Journal of Renewable Energy and Environment

Research Article

Journal Homepage: www.jree.ir

Prediction of Discharge Using Artificial Neural Network and IHACRES Models Due to Climate Change

Maryam Hafezparast*, Seiran Marabi

Department of Water Engineering, Faculty of Agriculture and Natural Sciences, Razi University, P. O. Box: 09914412984, Kermanshah, Kermanshah, Iran.

PAPER INFO

Paper history:
Received 21 November 2020
Accepted in revised form 10 July 2021

Keywords:
RCP8.5,
Runoff Prediction,
IHACRES,
MLP,
Kermanshah

ABSTRACT

Understanding of climate change and its impacts on river discharge has affected the quality and quantity of water and also supplying water requirements for drinking, agriculture and industry. Therefore, prediction of precipitation and temperature by climate models as well as simulation and optimization of their runoff with suitable models are very important. In this study, four climate models of the Fifth Coupled Model Inter comparison Project (CMIP5) and RCP8.5 scenario were used to forecast future precipitation and temperature for the next two periods including 2020-2052 and 2053-2085. Mean Observed Temperature-Precipitation (MOTP) method was used to reduce the uncertainty of climate models and the change factor method was used to downscale the climate data. Then, the Lumped-conceptual Identification of unit Hydrographs and Component flows from Rainfall, Evaporation and Stream flow data (IHACRES) model and multi-layer Artificial Neural Network (ANN) model were employed to estimate the effects of these parameters on the Khorramrood River runoff. The neural network model is written and implemented using Scikit-Learn library and the Python programming language. The comparison of performance of ANN models with different input variables like monthly precipitation, monthly precipitation of previous months, monthly discharge, monthly discharge of previous months, monthly temperature was made to find the best and most efficient network structure. The results showed that the precipitation in Khorramrood River basin based on the weighted combination model decreased by 8.18 % and 9.75 % in the first and the second periods, respectively, while the temperature increased by 1.85 and 4.22 °C, respectively. The discharge parameter in the calibration and validation period in the IHACRES model based on criteria to evaluate the parameters of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), The Coefficient of Determination (R), and the Nash-Sutcliffe Efficiency (NSE) performed better than the artificial neural network model. However, due to the small differences of these changes, the predictions were performed for both periods and using both models and the results indicated that future discharge in the IHACRES model decreased by 12.72 % during the first period and by 20.3 % in the second period, while the model of artificial neural network showed decrease rates of 2.12 % and 6.97 %, respectively.

https://doi.org/10.30501/jree.2021.257941.1162

1. INTRODUCTION

Human activities are one of the most important factors affecting water resources planning and regional hydrology [1, 2, 3]. Therefore, improving hydrological and regional climate simulation, especially precipitation and flow, is an important goal for meteorological and water professionals. Such improvements will increase the effectiveness of regional water resources planning and management and reduce flood and drought losses. Previous studies have shown that the slightest fluctuation in the probability or severity of precipitation has significant effects on runoff [4, 5]. There are three groups of hydrologic forecasting that have been used more than three decades: lumped conceptual models, models based on physical distributions, and empirical black box models [6]. There is a complex nonlinear relationship among discharge, precipitation, and temperature which affects the assessment climate change impacts on runoff [7]. Therefore, climate change scenarios in the future are very important for water resources planning and management, agriculture and water users [8, 1]. Climate change as one of the major challenges of the twenty-first century has affected human society. Rapid population growth and industrial development as well as deforestation and environmental degradation have led to an increase in greenhouse gas emitted from Earth's surface in recent decades. The increasing trend of warming has caused the Earth's surface temperature to rise in the current century. The rate of temperature increase is predicted between 0.3 and 4.8 °C under the four trends of greenhouse gas concentrations by 2100 [9]. The Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) in 2013 showed that global warming caused a change in the water cycle due to increased greenhouse gas concentrations. The consequences of this phenomenon have different effects on water resources systems and various aspects of human life the most important of which can be the changes in the spatial and temporal distribution of precipitation and its type, surface runoff, evaporation, groundwater recharge, and sea level rise

*Corresponding Author's Email: m.hafezparast@razi.ac.ir (M. Hafezparast)
URL: https://www.jree.ir/article_133315.html

Please cite this article as: Hafezparast, M. and Marabi, S., "Prediction of discharge using artificial neural network and IHACRES models due to climate change", ***Journal of Renewable Energy and Environment (JREE)***, Vol. 8, No. 3, (2021), 75-85. (https://doi.org/10.30501/jree.2021.257941.1162).

which ultimately affect human settlements and agricultural production. It, therefore, requires that the impacts and consequences of climate change on water resources be seriously considered. In recent years, the effect of this phenomenon on different catchments on the surface of the earth has been investigated. Most researchers around the world have used the Fifth Assessment Report to study climate change under new emission scenarios in different regions [10, 11, 12, 13, 3]. Some of them are listed below.

2. LITRATURE REVIEW OF EXSISTING METHODS

Tan studied the impacts of climate change on the Kalantan River in northeastern Malaysia. 36 Climate Change Downscaling Projects from five Atmospheric General Circulation Models (AGCMs) under three RCP Scenarios of 2.6, 4.5 and 8.5 for two future periods from 2015-2044 and 2045-2074 were studied with respect to the base period (1975-2004) [13]. The results of the five atmospheric general circulation models show the increase of 1.2 to 8.8 % in annual precipitation and 0.6 to 2.2 °C at maximum temperature. Decision making on water management and construction and operation of hydraulic structures requires reliable information about the flow discharge in the river basin to facilitate decision-making according to design flood discharge. IHACRES model is one of the semi-conceptual rainfall-runoff models that could generate effective rainfall and runoff simulation with inadequate information. Water resources management is a key issue for sustainable development in the future in arid and semi-arid regions like Western Australia. In a study conducted in this area, IHACRES rainfall-runoff model based on problem physics and artificial neural network models was used to simulate the runoff of the Marillana Basin in the Pilbara region [14]. Sadeghi Loyeh simulated the rainfall-runoff process using two conceptual models including HEC-HMS and IHACRES, and three experimental artificial neural network models, namely Multivariate Regression (MLR), and Simple Linear Regression (SLR), and monthly runoff time series and meteorological data of Lighvan river in Iran during 1972-2004 were used [15]. Ghanbarpour simulated and estimated runoff of Kasilian Basin using ANN, ARMA, SWRRB, and IHACRES despite lack of sufficient meteorological information, and the results of the study showed the proper performance of IHACRES and artificial neural network [16]. Karamouz developed IHACRES and ANNs models for long-term runoff simulation in Southeastern Iran and then, the two models were compared. At first, the rainfall was predicted using climatic signals and then converted to runoff. Therefore, daily precipitation was downscaled using SDSM and LARS-WG methods and the outputs of these two models were selected as inputs of the rainfall-runoff IHACRES model to simulate runoff. In the neural network model, Sea Level Pressure (SLP), Sea Surface Temperature (SST), and Sea Level Pressure Changes (ΔSLP) and runoff were introduced as input parameters and two MLP and ELMAN networks were investigated. The results pointed to the better performance of MLP network than ELMAN in artificial neural network model [17]. Pourkheirolah used hydrological modeling to assess the impact of climate change on the hydrological conditions of Dehloran Station. In this study, Csirok3-5-0 model output under RCP8.5 scenario was used. Precipitation and temperature values for future period (2016-2044) were calculated using the downscaled change factor method and IHACRES model was used to simulate basin runoff. The results showed that the average runoff decreased from 6.27 m^3/s in the base period to 5.78 m^3/s in the future period. Also, simulation of monthly basin runoff in the future period and comparison of its values with the observed period shows average decline of long-term annual runoff in the future period in the desired scenario [15]. Sayahi first calibrated IHACRES hydrological model using APHRODITE precipitation network data and CHCN-CAMS temperature dataset for the basin. Then, by introducing the temperature and precipitation scenario 2.6 of the fifth report to the mentioned hydrological model, discharge variations in the basin are predicted for the future periods. The results showed the rise of 0.17 to 2 degrees Celsius and a 3 to 75 percent of rainfall variation during 2011-2035 period compared to the 1983-2007 observation period. Runoff simulation results for the future period show the average annual runoff of 9.7 % compared to the observed period [18]. Hydrological models are vital and exigent tools for water resources and environmental planning and management. Three models of SWAT, IHACRES, and ANN were studied on daily, monthly, and annual bases in the Kan watershed, which were located in the west part of Tehran, Iran. ANN model showed a better performance for daily, monthly, and annual flow simulations compared with other two models (NSE=0.86, R^2=0.87, RMSE=2.2, MBE=0.08) and particularly for the simulation of maximum and minimum flow values. In addition, the performance of SWAT model (NSE=0.65, R^2=0.68, RMSE=3.3, MBE=-0.168) was better than that of the IHACRES model (NSE=0.57, R^2=0.58, RMSE=3.7, MBE=0.049). However, the results of the IHACRES model were still acceptable [19].

