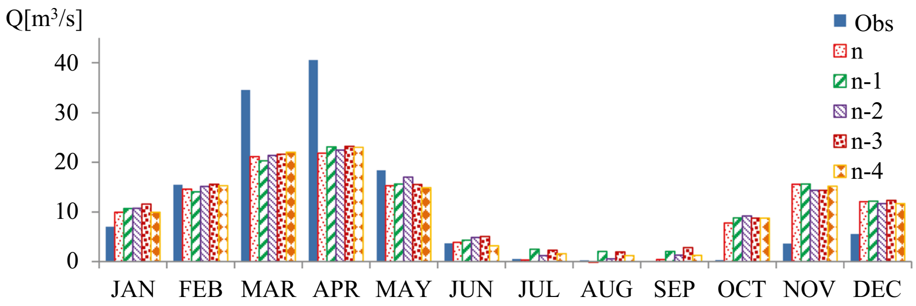


Fig. 8 Observed and simulated runoff in different precipitation delays using the ANN model

runoff data, from 1997 to 2008, the first three years were used for Warm Up (NYSKLP) the model, and it also was considered for the validation of the model from 2009 to 2014 (Fig. 9). In Fig. 10, the distribution diagram of the observed and simulated values and their correlation are shown, which shows an acceptable agreement among the data.

3.4.3 Model Performance Evaluation

During calibration, NSE and R^2 values were 0.82 and 0.84, respectively, and P-factor and R-factor values were 0.75 and 0.61, respectively, which they showed the appropriate accuracy. In the validation period, the model has a good performance, although its accuracy is a little lower than the calibration period, but the accuracy and efficiency of the model in simulating the runoff of Saghez watershed was evaluated as appropriate (Table 8). The graphical comparisons of the average observed and simulated runoff values of the watershed on

Table 7 Calibrated model parameters, initial limits and final limits obtained by SUFI-2 method

Row	Parameter's names	Initial range		Optimal range	
		Minimum	Maximum	Minimum	Maximum
1	r__GWQMN.gw	0.80	1.70	1.64	2.61
2	r__SLSUBBSN.hru	0.09	0.18	0.16	0.24
3	r__SMTMP.bsn	0.89	2.93	1.27	2.05
4	r__RCHRG_DP.gw	-0.01	-0.06	-0.03	-0.04
5	r__CN2.mgt	0.06	0.02	0.06	0.05
6	v__SOL_AWC().sol	0.10	0.36	0.01	0.19
7	v__ESCO.hru	0.94	1.00	0.98	1.03
8	v__OV_N.hru	0.39	0.72	0.49	0.60
9	v__SURLAG.bsn	-18.27	2.07	-19.55	-8.93
10	v__EPCO.hru	-0.33	0.64	0.58	1.60
11	v__ALPHA_BF.gw	0.15	0.44	-0.15	0.18
12	v__GW_REVAP.gw	0.00	0.08	0.04	0.07
13	v__GW_DELAY.gw	262.45	343.77	222.75	284.59
14	v__CH_N2.rte	0.16	0.22	0.20	0.24
15	v__CH_K2.rte	78.42	105.47	76.72	90.86
16	v__SFTMP.bsn	3.10	6.52	6.04	9.34

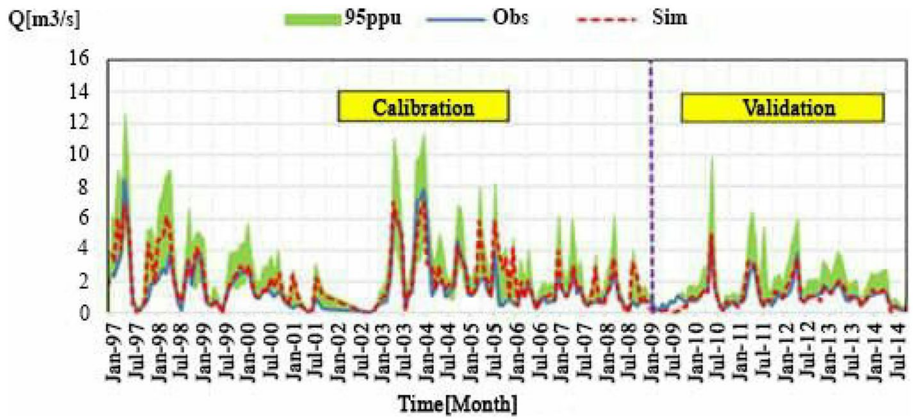


Fig. 9 Comparison of observed and simulated runoff on a monthly scale in the calibration and validation periods

monthly and annual scales in the base period (1997–2014) are shown in Figs. 11 and 12, respectively.

