Climate Change Impacts on the Streamflow of Zarrineh River, Iran: Postprint

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Abstract

Zarrineh River is located in the northwest of Iran, providing more than 40% of the total inflow into the Lake Urmia that is one of the largest saltwater lakes on the earth. Lake Urmia is a highly endangered ecosystem on the brink of desiccation. This paper studied the impacts of climate change on the streamflow of Zarrineh River. The streamflow was simulated and projected for the period 1992–2050 through seven CMIP5 (coupled model intercomparison project phase 5) data series (namely, BCC-CSM1-1, BNU-ESM, CSIRO-Mk3-6-0, GFDL-ESM2G, IPSL-CM5A-LR, MIROC-ESM and MIROC-ESM-CHEM) under RCP2.6 (RCP, representative concentration pathways) and RCP8.5. The model data series were statistically downscaled and bias corrected using an artificial neural network (ANN) technique and a Gamma based quantile mapping bias correction method. The best model (CSIRO-Mk3-6-0) was chosen by the TOPSIS (technique for order of preference by similarity to ideal solution) method from seven CMIP5 models based on statistical indices. For simulation of streamflow, a rainfall-runoff model, the hydrologiska byrans vattenavdelning (HBV-Light) model, was utilized. Results on hydro-climatological changes in Zarrineh River basin showed that the mean daily precipitation is expected to decrease from 0.94 and 0.96 mm in 2015 to 0.65 and 0.68 mm in 2050 under RCP2.6 and RCP8.5, respectively. In the case of temperature, the numbers change from 12.33°C and 12.37°C in 2015 to 14.28°C and 14.32°C in 2050. Corresponding to these climate scenarios, this study projected a decrease of the annual streamflow of Zarrineh River by half from 2015 to 2050 as the results of climatic changes will lead to a decrease in the annual streamflow of Zarrineh River from 59.49 m3/s in 2015 to 22.61 and 23.19 m3/s in 2050. The finding is of important meaning for water resources planning purposes, management programs and strategies of the Lake' s endangered ecosystem.

Full Text

Preamble

Climate change impacts on the streamflow of Zarrineh River, Iran

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Abstract: Zarrineh River is located in the northwest of Iran, providing more than 40% of the total inflow into Lake Urmia, which is one of the largest salt-water lakes on Earth. Lake Urmia is a highly endangered ecosystem on the brink of desiccation. This paper studied the impacts of climate change on the streamflow of Zarrineh River. The streamflow was simulated and projected for the period 1992–2050 through seven CMIP5 (Coupled Model Intercomparison Project Phase 5) data series (namely, BCC-CSM1-1, BNU-ESM, CSIRO-Mk3-6-0, GFDL-ESM2G, IPSL-CM5A-LR, MIROC-ESM, and MIROC-ESM-CHEM) under RCP2.6 (RCP, Representative Concentration Pathways) and RCP8.5. The model data series were statistically downscaled and bias-corrected using an artificial neural network (ANN) technique and a Gamma-based quantile mapping bias correction method. The best model (CSIRO-Mk3-6-0) was chosen by the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method from seven CMIP5 models based on statistical indices. For simulation of streamflow, a rainfall-runoff model, the Hydrologiska Byrans Vattenavdelning (HBV-Light) model, was utilized. Results on hydro-climatological changes in Zarrineh River basin showed that the mean daily precipitation is expected to decrease from 0.94 and 0.96 mm in 2015 to 0.65 and 0.68 mm in 2050 under RCP2.6 and RCP8.5, respectively. In the case of temperature, the numbers change from 12.33°C and 12.37°C in 2015 to 14.28°C and 14.32°C in 2050. Corresponding to these climate scenarios, this study projected a decrease of the annual streamflow of Zarrineh River by half from 2015 to 2050 as the results of climatic changes will lead to a decrease in the annual streamflow of Zarrineh River from 59.49 m^3/s in 2015 to 22.61 and 23.19 m^3/s in 2050. The finding is of important meaning for water resources planning purposes, management programs, and strategies of the Lake' s endangered ecosystem.

