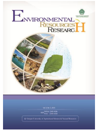

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Performance evaluation of artificial neural networks in statistical downscaling of monthly precipitation (Case study: Minab watershed)

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Abstract
Assessment of the impacts of climate change on water resources has been obtained significant attentions in the past decade. This paper assesses the climate change impacts on precipitation in the Minab basin, in the Hormozgan province in Iran. Two monthly precipitation downscaling methods were proposed based on multi-layer perceptron (MLP) and radial basis function (RBF) neural networks. The downscaling models were calibrated and validated using the large scale climatic parameters (predictors) derived from National Center for Environmental Prediction (NCEP)/ National Centre for Atmospheric Research (NCAR) reanalysis data set for downscaling monthly precipitation in the Minab basin in Iran. Pearson correlation was employed to choose the predictors among the NCEP/ NCAR reanalysis data set and final predictor combination for each station is assigned. The results of the downscaling models revealed that the MLP model produced more accurate and consistent results by downscaling the large scale climatic parameters compared to the RBF model. The proposed model can be reliably utilized for developing future projections of precipitation using the general circulation models outputs which can be employed also as the inputs in hydrological models.

Keywords: Climate Change, Statistical Downscaling, Artificial Neural Network, Multi-layer Perceptron, Radial Basis Function.

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Introduction

Global Circulation Models (GCMs) are the most efficient and reliable tools to assess the impacts of climate change at regional scale (Wilby *et al.,* 1998; Okkan and Inan, 2015; Sachindra and Perera, 2016). These models explain the atmospheric processes by employing mathematical formulations. These models have a coarse resolution (tens to hundreds of kilometers) and they are not suitable to resolve sub grid scales features (such as topography and clouds). Moreover, their results are not applicable to study where requires information at a fine scale (Wilby *et al.,* 2002; George *et al.,* 2015; Akbari *et al.,* 2016). In order to identify the impacts of coarse-scale atmospheric patterns at the local scale, downscaling techniques were developed (Fistikoglu, and Okkan, 2010). In the past decade, several downscaling approaches have been developed to tackle this problem. There are two main approaches which have been proposed for downscaling GCMs: dynamic downscaling and statistical downscaling (Christensen *et al.,* 2007; Kang *et al.,* 2015; Kourgialas *et al.,* 2015). According to Murphy (1998), dynamic downscaling approaches generally employ regional climate models (RCMs) which utilize coarse GCM data as boundary conditions in order to acquire a higher spatial resolution at the local climate domain. Outputs of these models are highly sensitive to the biases accruing from the GCMs and they are more time-consuming compared to the statistical downscaling techniques (Giorgi *et al.,* 2001; Anandhi *et al.,* 2008; Lin *et al.,* 2016).

According to Wilby *et al.* (1998), one of the most widely used methods in downscaling large scale climatic variables (predictors) to local scale (predictands) is statistical downscaling. These approaches were developed to construct relationships among large scale climatic parameters (predictors) and local surface parameters (predictands) (Wilby *et al.,* 1998).

In the recent years, the application of machine learning methods as statistical downscaling techniques has received much attention (Abdellatif et al., 2015; Joshi *et al.,* 2015; Lua *et al.,* 2016). Chen *et al.* (2010) employed support vector machine (SVM), multiple regression model and statistical downscaling model (SDSM) as statistical downscaling models for downscaling GCM outputs in the Shih-Men Reservoir basin in Taiwan. The results of this study indicated that the SVM model can offer more accurate and consistent results for generating daily precipitation properties.

Hashmi *et al.* (2011) employed Gene Expression Programming (GEP) and statistical downscaling model (SDSM) to predict watershed precipitation using GCM simulated climatic variables at the Clutha River watershed in New Zealand. The study showed that the GEP based downscaling model performs better than the SDSM model in the case of precipitation downscaling.

Acharya *et al.* (2013) evaluated the accuracy of extreme learning machine (ELM) and such multi-model ensemble (MME) approaches to estimate the Northeast monsoon rainfall from GCM large scale outputs to local scale in south peninsular India. The simulation results of this study indicated better performance of ELM-based models compared with other downscaling models.