According to this review, the first goal of this work is to use IHACRES and ANNs to build a hydrologic model in basin under climatic conditions to simulate stream flow. These models are assessed on a basin scale and at monthly time intervals. To study climate change in the Kangavar region and its effects on the flow of the Khorramrood River, first, the suitable CMIP5 climate models for the region were selected. Then, these data were downscaled at the Aran station, and then the MLP neural network and the lumped-conceptual IHACRES models were compared to predict future discharge. A comparison of performance of ANN models with different input variables (e.g., monthly precipitation, monthly precipitation of previous months, and total precipitation of previous months, monthly temperature) has been made to find the best and most efficient network structure. In addition, their efficiency in the estimation of different ranges of flow (from very high to very low flow) is determined based on the Flow Duration Curve (FDC). To ensure the validity of the results, Aran station is in natural regime. Selecting an appropriate model to simulate the stream flow in a watershed is a key challenge, and analyzing the performance of these models in different climate scenarios could help researchers to apply the suitable model to each case.

3. STEPS OF THE PROPOSED METHODOLOGY

In this study, the rainfall and temperature data were first obtained from climate models and, then, downscaled for the target area to evaluate the discharge changes of Khorramrood River, which is a tributary of the Gamasiab River and, also, the Anahita Dam was built on it. Next, the discharge variations due to climate change in the Khorramrood River were estimated using artificial neural network and semi-conceptual IHACRES model (Fig. 1). Neural network modeling was done in the Python programming language and the Scikit-Learn Library.

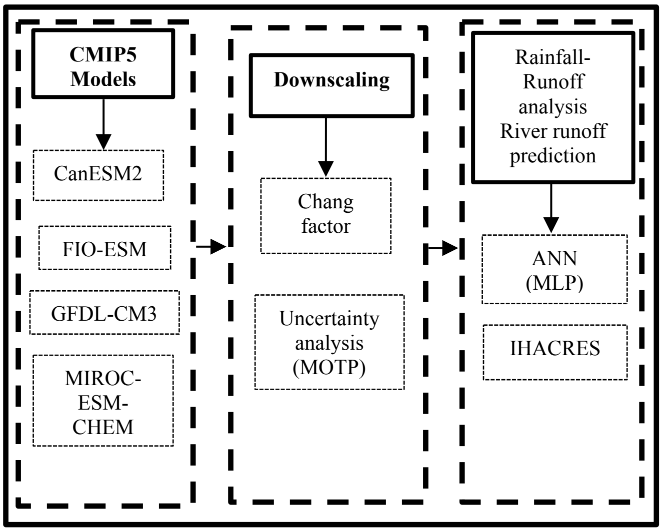

Figure 1. Flowchart of research

3.1. Climatic and hydrometric data

In order to study climate changes in the study area using RCP scenarios, monthly information of historical temperature and rainfall is required. Therefore, the Kangavar Synoptic Station information obtained over the course of 1983-2015 period, which is measured by Kermanshah Regional Meteorological Office, is used, as shown in Table 1. The measured quantitative monthly data including the flow discharge of Khorramrood River at Aran base station were obtained from Kermanshah Regional Water Authority, as shown in Table 2.

3.2. Study area

Kangavar County with an area of about 674 square kilometers is located in the east of Kermanshah province in West of Iran. Most western parts of Iran are composed of Zagros interconnected mountains and the fertile plain of Kangavar to the west of these highlands, which is located at an elevation of 1457 meters above sea level. The Central Zagros Highlands has covered the northern and northwestern parts of this vast plain. Aran base station is located at 47.925 °E longitude and 34.41 °N latitude. Much of precipitation occurs in December and January. The water in this region is supplied by rainfall stored in aquifers or from the many mirages of the area flowing into the rivers of Khorramrood, Asadabad, and Kangavar and the confluence of these rivers forms the water-filled Gamasiab River. Khoramrood River originates from southeast of Malayer highlands and joins Gamasiab River after irrigating agricultural land on its way to Hamadan and Kermanshah provinces (Fig. 2).

Figure 2. Geographical location of the Khorramrood watershed in Kermanshah Province and Iran

Table 1. Weather data of Kangavar synoptic station (1983-2015)

Month		Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Mean	**precipitation (mm)**	58	65	69	53	36	4	1	1	3	28	67	63
Max		283	305	339	108	211	21	8	13	19	83	347	176
Min		13	27	22	0	5	0	0	0	0	0	11	0
Mean	**Temperature (°C)**	-0.06	2.32	6.97	2.96	16.85	22.53	26.5	25.8	20.76	14.8	12.08	7.78
Max		4.47	6.87	11.0	7.28	20.06	25.87	29.8	28.3	23.89	17.6	15.41	10.87
Min		-8.65	-8.30	1.46	-1.22	13.70	18.61	23.36	22.21	17.97	12.80	9.94	5.54

Table 2. Khorramrood River flow in 1983-2015 (m^3/s)

Month	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Mean flow (m^3/s)	5.23	6.53	8.16	8.15	5.31	1.81	0.30	0.06	0.05	0.51	2.92	5.00

3.3. Climate scenarios (RCP)

At present, the most valid tool to generate climate scenarios is the Atmospheric-Ocean General Circulation Models (AOGCM) [20, 21]. The Intergovernmental Panel on Climate Change has used New RCP (Representative Concentration Pathways) scenarios as the trajectory of greenhouse gas concentrations to compile the Fifth Assessment Report (AR5). The new emission scenarios have four key trajectories called RCP2.6, RCP4.5, RCP6, and RCP8.5 that are named based on

Radiative Forcing in 2100 and can yield different levels of greenhouse gas emissions in any situation according to different characteristics of the technology level, socio-economic status, and future policies of a region. The variables in this scenario are:

- Emissions of gases such as SF_6, CFCs, PFCs, HFCs, N_2O, CH_4, CO_2.
- Emissions of chemically active gases and aerosols, Black Carbon (BC), SO_2, NH_3, organic carbon, VOCs, NO_x, CO_2, NH_3.
- The concentration of greenhouse gases including HFCs, PFCs, CFCs.
- The concentrations of aerosols & chemically active gases (O_3, aerosol).
- Land use and land cover data.

These scenarios were formulated in 2014 by the Scientific Committee under the auspices of the Intergovernmental Panel on Climate Change to provide a set of information whose results can track the main factors in climate change [9]. The present study was conducted based on downscaling of CMIP5 climate model data at Kangavar weather station and Aran Hydrometric station located in the Khorramrood River basin during the 33-year base period of 1983 to 2015. In order to create climate scenarios for the future 2020-2052 and 2053-2085 periods, the results of four models of the IPCC Fifth Assessment Report (AR5) under RCP8.5 scenario are used which have different resolutions, as shown in Table 3.