Keywords: climate change; water resources management; climate model intercomparison project phase 5 (CMIP5); artificial neural network (ANN); bias correction; hydrologiska byrans vattenavdelning (HBV-Light); Zarrineh River

1 Introduction

Considerable changes in precipitation and temperature regimes in the past few decades, resulting in socio-economic and environmental issues, necessitate hydrological simulations for estimation of future changes in streamflow conditions.

Global climate models (GCMs), also known as general circulation models, using a mathematical model of the general circulation of a planetary atmosphere or ocean, can be taken into consideration to obtain climate change projections for climatic parameters such as temperature and precipitation [?, ?, ?, ?]. GCM simulations are based on four global scenarios, RCP (Representative Concentration Pathways) 2.6, RCP4.5, RCP6.0, and RCP8.5, where RCP2.6 and RCP8.5 are the most optimistic and pessimistic scenarios, based on a possible range of radiative forcing values in 2100. Despite the increasing use of GCMs, the main problem with them is their coarse resolution, which makes them unable to provide reliable information at hydrological scales [?, ?]. Therefore, using downscaling approaches in relevant studies has become inevitable [?, ?, ?, ?, ?, ?, ?, ?].

Two major downscaling approaches, dynamical downscaling and statistical downscaling, are often used. Dynamical downscaling methods result in higher-resolution regional climate models (RCMs), used to preserve the physical coherence between atmospheric and land surface variables [?, ?]. However, the raw RCM simulations may still be biased [?, ?]. The statistical downscaling methods are based on statistical relationships between large-scale atmospheric variables (predictors) and local climate variables (predictands) [?, ?, ?]. Compared to dynamic downscaling, statistical downscaling involves simple computational skills to downscale GCM simulations [?, ?].

Artificial intelligence (AI), as a common method of statistical downscaling, is capable of analyzing long-series of hydrological data. In recent years, the use of AI methods such as artificial neural networks (ANNs) approaches is increasing. The success of this technique is primarily due to its ability to map highly non-linear relations between inputs and outputs of the model [?, ?]. Mendes and Marengo (2010) compared the performance of a temporal neural network model with an autocorrelation statistical downscaling model with emphasis on its ability to reproduce the observed climate variability and tendency for the period 1970–1999 in the Amazon region. The results showed that the neural network model remarkably outperforms the statistical models for the downscaling of daily precipitation variations. Skamarock et al. (2013) highlighted that ANN estimates of rainfall were more accurate than Weather Research and Forecasting model estimates, which applies dynamic downscaling approaches. Campozano et al. (2015) used the statistical downscaling model, the least squares support vector machines (LS-SVM) and ANNs to downscale precipitation data over the Paute River Basin in southern Ecuador. The results indicated that LS-SVM and ANNs performed better in downscaling of precipitation data.

As development and implementation of adaptive management strategies in water systems requires the cognition of future changes in water resources, in this study, the aim was to simulate and project the effects of climate change on Zarrineh River' s streamflow. In this regard, seven different climate model precipitation and temperature data series were downscaled using an ANN technique and bias correction method. Then the bias-corrected data were used in hydrological simulations of the streamflow. So, a toolbox was developed, which comprises the ANN toolbox of MATLAB (Matrix Laboratory), a program based on the bias correction method, a TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) program, and a rainfall-runoff model, namely the Hydrologiska Byrans Vattenavdelning (HBV-Light) model as the central engine.