Based on the results of comparing the observed and simulated flow values, the model has not had the appropriate ability to simulate high and flood flows, while it is more suitable for low flow or in other words low discharge.

Watershed Runoff The main inputs for SWAT model were the 2014 land use map and the predicted future climate data (2021–2050) for each study scenario. The recalibrated model implemented with constant conditions of other parameters. The results of each investigated scenario compared with the base period, and the amount of runoff changes was determined according to the climate change. The amount of flow in the future period compared to the base period based on all three investigated scenarios decreased drastically in February, March, and April when it had high rainfall and flow. In other months especially during the hot season, the amount of flow increased compared to the base period (Fig. 13).

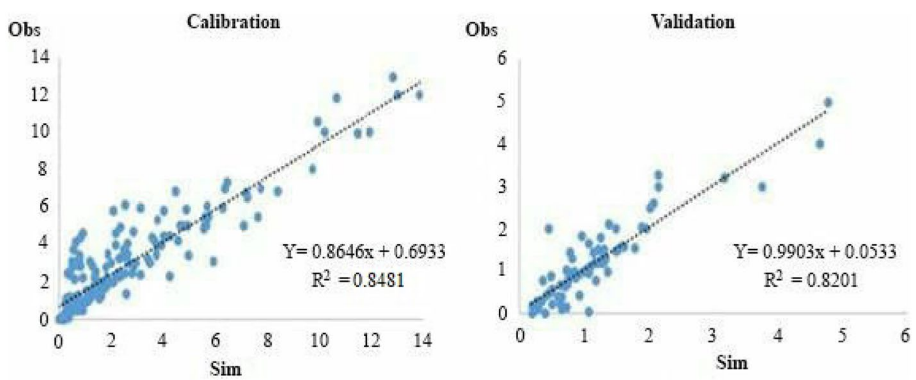


Fig. 10 Distribution and correlation of observed and simulated discharge values of the model in the calibration and validation periods

Table 8 Evaluating the efficiency of the model in simulating the monthly flow in Saghez watershed

Periods	P-factor	R-factor	NSE	R^2
Calibration	0.75	0.61	0.82	0.84
Validation	0.72	0.58	0.78	0.82

The study of different scenarios in the long term in the watershed showed that according to SSP1-2.6, SSP3-7.0 and SSP5-8.5 scenarios in the future period, the amount of flow will decrease which the amount of that according to the mentioned scenarios is equals to 17.5%, 23.7% and 26.3% decrease, respectively. The amount of discharge in the study watershed decreased by 22.8% on average, which is caused by the decrease in precipitation and the increase in temperature, wind speed and the rate of evaporation and transpiration (Fig. 14).

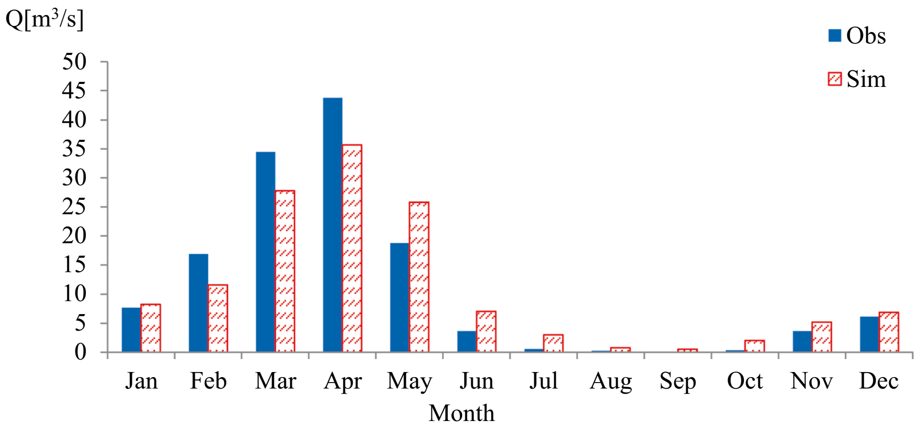


Fig. 11 Monthly observed and simulated runoff in the base period (1997–2014)