Table 3. AR5 models and their resolution

Model	(m × m)
CanESM2	128 × 64
FIO-ESM	128 × 64
GFDL-CM3	144 × 90
MIROC-ESM-CHEM	128 × 64

3.4. Uncertainty analysis with (MOTP)

In this method, the AR5 models are weighted based on the standard deviation of simulated mean temperature and precipitation in the base period of the average observational data.

$$W_i = \frac{(\frac{1}{\Delta P_i})}{\Sigma_{i=1}^{N}(\frac{1}{\Delta P_i})} \quad (1)$$

where W_i is weight of each model in the desired month and ΔP_i is the Long-term mean deviation of the simulated rainfall by each model in the base period from the mean observational data. By assigning rainfall values instead of high temperatures, weights corresponding to rainfall variables are also obtained [22].

3.5. Downscaling

The outputs of climatic models do not have the required accuracy of spatial and temporal analysis; therefore, the outputs of climate models need to be downscaled to the target area. Existing conventional downscaling methods including LARS-WG have not yet been updated for the new RCP scenarios and a number of primary variables of the SDSM method have not yet been prepared for AR5 models [23]. Therefore, the change factor method is considered for this study. In order to downscale the data locally, the proportional method was used whose climate variables simulated by AOGCM were extracted from the cellular information where the target area was located. The change factor method (Equations 2 to 5) was also used for temporal downscaling of the data [22].

$$\Delta Ti = \overline{T}_{AOGCM,Fut,i} - \overline{T}_{AOGCM,Base,i} \quad (2)$$

$$\Delta P_i = (\frac{\overline{P}_{AOGCM,Fut,i}}{\overline{P}_{AOGCM,Base,i}}) \quad (3)$$

$$T = T_{Obs} + \Delta T \quad (4)$$

$$P = P_{Obs} \times \Delta P \quad (5)$$

In Equation 2, ΔTi is the temperature variation for the long-term average of 33 years in each month, $\overline{T}_{AOGCM,Fut,i}$ is the simulated average temperature by each AOGCM in the future period for each month, $\overline{T}_{AOGCM,Base,i}$ is the simulated average temperature by each AOGCM in the observed period for each month, and the above items are considered for rainfall in Equation 3. In Equation 4, T is the time series derived from the climate temperature scenario for the future period, while Tobs is time series of the observed temperature in the base period (1983-2015). Equation 5 is time series of rainfall due to precipitation changes in Equation 3.

3.6. Rainfall-runoff simulation

Analysis of climate parameters variation on river discharge of the basin is possible using Rainfall-Runoff models. The changes in river discharge are important to satisfy water demands for agriculture, drinking, and industry demands. In this study, the IHACRES rainfall-runoff model and the artificial neural network model were employed to produce monthly runoff, and the results of both models were compared and the variations of climatic parameters on runoff were extracted.

3.7. IHACRES model

In IHACRES model, two nonlinear modulus reduction (loss) and linear unit hydrograph are used for runoff production. IHACRES model has two parts: (a) a part that converts rainfall at time k (rk) to effective rainfall (uk) (part of the rainfall that eventually enters the river) and the excess rainfall that is eventually removed by evapotranspiration (assuming the basin is impenetrable); (b) A linear conversion function (or UH unit hydrograph) that converts effective rainfall into the modeled flow (Xk). Here, these sections are called the loss section and the conversion function (unit hydrograph), respectively. The loss section is considered for all nonlinear rainfall-runoff processes on a watershed scale, while the conversion function is based on linear system theory. The IHACRES model has six parameters of which three parameters are related to the nonlinear loss section including (1/C), ($w\tau$), and f, which are the watershed storage capacity, the time constant at which the watershed wetness decreases, and the basin temperature modulation factor, respectively. Meanwhile, the other three parameters corresponding to the linear conversion function include τ (q) and τ (s), which are the times required for the fast and slow stream flows, and the V (S) represents the volume of the slow stream involved in the creation of the river. Examples of studies that have used IHACRES model can be found in the studies of [24], [25] and [26].

In this research, observational data of temperature, precipitation, and monthly discharge in the base period were used for calibration purpose. First, the IHACRES model should be calibrated for the study area and after model calibration, the monthly runoff in the basin is predicted by introducing downscaled temperature and rainfall data of the climate models for the next two periods and finally, the results of the model performance are discussed.

3.8. Artificial neural network (ANN)

Artificial neural networks are one of the most widely used structures in artificial intelligence that can even be considered as the basis of branches of artificial intelligence. Artificial neural networks are the intersection of biology, psychology, mathematics, and computers. Today, these structures are used in various engineering and basic sciences to automate, classify, and estimate complex functions. Although the age of neural networks has not exceeded 80 years, its application has now expanded to such an extent that its role in the advancement of various scientific fields cannot be ignored [27]. The use of Python programming language libraries in the neural network facilitates very good prediction of parameters based on appropriate predictors.

3.9. Multi-layer perceptron

Two or more neurons can be combined into a single layer. A particular network itself can consist of multilayers in which each layer in the grid has its own weight matrix, bias vector, and output. Relation 6 shows the multi-layer perceptron formula where f is the nonlinear activation function; w_j represents the weights of each layer; b is the bias, x_j represents the inputs, and y is the target [28].

$$y = f(\textstyle\sum_j w_j x_j + b) \tag{6}$$

Python language now provides the best and most convenient algorithms for data analysis and artificial intelligence. The MLP method of scikit-learn library was used for this purpose. The codes are available on: https://github.com/maryamhafezparast.

Using following formula (Equation 7) helps determine the total number of hidden layers needed.

$$N_h = N_s/(\alpha * (N_i + N_o)) \tag{7}$$

where N_i is the number of input neurons, N_o the number of output neurons, N_s the number of samples in the training data set, and α an arbitrary scaling factor measured between 2-10.

In this study, the MLP multilayer perceptron networks with different hidden layers (Equation 7) and the number of neurons have been calibrated to model the runoff of Khorramrood River using artificial neural networks, which are widely used in hydrological modeling [29, 30]. 70 % of the data were considered for network training and 30 % for network testing period. Relation 8 was used to normalize the data [31].

$$X_{normal} = \left(\left(\frac{X_t - X_{min}}{X_{max} - X_{min}}\right) \times 2\right) + 1 \tag{8}$$

3.10. Performance criteria

In order to compare and evaluate the performance of the studied models, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), the coefficient of determination (R), and the Nash Sutcliffe coefficient (NSE) were used.

$$RMSE = (\frac{1}{N}\sum_{i=1}^{n}(P_i - O_i)^2)^{0.5} \tag{9}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|P_i - O_i| \tag{10}$$

$$R = \sqrt{\frac{(\sum_{i=1}^{n}(P_i - \bar{P})(O_i - \bar{O}))^2}{\sum_{i=1}^{n}(P_i - \bar{P})^2(O_i - \bar{O})^2}} \tag{11}$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}|O_i - P_i|}{\sum_{i=1}^{N}|O_i - \bar{O}_i|} \tag{12}$$

where n is the number of data, O_i is the observed values, P_i is the computational values by the model, and $\bar{O}_i$ and $\bar{P}$ are the average observational and computational values by the model.

4. RESULTS AND DISCUSSION

The results of this study include downscaling results of 5 CMIP5 climate change models that show rainfall and temperature values in the first and second future periods and then, the role of these input variables in producing Khoramrood River discharge is estimated using artificial neural network and IHACRES models. Next, the results of both models are compared and the advantages and disadvantages of these methods are compared with the results reported by other researchers.

4.1. Reduction of uncertainty with MOTP

As mentioned, the uncertainty of each model can be reduced using the MOTP method and a weighted combination model is obtained by considering the weight of different climatic models. In this case, the results of this model can be used to predict the parameters in the future as an average of all the models used in the research. Meanwhile, in this method, weights of rainfall and temperature parameters of each climate model were determined separately for each month, as presented in Tables 4 and 5.