2.1 Study Area

Zarrineh River basin (35°40 -37°26 N, 45°46 -47°22 E), with an area of 1.18$×10^{4}$ km^2, is located in the northwest part of Iran [Figure 1: see original paper]. It provides more than 40% of the total inflow into Lake Urmia, which is on the brink of desiccation with a recorded annual water level reduction of about 40 cm over 1998–2018 [?, ?]. Lake Urmia, the largest lake in the country and the second largest saltwater lake on Earth, has encountered a critical problem due to ineffective water resources management (comprising agricultural development and low irrigation water use efficiency, over allocation of the lake' s inflows, irrigation projects and overuse of surface water and groundwater, etc.) and climate change [Figure 2: see original paper].

The mean annual precipitation and the annual mean temperature in the basin were reported to be about 292.00 mm and 13.26°C between 1992 and 2005, respectively. The potential daily evapotranspiration was about 4.17 mm. However, these reported numbers did not follow a specific trend during the period [?, ?, ?, ?, ?]. If a methodical comprehensive plan is built and implemented, reviving the shriveled lake is possible. As Zarrineh River feeds Urmia Lake, modeling the rainfall-runoff process in the river under the influence of future climate changes is crucial. The results are of important meaning for appropriate decision-making and water allocation in the basin.

2.2 Data

Zarrineh River basin, used as the case study of this work, was divided into twelve 0.5-degree cells. The cells were named from the top left. The study area lacks an adequate system to collect weather data. For this study, the observed daily mean temperature, provided by the Iranian Meteorological Organization (http://reports.irimo.ir/), were used as predictands at three observation sites, which are evenly distributed across the entire area of the basin and a bilinear interpolation technique was employed for developing gridded temperature data. Also, daily precipitation sums were provided from the Global Precipitation Climatology Center (GPCC), providing gridded gauge-analysis products, derived from quality-controlled station data. Here in the GPCC website (http://gpcc.dwd.de/), the gridded daily precipitation data is available in netCDF (Network Common Data Form) format with a spatial resolution of 0.5°. Also, seven different CMIP5 models for the most optimistic scenario, RCP2.6, and the most pessimistic scenario, RCP8.5, providing the predictor data, were gathered from the CERA (Climate and Environmental Data Retrieval and Archive System) website (https://cera-www.dkrz.de/) . For calibration of the HBV-Light (Hydrologiska Byrans Vattenavdelning) model, measured streamflow values of Zarrineh River were used. More information of the four stream gauging stations has been provided in Table 1. It should be noted that the calibration period of the study was 1992–2005, the evaluation was performed for the verification period 2006–2015, and the projection period was considered for 2016–2050.

2.3 Artificial Neural Network

ANNs are pattern recognition tools, which are able to find confirmable relationships between a set of inputs and the corresponding outputs [?, ?, ?]. In 1957, Rosenblatt introduced the simplest form of feed-forward neural network, called perceptron. But as the inputs were fed directly to the output unit via the weighted connections in the method, it was proved that they could not be trained to distinguish different classes of patterns [?, ?].

A multilayer perceptron (MLP) is a feedforward ANN, comprising at least three layers of nodes: an input layer, a hidden layer, and an output layer. As the MLP finds non-linear relationships among the nodes, it overcomes many limitations of the single layer perceptron [?, ?]. Two important characteristics of the MLP are: its nonlinear processing elements which have a smooth nonlinearity; and their massive interconnectivity. The effectiveness of an ANN model is gauged by MSE (Mean Squared Error) and R^2, which are derived from comparing the output data with the corresponding target output for the pattern. The best performance can be yielded by specifying the network architecture and by finding the optimal values of connection weights [?, ?]. The network size depends on the number of nodes and layers. However, in the process of finding the optimal values for the connection weights, selection of a training algorithm is important. There are several training processes which differ in how the weights are obtained. In this study, the standard back propagation algorithm was used in ANN training based on its popularity. Detailed information about the proposed ANN approach is provided in [?, ?, ?, ?].