Kourgialas *et al.* (2015) applied artificial neural network (ANN) and principal component analysis (PCA) to predict hydrological extremes under climate change scenarios in the Koiliaris River basin. As demonstrated in the research, the ANN offered promising results for assessing the impacts of climate change as a statistical downscaling tool in this basin.

Sarhadi *et al.* (2015) employed Support Vector Regression (SVR) and Relevance Vector Machine (RVM) as a statistical downscaling method to downscale global climate models (GCMs). Their results revealed the capability of the statistical downscaling by RVM to predict future variations in rainfall.

Furthermore, Shenify *et al.* (2015) applied hybrid Support Vector Machine with Discrete Wavelet Transform (SVM-WT) model, artificial neural network (ANN) and genetic programming (GP) to predict precipitation in Serbia. The result of the research indicated the superiority of the hybrid approach compared with other proposed models. The goal of this article is to identify a set of the most relevant large scale climatic input parameters (predictors) among NCEP/NCAR reanalysis data set for downscaling monthly precipitation in Minab basin in Iran. Furthermore, to investigate the results of downscaling to local scale variables such as precipitation using two machine learning approaches in the Minab basin, south-east of Iran. Overall, this research discusses the calibration and validation of multi-layer perceptron (MLP) and radial basis function (RBF) neural networks based statistical downscaling models in order to downscale monthly general circulation model outputs to monthly precipitation and thus aims to provide a comparison between the two data-driven techniques. The employed approaches are efficient and reliable in regenerating monthly precipitation time series for future assessment of climate change impacts.

The reminder of this research is organized as follows. First, the study area and data are explained. The next section is a description of the employed artificial intelligence methods which are used to transform information from GCMs to local scale. The methodology proposed for downscaling of precipitation is provided and the results are then presented for further discussion. In the last part of this study the conclusions are presented.

Materials and Methods

Study Area and Data Collection

The Minab basin in the Hormozgan province in Iran was selected as the study area for this research. This basin located between 56° 51' 07" and 57° 53' 00" longitude and 26° 51' 31" to 28° 30' 25" latitude (Figure 1). The Minab basin is under the influence of an arid and sub humid climate. The total area of the basin is 10171 km^2 and the annual average rainfall is around 185 mm which 80% occurs during winter and autumn. The normal mean monthly maximum and minimum temperatures of the region are 42°C and 20°C, respectively. Due to the issue of water scarcity in the Minab basin, detailed and accurate precipitation forecasting can help water resource managers to apply more effective and sustainable policies to construct more reliable strategies. There is only one meteorological station in the study area and therefore for more investigation, two nearest stations to the border of basin have been selected in this research. (Table 1). The monthly rainfall records of these stations are obtained from the Iranian Meteorological Organization (www. weather.ir).

The Multi-layer Perceptron (MLP)

An artificial neural network (ANN) is a data processing method which has analogous performance to the biological neural networks of the human brain (Haykin, 1999). MLPs are the most popular and the simplest type of ANN. These approaches are widely used to construct the relationship between input and outputs (Ahmed *et al*., 2015). Multi-layer perceptron are feed-forward networks which include one or more hidden layers (Haykin, 1999). The MLP applied in this research contained a three-layer architecture consisting of an input layer, a hidden layer and an output layer. Figure 2 shows a typical MLP feedforward network for this study with one hidden layer. According to Hornik *et al.* (1989), the advantages of MLPs make this method easy to use and capable of estimating any input/output relation for more accurate prediction. The Levenberg–Marquardt (LM) algorithm (Levenberg, 1944; Marquardt, 1963) is an efficient learning approach for multi-layer feedforward networks. This method is a modified version of the classic Newton approach for obtaining an optimum solution to the optimization problem. This method employs an approximation to the Hessian matrix in the following equation (Equation 1).

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \qquad (1)$$

In which x is the neural network weights, J is the performance criteria Jacobian matrix and μ and e are learning process parameter and residual error vector, respectively. The

LM training algorithm has been successfully applied in different studies (Banerjee *et al.,* 2009; Chang *et al.,* 2015).

The methodology adopted for this research is illustrated in Figure 3.