4.2. Comparing performance of climate models with observed data

In this section, the error criterion for evaluating the performance of climate models was used in this study. These criteria include coefficient of determination (R^2), the Nash Sutcliffe coefficient (NSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The historical long-term averages of each climate model and the combined model were compared to observational data during the base period (1983-2015), as shown in Tables 6 and 7. It is observed that the performance of the combined model and the climate models of the fifth report used in this study to simulate rainfall and temperature for the studied station shows a high correlation coefficient with relatively low error indicators. Therefore, it can be concluded that all models have a good ability to simulate the climate variables of Khorramrood River basin and one can trust the output of models for the studied basin. It should be noted that the weighted combination model had better performance than the other models, but all models have generally good predictability in this basin.

Table 4. Weight of each climate model for rainfall separated by months

Models	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
MIROC	0.35	0.11	0.34	0.29	0.12	0.14	0.21	0.28	0.20	0.16	0.51	0.39
CANSM2	0.21	0.11	0.21	0.21	0.17	0.27	0.17	0.17	0.20	0.43	0.15	0.30
FIO	0.14	0.39	0.22	0.18	0.47	0.43	0.41	0.23	0.19	0.29	0.14	0.16
GFDL	0.30	0.39	0.23	0.31	0.24	0.16	0.21	0.32	0.41	0.11	0.20	0.15

Table 5. Weight of each climate model for the temprature separated by months

Models	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
MIROC	0.34	0.22	0.23	0.28	0.23	0.22	0.20	0.24	0.18	0.20	0.20	0.19
CANSM2	0.17	0.25	0.27	0.26	0.25	0.32	0.28	0.28	0.40	0.48	0.45	0.33
FIO	0.24	0.20	0.18	0.21	0.26	0.24	0.23	0.19	0.19	0.15	0.15	0.21
GFDL	0.25	0.33	0.31	0.25	0.27	0.22	0.28	0.29	0.23	0.17	0.20	0.27

Table 6. Comparing performance criteria of climate models using the observed precipitation

	Precipitation			
Models	**NSE**	**MAE**	**RMSE**	**R**
Weighted Model	0.91	5.22	6.90	0.97
MIROC-ESM-CHEM	0.86	7.41	8.96	0.97
FIO-ESM	0.73	9.03	12.34	0.92
GFDL-CM3	0.82	8.02	9.93	0.95
CanESM2	0.75	9.52	12.03	0.92

Table 7. Comparing performance criteria of climate models by the observed temperature

	Temperature			
Models	**NSE**	**MAE**	**RMSE**	**R**
Weighted Model	0.97	1.23	1.3	0.99
MIROC-ESM-CHEM	0.97	1.37	1.45	0.99
FIO-ESM	0.97	1.49	1.54	0.99
GFDL-CM3	0.97	1.1	1.27	0.99
CanESM2	0.98	1.106	1.21	0.995

4.3. Prediction of temperature and precipitation with climate models

After downscaling the data for each climate model, the rainfall and temperature of each model and also the number of changes in these parameters (during the first and second future periods) with observational value could be observed. In Figs. (3, 4), rainfall and temperature variations for each model are specified as column chart and the observational value and weighted combination model for periods (2020-2052) and (2053-2085) are linear chart.

The results of the rainfall parameter under RCP 8.5 scenario showed that some models such as CanESM2, FIO-ESM, GFDL-CM3, and weighted combination model have predicted decreases of 13.86 %, 2.65 %, 23.47 %, 8.18 % in the first period compared to the base period. In the second period, this trend continues: CanESM2 model (6.61 %), FIO-ESM model (9.25 %), GFDL-CM3 model (26.33 %), and weighted combination model were reduced by 9.75 % compared to the base period. However, the MIROC-ESM-CHEM model showed an increase of 6.66 % for both first and second durations.

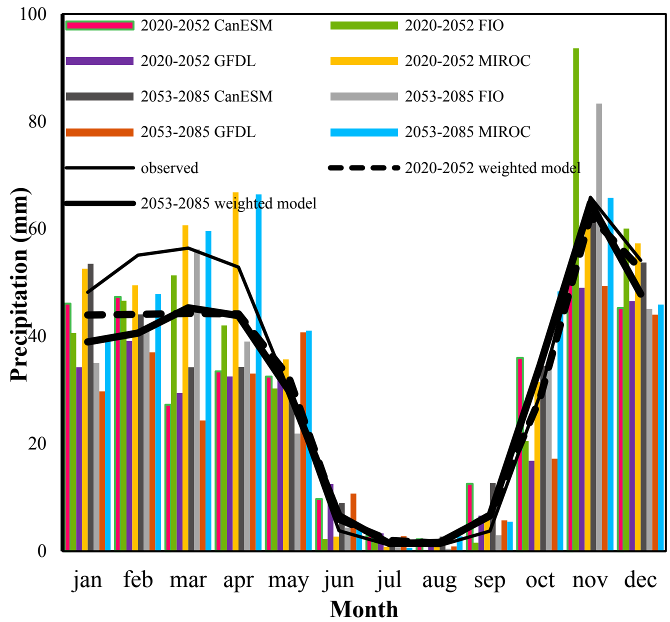

Figure 3. Rainfall changes in climate models under Scenario 8.5

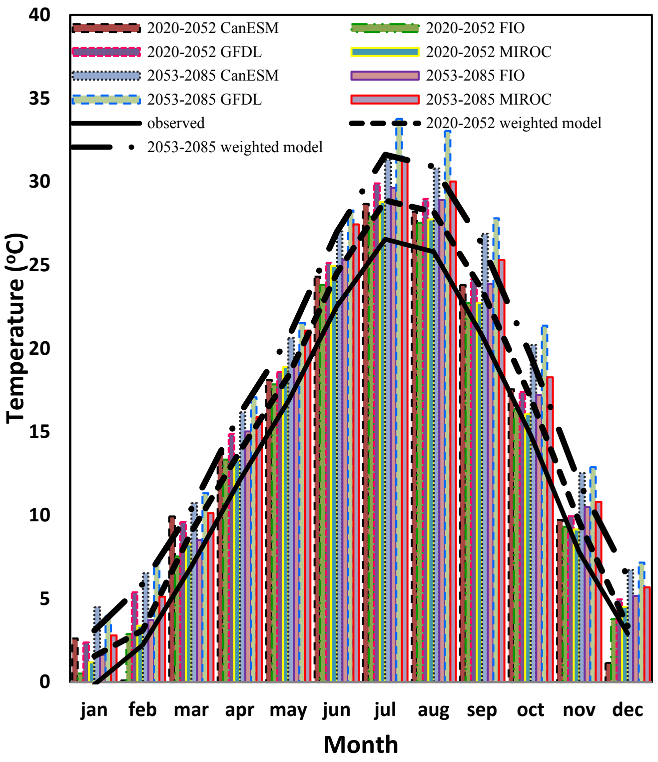

Figure 4. Temprature changes in climate models under Scenario 8.5

In the spring, the longest difference in long-term rainfall is observed in March using GFDL-CM3 model during 2053-2085 period. The results of the temperature predicted by climate models used for Khorramrood river basin have generally predicted an increasing temperature trend in which the increasing changes in the second future period are much more than the first period. In the first period, CanESM2, FIO-ESM, GFDL-CM3, MIROC-ESM-CHEM, and weight combination model increased 1.5, 1.21, 2.69, 1.66 and 1.85 °C, respectively, compared to the base period. In the second period, CanESM2 of 4.58 °C, FIO-ESM of 2.48 °C, GFDL-CM3 of 5.54 °C, MIROC-ESM-CHEM of 3.73 °C, and weight combination model increased by 4.22 °C compared to the base period.

4.4. Calibration and verification of IHACRES

In order to calibrate and validate the IHACRES rainfall-runoff model, it was tested for model calibration for several years. The results indicated that the period 1988, 2006 to 7, 12 correlated well with the observation period. After calibrating the model and parameters of the rainfall-runoff model, the rest of the data were employed to validate the model. The calibration parameters of the IHACRES model are shown in Table 8.