In the present work, to implement the ANN models, the ANN toolbox of MATLAB was used, and the transfer function of hidden layer was taken as tansigmoid while function of the output layer was a linear transfer function. The ANN models were trained on 70% dataset to predict precipitation and temperature for the twelve different 0.5-degree cells of the study area. The remaining 30% dataset was used for testing and validation of the models. In this study, it was desired to produce an output of temperature and precipitation and to establish the relationship between GCM simulations and observed temperature and rainfall data. ANNs were trained separately for temperature and precipitation, so each network produced only one output variable, corresponding to the target layer of the ANN.

2.4 Bias Correction

Simulated precipitation and temperature by GCMs are often characterized by considerable biases due to their coarse spatial resolution [**?**, **?**], limiting their direct application for basin-scale hydrological modeling. To address the systematic errors of GCMs, most climate studies use bias correction methods to bias-correct the climate model outputs. This study describes how to use an efficient statistical bias correction method over the study area and improve the performance of the downscaled data, derived from the ANN models. The quantile mapping (QM) method (also known as distribution mapping method) was applied to correct precipitation and temperature data and is utilized to match the distribution function of the data, derived from ANN, with the observed distribution function. As it is used to adjust mean, standard deviation, and quantiles, it preserves the extremes [**?**, **?**], but it also has its limitation due to the assumption that both meteorological variables follow the same distribution, which may cause new biases [**?**, **?**].

The Gamma distribution [**?**, **?**] with shape parameter α and scale parameter β is often used for precipitation distribution [**?**, **?**]:

$$f(x;\alpha,\beta) = \frac{x^{\alpha-1}e^{-x/\beta}}{\beta^{\alpha}\Gamma(\alpha)}$$

where Γ(x) is the gamma function for the variable x. The QM method of precipitation is expressed mathematically in terms of the Gamma cumulative distribution function f_y and its inverse f_y^{-1} as:

$$P_{cor,m,d} = f^{-1}_{y,obs,m}(f_{y,ANN,m}(P_{ANN,m,d};\alpha_{ANN,m},\beta_{ANN,m});\alpha_{obs,m},\beta_{obs,m})$$

where P_{cor,m,d} is corrected precipitation; P_{ANN,m,d} is the precipitation derived from the ANN models on the day d of month m; α{*ANN,m*} *and* β{ANN,m} are the shape parameter and scale parameter from the ANN data on the month m; and α{*obs,m*} *and* β{obs,m} are the shape parameter and scale parameter from the observational data on the month m.

For temperature, the Gaussian (or normal) distribution [**?**, **?**] with mean (μ) and standard deviation (σ) is usually presumed to fit temperature best [**?**, **?**]:

$$f_N(x;\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}$$

where f_N is the calculated Gaussian distribution and R is a real number. For temperature, the QM method is expressed mathematically in terms of the Gaussian cumulative distribution function:

$$T_{cor,m,d} = f_{N,obs,m}^{-1}(f_{N,ANN,m}(T_{ANN,m,d}; \mu_{ANN,m}, \sigma_{ANN,m}); \mu_{obs,m}, \sigma_{obs,m})$$

where T_{cor,m,d} is the corrected temperature; T_{ANN,m,d} is the temperature derived from ANN models on the day d of month m; µ_{ANN,m} and σ^2{ANN,m} *are the mean and variance from the ANN data on the month m; and* μ{obs,m} and σ^2_{obs,m} are the mean and variance from the observational data on the month m.

2.5 TOPSIS Method

TOPSIS is a multi-criteria decision making method, which is based on the idea that the selected alternative should have the shortest geometric distance from the positive ideal solution and the longest distance from the negative ideal solution [**?**, **?**]. The method was first developed by Hwang and Yoon (1981). The procedure consists of the six following steps [**?**, **?**, **?**]:

Step 1: Establishing a performance matrix. The decision-matrix (M) consists of m alternatives (A_m) and n criteria (C_n), with the intersection of each alternative and criterion given as z_{ij}:

$$M = \begin{pmatrix} z_{11} & z_{12} & \cdots & z_{1n} \\ z_{21} & z_{22} & \cdots & z_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ z_{m1} & z_{m2} & \cdots & z_{mn} \end{pmatrix}$$

where i and j represent the number of row and column, respectively.