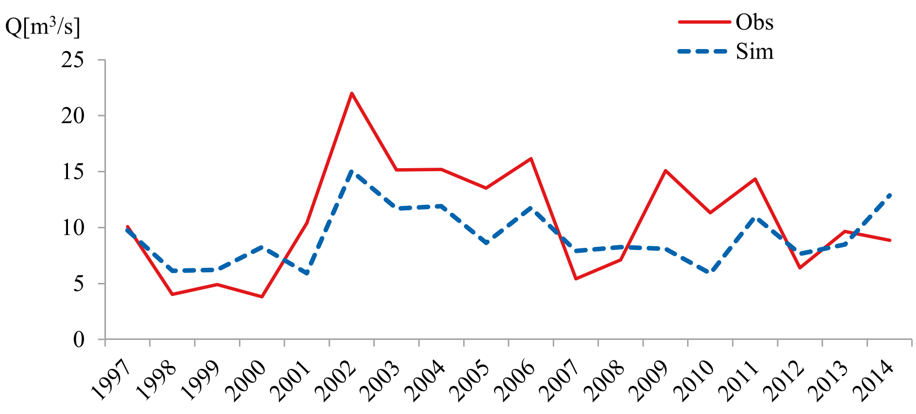


Fig. 12 Average annual observed and simulated runoff in the base period (1997–2014)

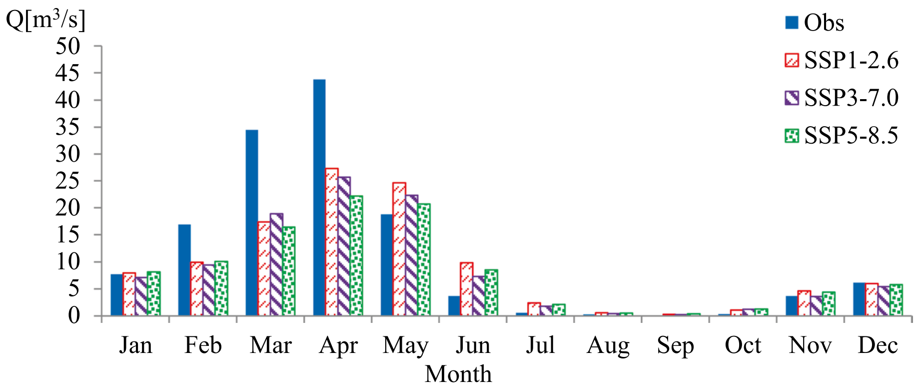


Fig. 13 The surface runoff changes on a monthly basis based on different scenarios in the future period (2021–2050) compared to the base period

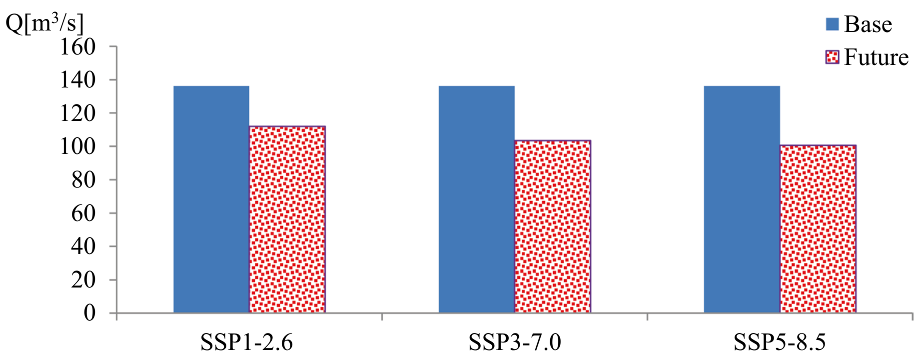


Fig. 14 Long-term runoff changes in the future period compared to the base period based on different scenarios in the study watershed

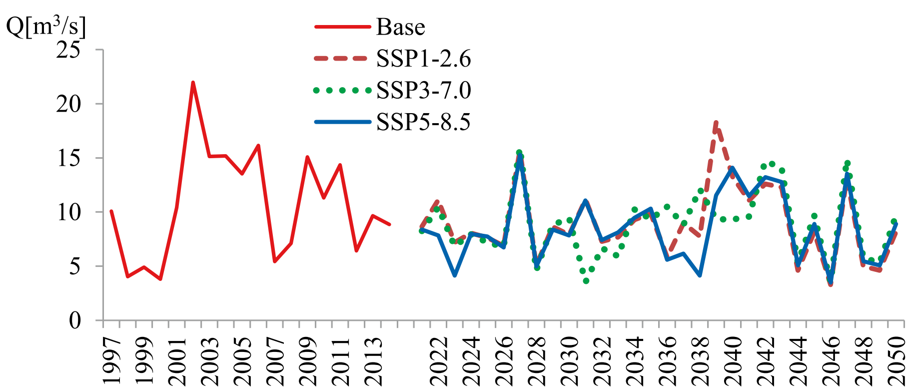


Fig. 15 The average time series of runoff changes based on three different study scenarios during the base and future periods