The simulation results of the IHACRES model for calibration and validation periods are presented in Figures 5 and 6. Comparative results of the simulated and observed runoff hydrographs pointed to a good compatibility between hydrographs. Meanwhile, the IHACRES model has simulated the occurrence time of peak discharge well. Validation of model results is essential to increasing user confidence for model simulation capability. Therefore, without changing the values of the input parameters, the calibrated model was used for the validation period.

Table 8. The calibration coefficients of IHACRES model

Parameter	Description	Optimum value
C	Humidity storage capacity	0.0024
T(W)	Drying time	1
F	Watershed temperature coefficient	2.4
I	Humidity threshold coefficient	0
P	Soil humidity intensity	1
a(s)	Drought index	-0.198
B(s)	Peak index	2.25
T(s)	Slow-down flow	0.617
V(s)	Volume ratio	2.8
T_{ref}	Reference temperature	20

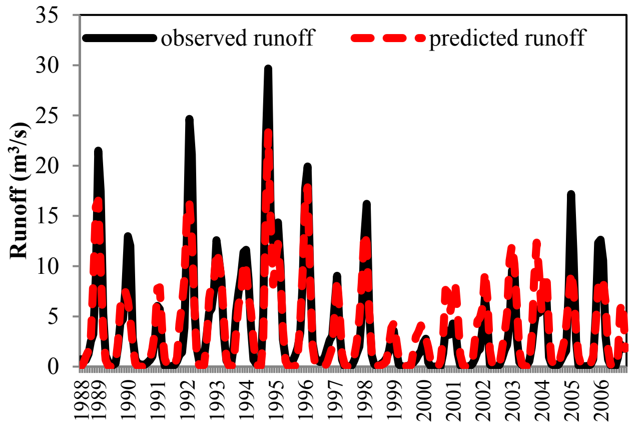

Figure 5. The simulated and observed runoffs during the calibration period for the IHACRES model

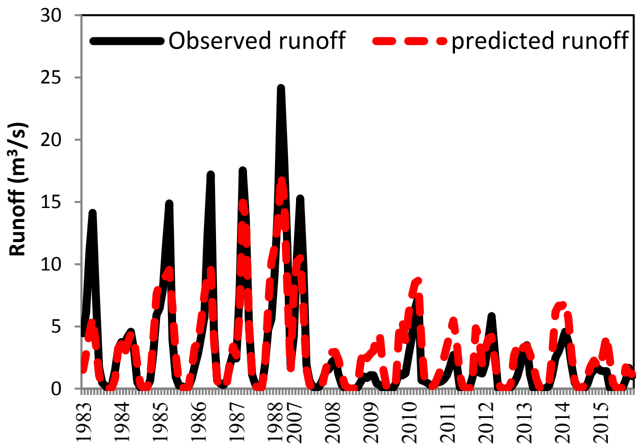

Figure 6. The simulated and observed runoffs during the validation period for the IHACRES model

4.5. Calibration and verification of ANN

The number of neurons in the input and output layers is determined by the nature of the problem under investigation. In this study, the number of neurons in the hidden layer was determined through trial and error in order to reduce the error. The process began with a small number of neurons and additional neurons were added until increase in the number of neurons had no effect on error recovery. The characteristics of the chosen network to simulate runoff using artificial neural network are listed in Table 9. The results showed that having only one hidden layer was better than more hidden layers and this could be due to the lack of direct correlation between the middle layers with the network output and the minor impact of the middle layer changes on weight adjustment. Finally, the outputs of the selected models were compared with the observed values and the optimal model was selected.

Table 9. Properties of the selected ANN model

Model characteristic	
Input variable	P(t) , P(t-1) ,Q(t-1),Q(t-2)
Target	Q(t)
Network	MLP
Percentage of verification	70
Percentage of calibration	30
Number of hidden layers	1
Number of neurons in the hidden layer	13
Number of iterations	2000

Figures 7 and 8 show the observed and simulated hydrographs during the calibration and validation periods in the selected ANN model. The simulated discharge at the peak points overlapped well with the observed data, but the monthly patterns of discharge variations are weaker during the calibration and validation periods.

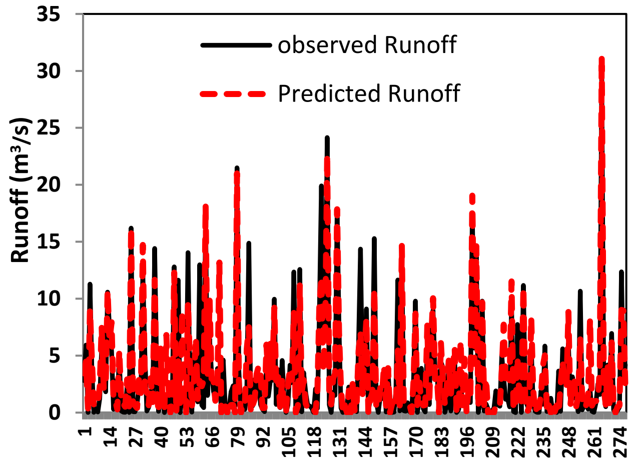

Figure 7. Observed and simulated runoffs for duration of calibration for the ANN model

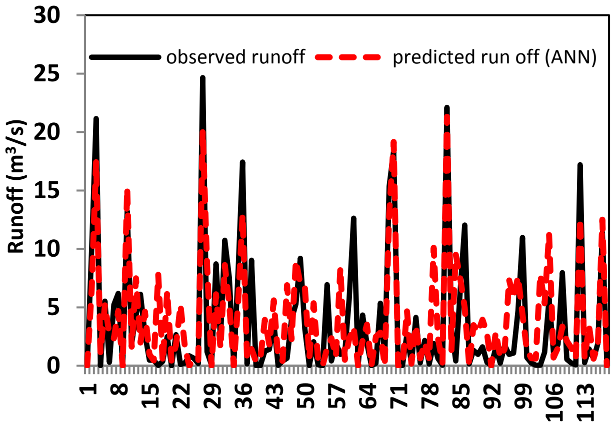

Figure 8. Observed and simulated runoffs for validation duration for ANN model

According to [32, 33] studies, model simulation can be recognized satisfactorily when the R^2 statistical index is more than 0.6 and the Nash-Sutcliffe efficiency (NSE) is greater than 0.5, which was used as a criterion for evaluating hydrological models in the studies conducted by [34], [35], [36], and [37]. After calibrating the artificial neural network models and IHACRES, the results of the models were compared. In both models, acceptable results were obtained in the calibration phase; however, the artificial neural network model in the validation phase reportedly achieved weaker values than the IHACRES model, as shown in Table 10.

Table 10. Comparing performance criteria in ANN and IHACRES

Performance criteria		R^2	RMSE	MAE	NSE
ANN	Calibration	0.82	2.33	1.46	0.6
	Verification	0.64	3.01	2.18	0.51
IHACRES	Calibration	0.9	2.08	1.29	0.71
	Verification	0.84	2.24	1.39	0.61

4.6. Prediction of runoff with IHACRES model

Following the calibration and validation of artificial neural network and IHACRES models, without changing the model parameters and only by changing the model inputs including rainfall and temperature of climate models, the river discharge during the first and second periods was predicted. For the forecast period, only the downscaled output of the weight combination model as a selected climate scenario was used. Figures 9 and 10 show the predicted rainfall against the predicted discharge for the RCP8.5 scenario.