Step 2: Normalizing the decision-matrix. In the classical TOPSIS approach, the normalized matrix can be obtained using the following transformation formula:

$$N_{ij} = \frac{z_{ij}}{\sqrt{\sum_{i=1}^{m} z_{ij}^2}}$$

where N_{ij} is a member of the normalized matrix.

Step 3: Calculating the weighted normalized decision matrix (V). The weighted normalized matrix is calculated as:

$$V = W \times N$$

where these weights W_{n×n} are calculated by entropy, AHP (Analytic Hierarchy Process), and direct assignation, etc.

Step 4: Determining the positive ideal solution ($\mathbf{A^+}$) and negative ideal solution ($\mathbf{A^-}$).

$$A^+ = \{(\max v_{ij} | j \in J), (\min v_{ij} | j \in J')\}$$

$$A^- = \{(\min v_{ij} | j \in J), (\max v_{ij} | j \in J')\}$$

where J is associated with benefit criteria; J is associated with cost criteria; and v_{ij} is the component of matrix V in the ith line and jth column calculated from Equation 7.

Step 5: Calculating the separation measures. The separation of each alternative from the A^+ (d_i$^+$) and the separation of each alternative from the A^- (d_i$^-$) are given as:

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, \quad i = 1, 2, ..., m$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}, \quad i = 1, 2, ..., m$$

Step 6: Calculating the relative closeness (CL_i*) to the ideal solution.

$$CL_i^* = \frac{d_i^-}{d_i^+ + d_i^-}, \quad i = 1, 2, ..., m$$

Alternatives are ranked according to CL_i. *The higher CL_i* value, the higher the priority of the ith alternative [?, ?].

2.6 Hydrological Modeling

HBV-Light, a conceptual, continuous, and semi-distributed streamflow model developed by Sten Bergstrom in 1992 and 1995, was used to simulate daily streamflow values for the study area. HBV-Light includes some different routines and it can simulate snow, soil water, evaporation, groundwater, and channel routing [?, ?]. HBV-Light requires daily temperature, precipitation, and long-term average of potential evaporation values as driving variables. In this study, for the best GCM in the study area, chosen by TOPSIS method, 48 possible daily temperature and precipitation series in the twelve 0.5-degree cells, derived from the QM method based on the two scenarios of RCP2.6 and RCP8.5, were available to run the HBV-Light models. First, the HBV-Light models were calibrated and validated to measured streamflow values. For this purpose, the monthly averages of HBV-Light-simulated streamflow were analyzed and were compared to the observed values from 1992 to 2015. Then, these HBV-Light parameter sets were used to simulate streamflow with the corrected GCM simulations as driving conditions between 1992 and 2050. [Figure 3: see original paper] shows the flowchart of the study.

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3 Results

3.1 Statistical Evaluation of the Bias-Corrected ANN Simulations

At this stage, we applied three statistical metrics to evaluate the performance of raw GCMs data over the study area and to assess the inter-model differences. The evaluation started by comparing the mean daily precipitation of GPCC data and individual model mean during the historical period of 1992–2005. In addition, we used the mean absolute error (MAE) to compare the observed climate data with the corrected forecasted data and used the coefficient of determination (R^2) to show the statistical relationship between the observation data set with the corrected data . Results from Table 3 highlight the need for correcting GCMs outputs before any further analysis. We established the relationship between GCM simulations and observed temperature and rainfall data to implement the ANN models. In addition, we used the bias correction methods of precipitation and temperature to improve the performance of each ANN model. Precipitation and temperature correction methods were conducted on a daily basis from 1992 to 2050 .