Scenarios The study of river discharge changes during the study statistical period (1997–2050) indicated a decreasing trend of runoff based on all three study scenarios in Saghez watershed. The highest and the lowest changes are related to SSP5-8.5 and SSS1-2.6 scenarios, respectively (Fig. 15).

4 Conclusion

The purpose of this study was predicting the climatic parameters and runoff changes using CMIP6, SWAT and ANN models under three SSP scenarios in Saghez watershed for the future period (2021–2050). After the evaluation of the models for the base period (1985–2014) and determining the accuracy of these models, the climate parameters and runoff changes were forecasted for the future period (2021–2050). The results of forecasting the temperature, precipitation, wind speed and relative humidity in the study area based on selected models showed that the amount of precipitation in the forecasted future period (2021–2050) will have a decrease of 1.6%. In terms of the temperature parameter, the assessment indicated that the minimum and maximum temperatures will increase 1.4 ℃ and 1.6 ℃, respectively. Also, the average temperature will have an increase of 1.5 ℃. The study of relative humidity and wind speed also showed that these two parameters will increase by 1.2% and 2.4%, respectively. Based on the results of the CMIP6 models and the Linear Scaling Bias Correction (LSBC), the temperature had a warming trend that leads to evaporation and transpiration, a decrease in snowfall, and an increase in torrential rains and floods. This can also lead to a decrease in the storage and supply of water resources in the watershed, an increase in torrential rains damages and washing away the fertile soils. Therefore, emphasis and attention to natural resources, watershed, reservoirs and strengthening of pastures is so important to reduce the effects of heavy rains.

The analysis of the parameters affecting the runoff of the study watershed using the artificial neural network showed that the precipitation parameter with a delay of two days, the wind speed and maximum relative humidity parameters,respectively, have the greatest effect on the runoff of the study area.

The results of the SWAT model based on different scenarios showed that the long-term average annual runoff in the future period will decrease by 22.8% compared to the base period. In the future period, although the amount of precipitation and relative humidity will not decrease much, but the minimum and maximum temperature and the wind speed will increase significantly in this period. Therefore, an increase in temperature and wind speed leads to an increase in evaporation and transpiration, and as a result, a decrease in river flow. In conclusion, the decrease in the amount of runoff can be considered as a result of the increase in temperature, which followed by the increase in the rate of evaporation and transpiration and decrease in rainfall. When the amount of rainfall decreases and the temperature increases, the amount of runoff will decrease in the future period. Despite the decrease in the total volume of runoff in the future period, this decrease is related to high and medium flows, but in low flows the volume of runoff in the future periods will decrease less. This phenomenon is due to the greater effect of temperature variable on low flows and the greater effect of rainfall variable on high flows.

The findings of this research can help to reduce the climate change impacts in order to management of water resources, prevent the reduction of soil fertility and increase agricultural and industrial products to improve human life economically and socially because in many areas people's social lives rely on the economy and the economy relies on the agriculture products.

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Authors Contributions **Keivan Karimizadeh:** Conceived of the presented idea and developed the theory, performed the computations, Concepts, Design, Definition of intellectual content, literature search, experimental studies, data acquisition, data analysis, Statistical analysis, manuscript preparation, and manuscript editing. **Jaeeung Yi:** Encouraged and developed the theoretical formalism, verified the analytical methods, literature search, and manuscript editing. All authors discussed the results and contributed to the final manuscript.

Availability of Data and Materials The data used in this paper have been prepared through the Meteorological Organization and Water Resources Research Center of Iran and Earth System Grid Federation (ESGF) from this link: https://esgf-node.llnl.gov/search/cmip6/

Code Availability In this paper, the codes in MATLAB 2018 software used to re-gridding the models.

Declarations

Ethical Approval Not applicable.

Consent to Participate Not applicable.

Consent to Publish Not applicable.

Competing Interests The authors declare that they have no competing interests.

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