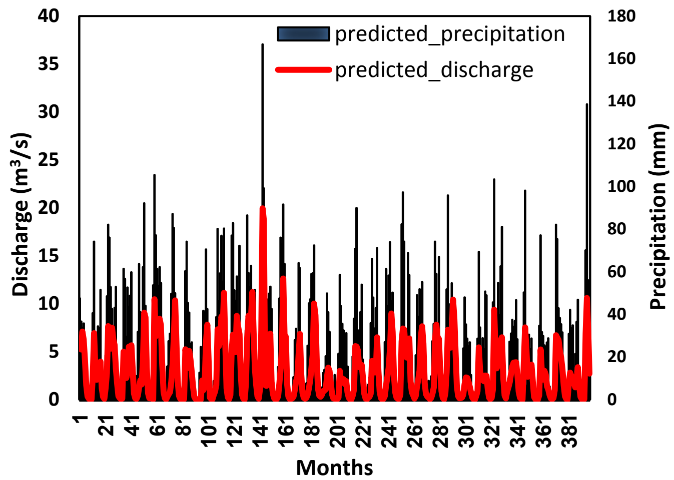

Figure 9. Predicted discharge of IHACRES model against precipitation in (2020-2053)

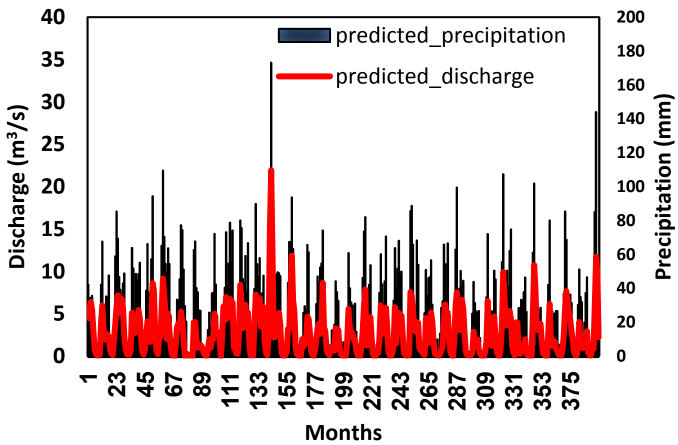

Figure 10. Predicted discharge of IHACRES model against precipitation in (2053-2085)

4.7. Prediction of runoff with ANN model

The prediction of discharge during the first and second periods for the weighted combination model was also done using the artificial neural network model. Figures 11 and 12 show the amount of rainfall predicted by Scenario 8.5 for the first and second periods against the predicted discharge. The results indicate that the neural network model has predicted more discharge than the IHACRES. Therefore, the long-term average discharge in the neural network model during the first period is 0.35, while during the second period is 0.44 cubic meters per second.

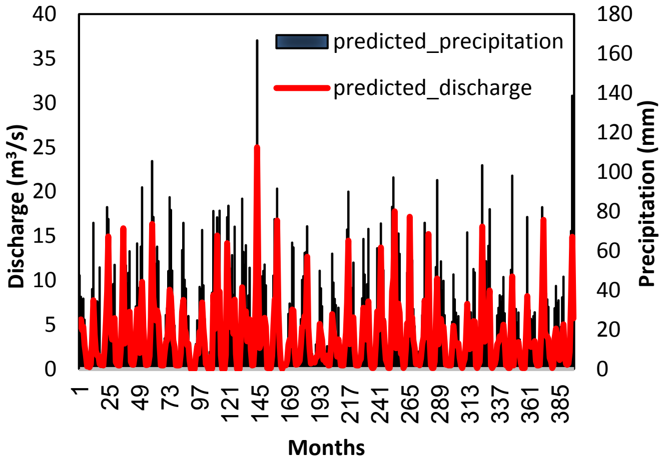

Figure 11. Predicted discharge of ANN model against precipitation in (2020-2052)

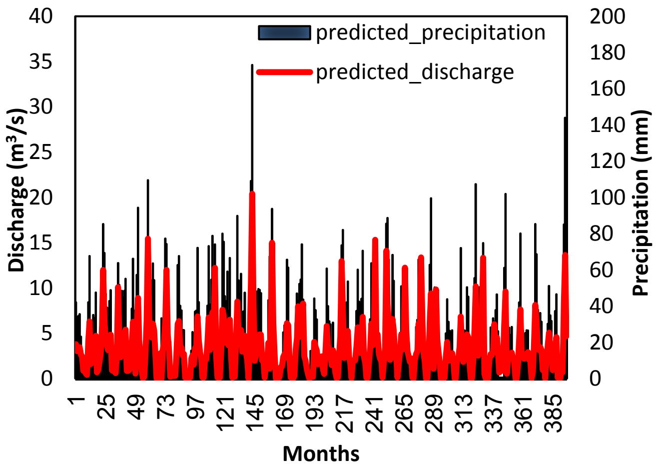

Figure 12. Predicted discharge of ANN model against precipitation in (2053-2085)

The results of the statistical characteristics of the discharge prediction in these models show decrease in discharge compared to the observation period in both models and both periods. The IHACRES model predicts a decrease of 12.72 % in the first period and 20.3 % in the second period, while the ANN model predicts a decrease of 2.12 % during the first period and 6.97 % during the second period.

4.8. Comparison of long-term monthly averages

In order to better analyze the output results of hydrological models, the monthly long-term average of the river flow was extracted. In both models and in both periods, a sharp decrease in peak discharge in March, April, and May of about five cubic meters per second is evident. While the peak flow in October and November shows a sharp increase of about three cubic meters per second in Figure 13.

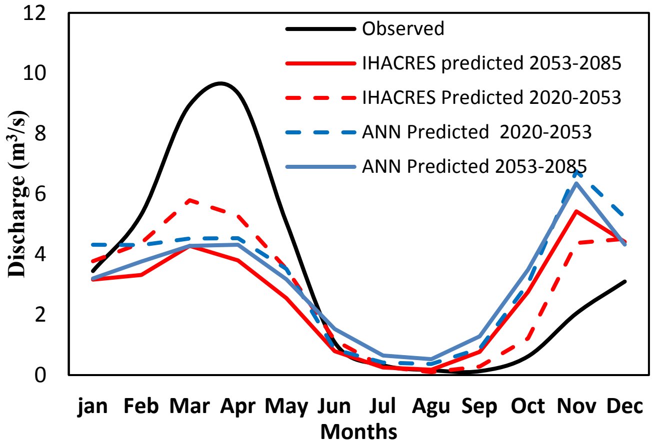

Figure 13. Comparison of long-term monthly averages of discharg

4.9. Comparison of models with duration curves

Flow Duration Curve (FDC) is a classic method used to graphically represent the relationship between frequency and flow rate. Various factors are involved in the shape (FDC) including climatic parameters and basin physiology. Figure 14 presents the flow duration curve for each category of flow range based on the quantile-domain model comparison. The results show that both the semi-conceptual and data-driven models underestimate the peak discharge of the catchments under climate change, which is related to the decrease in rainfall and increase in temperature in the context of climate change in the region. The FDC diagram shows that in the observed discharge mode, 10 % of the time, the flow is more than 90 cubic meters per second, while in the predicted discharge, it is more than 6 cubic meters per second. In general, the river is dry 25 % of the time. The results of this investigation of a specific study basin with monthly flow comparisons may not be applicable for the selection of robust rainfall-runoff models for climate change assessment studies. Therefore, climate change impact in the study basin should be assessed with more conceptual, distributed, and data-driven models together.

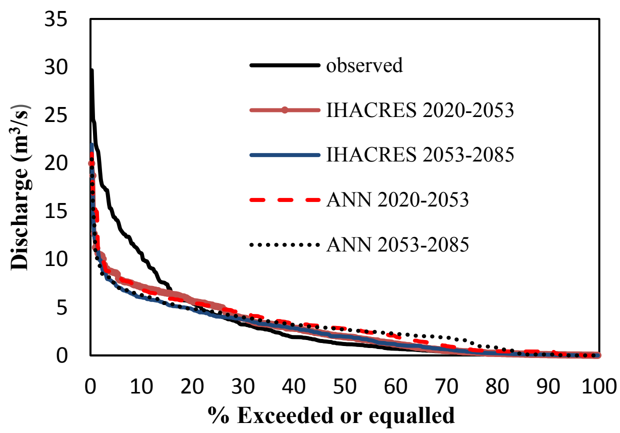

Figure 14. Flow duration curves of the observed and predicted flows

5. CONCLUSIONS AND REMARKS

The need for river discharge variations in the present and future periods is very important to satisfy the demands for drinking, industry, and agriculture and studying these variations for future periods using CMIP5 climate models is a good option. The output of these models often includes meteorological variables and hydrological models play an important role in applying the effects of these climate variables to river runoff. Therefore, in this study, the results of a semi-conceptual hydrological and MLP artificial neural network models were evaluated and predicting future discharge was performed with both models. The results also showed a decrease runoff in the future for both models, but Artificial neural network model predicts generally more discharge in the future than IHACRES model and since the IHACRES model in this study shows more accurate quantitative evaluation criteria during the calibration and validation period, it is more acceptable to predict the future period.