3.2 TOPSIS Method

The best CMIP5 model was chosen by TOPSIS method. Development of the TOPSIS algorithm was done based on the statistical evaluation of the bias-corrected ANN simulations from 1992 to 2005 in the study area. As a non-limiting sample, indicates that the highest priority of model selection is belonged to CSIRO-Mk3-6-0. Therefore, in the next step, this model was used to simulate Zarrineh River' s streamflow under the RCP2.6 and RCP8.5 in the HBV-Light models. In this table, the bias-corrected ANN simulations for daily precipitation and temperature were evaluated statistically during 1992–2005.

shows the annual mean observed and corrected precipitation and temperature from 1992 to 2005 by the bias-corrected ANN data, derived from CSIRO-Mk3-6-

0 in Zarrineh River basin. Based on the table, a fairly good consistency between the observed and simulated data was revealed. Results indicate that the coefficient of determination between the annual mean observed and bias-corrected ANN data in the target period is 0.81 and 0.93 in the case of precipitation and temperature, respectively.

[Figure 4: see original paper] indicates the observed and corrected mean precipitation and temperature from 1992 to 2005 by bias-corrected ANN data for daily precipitation and temperature, derived from CSIRO-Mk3-6-0. In this figure, the cells were named from the top left.

In the validation period of 2006–2015, bias-corrected ANN data for precipitation and temperature data of CSIRO-Mk3-6-0 projects, based on RCP2.6 and RCP8.5, were assessed based on the observed data. The coefficient of determination in the validation period for bias-corrected ANN data for precipitation was 0.50 and 0.51 in the case of RCP2.6 and RCP8.5, respectively. These numbers change to 0.70 and 0.74 when it comes to temperature. As Figures 5 indicate, results achieved an acceptable agreement between the annual mean observed and bias-corrected ANN data. Bias-corrected ANN data for precipitation data of CSIRO-Mk3-6-0 reveals that the daily mean precipitation is expected to decrease from 0.94 and 0.96 mm in 2015 to 0.65 and 0.68 mm in 2050 based on RCP2.6 and RCP8.5, respectively. In the case of temperature, the numbers change from 12.33°C and 12.37°C in 2015 to 14.28°C and 14.32°C in 2050, respectively. This data was next used to simulate Zarrineh River' s streamflow in the HBV-Light models.

[Figure 5: see original paper] Assessment of bias-corrected ANN simulations of monthly mean precipitation (a) and temperature (b) derived from CSIRO-Mk3-6-0 in the validation period (2006–2015)

3.3 Evaluation of the Hydrological Models

The chosen CMIP5 model (CSIRO-Mk3-6-0), operated under RCP2.6 and RCP8.5, was used to simulate Zarrineh River' s streamflow in the HBV-Light models from 1992 to 2050. For the evaluation of the models, statistical indexes such as the coefficient of determination were used. Also, monthly mean streamflow in hydrological simulations for the catchment were compared with the observed data between 1992 and 2015. In general, it can be said that the agreement between the observed and simulated values both in the calibration period of 1992–2005 and in the validation period of 2006–2015 is acceptable. The observed monthly streamflow in 2015 and corresponding simulated streamflow in HBV-Light models by the corrected data, derived from CSIRO-Mk3-6-0, operated under RCP2.6 and RCP8.5, were summarized in Tables 7 and 8. Generally, all simulations were in good agreement with the observations and there was no significant difference between these results and the observed values.

Upon assuring that the models simulate the streamflow of Zarrineh River within plausible limits, future projections of the river flow were achieved. Future projections for the period of 2016–2050 of streamflow for the study site, simulated by bias-corrected ANN data for daily precipitation and temperature, derived from CSIRO-Mk3-6-0, operated under RCP2.6 and RCP8.5, were generally in agreement in terms of the general trend [Figure 6: see original paper]. A more detailed look at the figure reveals that the annual streamflow of Zarrineh River is expected to decrease from 59.49 m^3/s in 2015 to 22.61 and 23.19 m^3/s in 2050 based on RCP2.6 and RCP8.5, respectively.