Since the simulation and prediction of river discharge with IHACRES and ANN models has been done in some parts of the world, the present research attempts to compare the results of researchers who used these models with the results obtained from this study. In this way, a study by [16] predicted stream flow in Kasilian watershed in northern Iran and demonstrated that neural network and IHACRES models outperformed autoregressive integrated moving average and deseasonalized autoregressive moving average models which is in line with the results of the present study. The results of comparison of hydrological models for evaluating water resources in a low-data area by [38] showed that the selected simple conceptual models (GR4J and IHACRES) had a better daily performance than the more complex model (SWAT). The results of the present study also indicate that the IHACRES model has a good ability to simulate monthly runoff.

However, the use of climate models of the fifth scenario in hydrology has been evaluated since 2013 at the same time with their release [9]. Zulkarnain [39] showed that the performance of the multilayer neural network model was better than the IHACRES model, and this model could simulate runoff using the rainfall inputs and rainfall of previous months as well as runoff that occurred in previous months, which is not in line with the present study. In another study [40] found that the ANN model could simulate observed runoff and evaluated the comparison of IHACRES and neural network models for daily river discharge, but cannot keep the trends in daily and annual series. The present study also mentions this point about the artificial neural network model which failed to simulate the behavioral pattern of the observed time series. Ahooghalandari evaluated that the ANN was introduced as a good option for complex hydrological systems. Also, data derived from two adjacent stations were employed to improve the results of artificial neural networks compared to the IHACRES model, which is in line with the present study [14]. The results of the present study are also in line with the research of [17] who found that IHACRES performance was better than the ANN model, even though it was a more data intensive model than the ANN model. In doing so, three models of SWAT, IHACRES, and ANN on daily, monthly, and annual bases in the Kan watershed are used by [19]. According to the results, the performance of the three considered models is generally suitable for rainfall-runoff process simulation; however, ANN model exhibits a better performance for daily, monthly, and annual flow simulations than other two models.

6. ACKNOWLEDGEMENT

The authors would like to thank Kermanshah Regional Water Company and Kermanshah Province Meteorological Administration. The authors received no financial support for the research, authorship, and publication of this article. This manuscript is the result of the research of S. Marabi under the supervision of M. Hafezparast. Authors designed the study, developed the methodology, discussed the results and wrote the paper. (https://github.com/maryamhafezparast).

REFERENCES

1. Fu, G., Charles, S.P., Chiew, F.H., Teng, J., Zheng, H., Frost, A.J., Liu, W. and Kirshner, S., "Modelling runoff with statistically downscaled daily site, gridded and catchment rainfall series", ***Journal of Hydrology***, Vol. 429, No. 7, (2013), 254-265. (https://doi.org/10.1016/j.jhydrol.2013.03.041).
2. Hao, X., Chen, Y., Xu, C. and Li, W., "Impacts of climate change and human activities on the surface runoff in the Tarim River Basin over the last fifty years", ***Water Resources Management***, Vol. 22, (2008), 1159-1171. (https://doi.org/10.1007/s11269-007-9218-4).
3. Zhang, D., Chen, X., Yao, H. and Lin, B., "Improved calibration scheme of swat by separating wet and dry seasons", ***Ecological Modelling***, Vol. 301, (2015), 54-61. (https://doi.org/10.1016/j.ecolmodel.2015.01.018).
4. Risbey, J.S. and Entekhabi, D., "Observed Sacramento Basin stream flow response to precipitation and temperature changes and its relevance to climate impact studies", ***Journal of Hydrology***, Vol. 184, No. 3-4, (1996), 209-223. (https://doi.org/10.1016/0022-1694(95)02984-2).
5. Ouyang, F., Zhu, Y., Fu, G., Lü, H., Yu, Zh. and Chen, X., "Impacts of climate change under CMIP5 RCP scenarios on streamflow in the Huangnizhuang catchment", ***Stochastic Environmental Research and Risk Assessment***, Vol. 29, (2015), 1781-1795. (https://doi.org/10.1007/s00477-014-1018-9).
6. Hafezparast, M., Araghinejad, S., Fatemi, S.E. and Bressers, H., "A conceptual rainfall-runoff model using the auto calibrated NAM models in the Sarisoo River", ***Hydrology Current Research***, Vol. 4, No. 1, (2013), 1-6. (https://doi.org/10.4172/2157-7587.1000148).
7. Fu, G., Charles, S.P. and Chiew, F.H.S., "A two-parameter climate elasticity of streamflow index to assess climate change effects on annual streamflow", ***Water Resources Research***, Vol. 43, No. 11, (2007), 1-12. (https://doi.org/10.1029/2007WR005890).
8. Liu, Z., Xu, Z., Charles, S.P., Fu, G. and Liu, L., "Evaluation of two statistical downscaling models for daily precipitation over an arid basin in China", ***International Journal of Climatology***, Vol. 31, No. 13, (2011), 6006-6060. (https://doi.org/10.1002/joc.2211).
9. Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V. and Midgley, P.M., IPCC, Summary for policymakers, Climate change: The physical science basis, contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, (2013). (https://www.cambridge.org/core/books/climate-change-2013-the-physical-science-basis/summary-for-policymakers/356E277FD1FBC887845FB9E8CBC90CCD).
10. Ma, C., Pan, S., Wang, G., Liao, Y. and Xu, Y.P., "Changes in precipitation and temperature in Xingjian River Basin, China", ***Theoretical and Applied Climatology***, Vol. 123, No. 3-4, (2016), 859-871. (https://doi.org/10.1007/s00704-015-1386-1).
11. Kharin, V.V., Zwiers, F.W., Zhang, X. and Wehner, M., "Changes in temperature and precipitation extremes in the CMIP5 ensemble", ***Journal of Climate Change***, Vol. 116, (2013), 345-357. (https://doi.org/10.1029/2005JD006290).
12. Chadwick, R., Boutle, I. and Martin, G., "Spatial patterns of precipitation change in a CMIP5: Why the rich do not get richer in the tropics", ***Journal of Climate***, Vol. 26, No. 11, (2013), 3503-3566. (https://doi.org/10.1175/JCLI-D-12-00543.1).
13. Tan, M.L., Ficklin, D.L., Ibrahim, A.L. and Yusop, Z., "Impacts and uncertainties of climate change on stream flow of the Johor River Basin, Malaysia using a CMIP5 general circulation model ensemble", ***Journal of Water and Climate Change***, Vol. 5, No. 4, (2014), 676-695. (https://doi.org/10.2166/wcc.2014.020).

14. Ahooghalandari, M., Khiadani, M. and Kothapalli, G., "Assessment of artificial neural networks and IHACRES models for simulating stream flow in Marillana catchment in the Pilbara, Western Australia", ***Australasian Journal of Water Resources***, Vol. 19, No. 2, (2015), 116-126. (https://doi.org/10.1080/13241583.2015.1116183).

15. Sadeghi Loyeh, N. and Jamnani, M.R., "Comparison of different rainfall-runoff models performance: A case study of Liqvan catchment, Iran", ***European Water***, Vol. 57, (2017), 315-322. (http://www.ewra.net/ew/pdf/EW_2017_57_44.pdf).