Performance of the HBV-Light (Hydrologiska Byrans Vattenavdelning) models simulated by bias-corrected ANN data for daily bias-corrected precipitation and temperature, derived from CSIRO-Mk3-6-0, operated under RCP2.6 and RCP8.5 in 2015

Monthly mean streamflow of the HBV-Light models simulated by bias-corrected ANN data for daily bias-corrected precipitation and temperature, derived from CSIRO-Mk3-6-0, operated under RCP2.6 and RCP8.5 in 2015

[Figure 6: see original paper] Annual mean streamflow of the Zarrineh River in the HBV-Light (Hydrologiska Byrans Vattenavdelning) models simulated by bias-corrected ANN data, derived from CSIRO-Mk3-6-0, operated under RCP2.6 and RCP8.5 from 2015 to 2050

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4 Discussion

Climate change is expected to alter the magnitude and timing of runoff and, consequently, have significant implications for existing water resources systems as well as for planning and management of future water resources [?, ?]. Zarrineh River basin faces high pressure on water due to ineffective water resources management, as well as climate change [?, ?, ?, ?]. So, a better understanding of the impact of climate change on water resources in the basin is necessary [?, ?, ?, ?, ?, ?, ?]. The present study aimed to simulate and project the streamflow of Zarrineh River from 1992 to 2050. For this purpose, a toolbox was developed, comprising the ANN method for downscaling the large-scale data, a bias correction method for generating unbiased climate datasets, a TOPSIS program for choosing the best CMIP5 model, and a rainfall-runoff model, namely HBV-Light for investigating the effects of climate change on water resources. The results indicated that the daily mean precipitation is expected to decrease from 0.94 and 0.96 mm in 2015 to 0.65 and 0.68 mm in 2050 based on RCP2.6 and RCP8.5, respectively. In the case of temperature, the numbers change from 12.33°C and 12.37°C in 2015 to 14.28°C and 14.32°C in 2050, respectively. In addition, the annual streamflow of Zarrineh River is expected to decrease by half from 2015 to 2050.

Results from this study, along with previous studies, showed that the combination of the ANN method and bias correction method can improve the performance of the forecasted data. As the results showed that the performances of bias correction methods are not robust in all of the months. To evaluate the robustness of the performances of the methods in different hydrological seasons, the streamflow can be divided into different periods according to the hydrographs. As statistical downscaling methods rely heavily on the assumption that currently observed relationships will carry into the future, using two statistical downscaling methods simultaneously may result in similar consequences for both RCP2.6 and RCP8.5.

The proposed approach can be further strengthened and extended from several aspects. Future research will, hopefully, combine and apply the ANN method and different bias correction methods to other study areas as the accuracy of the method depends on several spatial and temporal conditions. A major extension may be considering land cover-use change, where any change in land cover may also result in a decrease in streamflow while sensitivity analysis is an approach to handle this type of challenge. It is undeniable that other potential topics can be covered in future studies in Zarrineh River basin to quantify the impacts of different future scenarios and to reduce the negative effects of climate change and human activities on local water resources.

5 Conclusions

Considerable changes in precipitation and temperature regimes in the past few decades have resulted in socio-economic and environmental problems. Accordingly, it is required to estimate future changes, being used in hydrological simulations of streamflow. In spite of the increasing use of GCM simulations in hydro-climatic studies, their direct application is contestable due to the biases. This paper introduces a new approach for forecasting rainfall and temperature, using an ANN technique. To improve its performance, a bias correction method may be used. So, a toolbox was developed, comprising the ANN method, a bias correction and a TOPSIS program, and a rainfall-runoff model, namely the HBV-light model, where the effects of climate change on water resources were investigated. The toolbox was utilized for the case of Zarrineh River basin. Future projections of streamflow revealed that the annual streamflow is expected to decrease by half from 2015 to 2050.

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Note: Figure translations are in progress. See original paper for figures.