16. Ghanbarpour, M.R., Amiri, M., Zarei, M. and Darvari, Z., "Comparison of stream flow predicted in a forest watershed using different modelling procedures: ARMA, ANN, SWRRB, and IHACRES models", ***International Journal of River Basin Management***, Vol. 10, No. 3, (2012), 281-292. (http://dx.doi.org/10.1080/15715124.2012.699893).

17. Karamouz, M., Fallahi, M., Nazif, S. and Farahani, M.R., "Long lead runoff simulation using data-driven models", ***International Journal of Civil Engineering***, Vol. 10, No. 4, (2012), 328-336. (http://ijce.iust.ac.ir/article-1-414-en.html).

18. Sayahi, S., Shahbazi, A. and Khademi, Kh., "Simulation of the climate change impact on monthly runoff of Dez watershed using IHACRES model", ***Journal of Water Science Engineering***, Vol. 7, No. 15, (2017), 7-18. (In Farsi with English Abstract). (http://wsej.iauahvaz.ac.ir/article_531584.html).

19. Ahmadi, M., Moeini, A., Ahmadi, H., Motamedvaziri, B. and Zehtabiyan, Gh.R., "Comparison of the performance of SWAT, IHACRES and artificial neural networks models in rainfall-runoff simulation (Case study: Kan watershed, Iran)", ***Physics and Chemistry of the Earth***, Vol. 111, (2019), 65-77. (https://doi.org/10.1016/j.pce.2019.05.002).

20. Mitchell, T.D., "Pattern scaling: An examination of accuracy of the technique for describing future climates", ***Climatic Change***, Vol. 60, (2003), 217-242. (https://doi.org/10.1023/A:1026035305597).

21. Wilby, R.L. and Harris, I., "A framework for assessing uncertainties in climate change impacts: Low flow scenarios for the River Thames, UK", ***Water Resources Research***, Vol. 42, No. 2, (2006), 1-10. (https://doi.org/10.1029/2005WR004065).

22. Massah Bavani, A. and Morid, A.R., "The impacts of climate change on water resources and agricultural production", ***Journal of Water Resources Research***, Vol. 1, No. 1, (2005), 40-47. (In Farsi with English Abstract). (http://iwrr.sinaweb.net/article_32831.html?lang=en).

23. Moazami Goudarz, F., Sarraf, A. and Ahmadi, H., "Prediction of runoff within Maharlu basin for future 60 years using RCP scenarios", ***Arabian Journal of Geosciences***, Vol. 13, No. 605, (2020). (https://doi.org/10.1007/s12517-020-05634-x).

24. Hansen, D.P., Ye, W., Jakeman, A.J., Cooke, R. and Sharma, P., "Analysis of the effect of rainfall and streamflow data quality and catchment dynamics on streamflow prediction using the rainfall-runoff model IHACRES", ***Environmental Software***, Vol. 11, (1996), 193-202. (https://doi.org/10.1016/S0266-9838(96)00048-2).

25. Post, D.A. and Jakeman, A.J., "Predicting the daily stream flow of ungauged catchments in S.E. Australia by regionalizing the parameters of a lumped conceptual rainfall-runoff model", ***Ecological Modelling***, Vol. 123, (1999), 91-104. (https://doi.org/10.1016/S0304-3800(99)00125-8).

26. Schreider, S.Y., Jakeman, A.J. and Pittock, A.B., "Modelling rainfall-runoff from large catchment to basin scale: The Goulburn Valley, Victoria", ***Hydrological Processes***, Vol. 10, (1996), 863-876. (https://doi.org/10.1002/(SICI)1099-1085(199606)10:6<863::AID-HYP376>3.0.CO;2-8).

27. Haykin, S., Neural networks: A comprehensive foundation, 2nd Edition, Prentice Hall, Englewood Cliffs, New Jersey, USA, (1999), 1-696. (https://www.amazon.com/Neural-Networks-Comprehensive-Foundation-2nd/dp/0132733501).

28. Bhattacharyya, B., Price, R.K. and Solomatine, D.P., "Machine learning approach to modelling sediment transport", ***Journal of Hydraulic Engineering***, Vol. 133, No. 4, (2007), 440-450. (https://doi.org/10.1061/(ASCE)0733-9429(2007)133:4(440)).

29. Dawson, C.W. and Wilby, R.L., "Hydrological modelling using artificial neural networks", ***Progress in Physical Geography***, Vol. 25, No. 1, (2001), 80-108. (https://doi.org/ 10.1177/030913330102500104. 2001).

30. Kamruzzaman, J. and Aziz, M.A., "Note on activation function in multilayer feed forward learning", ***Proceedings of the 2002 International Joint Conference on Neural Networks. IJCNN'02 (Cat. No.02CH37290)***, Honolulu, HI, USA, (2002). (https://doi.org/10.1109/IJCNN.2002.1005526).

31. Asadollahfardi, G., Taklify, A. and Ghanbari, A., "Application of artificial neural network to predict TDS in Talkheh Rud River", ***Journal of Irrigation and Drainage Engineering***, Vol. 138, No. 4, (2011), 363-370. (https://doi.org/10.1061/(ASCE)IR.1943-4774.0000402).

32. Bannem, J. and Shoemaker, C.A., "An analysis of high-flow sediment event data for evaluating model performance", ***Journal of Hydrological Processes***, Vol. 19, (2005), 605-620. (https://doi.org/10.1002/hyp.5608).

33. Santhi, C., Arnold, J.G., Williams, J.R., Dugas, W.A., Srinivasan, R. and. Hauck, L.M., "Validation of the SWAT model on a large river basin with point and nonpoint sources", ***Journal of American Water Resources Assocciation***, Vol. 37, No. 5, (2001), 1169-1188. (https://doi.org/10.1111/j.1752-1688.2001.tb03630.x).

34. Sevat, E. and Dezetter, A., "Selection of calibration objective functions in the context of rainfall-runoff modeling in a Sudanese savannah area", ***Hydrological Science Journal***, Vol. 36, No. 4, (1991), 307-330. (https://doi.org/10.1080/02626669109492517).

35. Boyle, D.P., Gupta, H.V. and Sorooshian, S., "Toward improved calibration of hydrologic models: Combining the strengths of manual and automatic methods", ***Water Resources Research***, Vol. 36, No. 12, (2000), 3663-3674. (https://doi.org/1029/2000WR900207).

36. Legates, D.R. and McCabe, G.J., "Evaluating the use of “goodness-of-fit” measures in hydrologic and hydro climatic model validation", ***Water Resources Research***, Vol. 35, No. 1, (1999), 233-241. (https://doi.org/10.1029/1998WR900018).

37. Pourkheirollah, Z., Hafezparast, M. and Fatemi, S.E., "Changes in precipitation, temperature and discharge under RCP scenarios case study: Dehloran city", ***Proceedings of the Second Iran National Conference***, Shahrekord University, (2017). (In Farsi with English Abstract). (https://civilica.com/papers/l-8405/).

38. Tegegne, G., Kwan Park, D. and Kim, Y., "Comparison of hydrological models for the assessment of water resources in a data-scarce region, the Upper Blue Nile River Basin", ***Journal of Hydrology: Regional Studies***, Vol. 14, (2017), 49-66. (https://doi.org/10.1016/j.ejrh.2017.10.002).

39. Zulkarnain, H., Shamsudin, S. and Harun, S., "Minimum input variance for modelling rainfall-runoff using ANN", ***Jurnal Teknologi***, Vol. 69, No. 3, (2014), 113-118. (https://doi.org/10.11113/jt.v69.3154).

40. Zulkarnain, H., Shamsudin, S., Harun, S., Marlinda, A. and Hamidon, N., "Suitability of ANN applied as a hydrological model coupled with statistical downscaling model: A case study in the northern area of Peninsular Malaysia", ***Environmental Earth Sciences***, Vol. 74, No. 1, (2015), 463-477. (https://doi.org/10.1007/s12665-015-4054-y).