Table 1. Meteorological stations in the study area

Station name	Elevation (m)	Latitude (˚N)	Longitude (˚E)
Kahnooj	469.7	28˚ 03'	57˚ 75'
Rodan	200	27˚ 44'	57˚ 17'
Minab	29.6	27˚ 15'	57˚ 05'

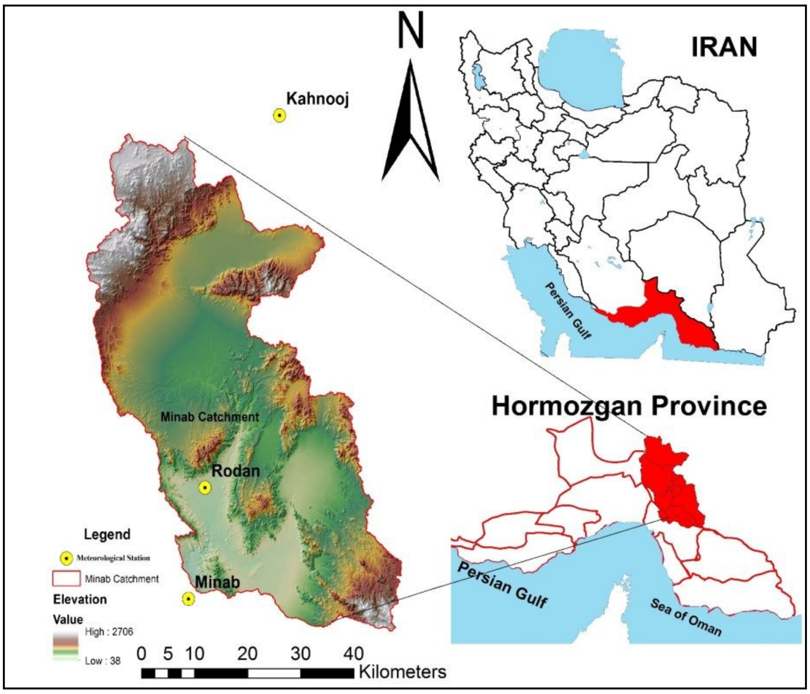

Figure 1. Location map of the study region in Hormozgan Province of Iran (the aerial image obtained through the website of USGS).

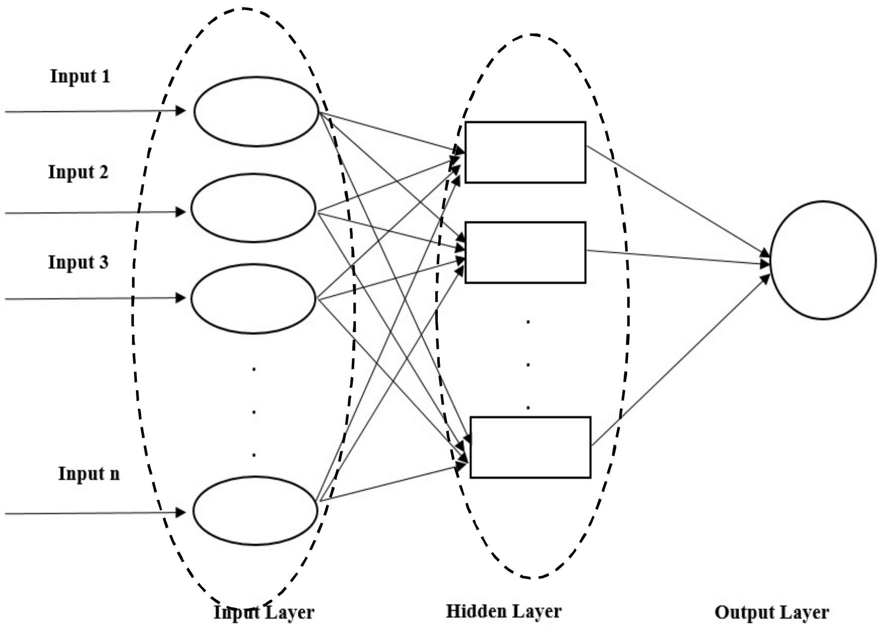

Figure 2. A schematic architecture of the three-layer ANN for the study area.

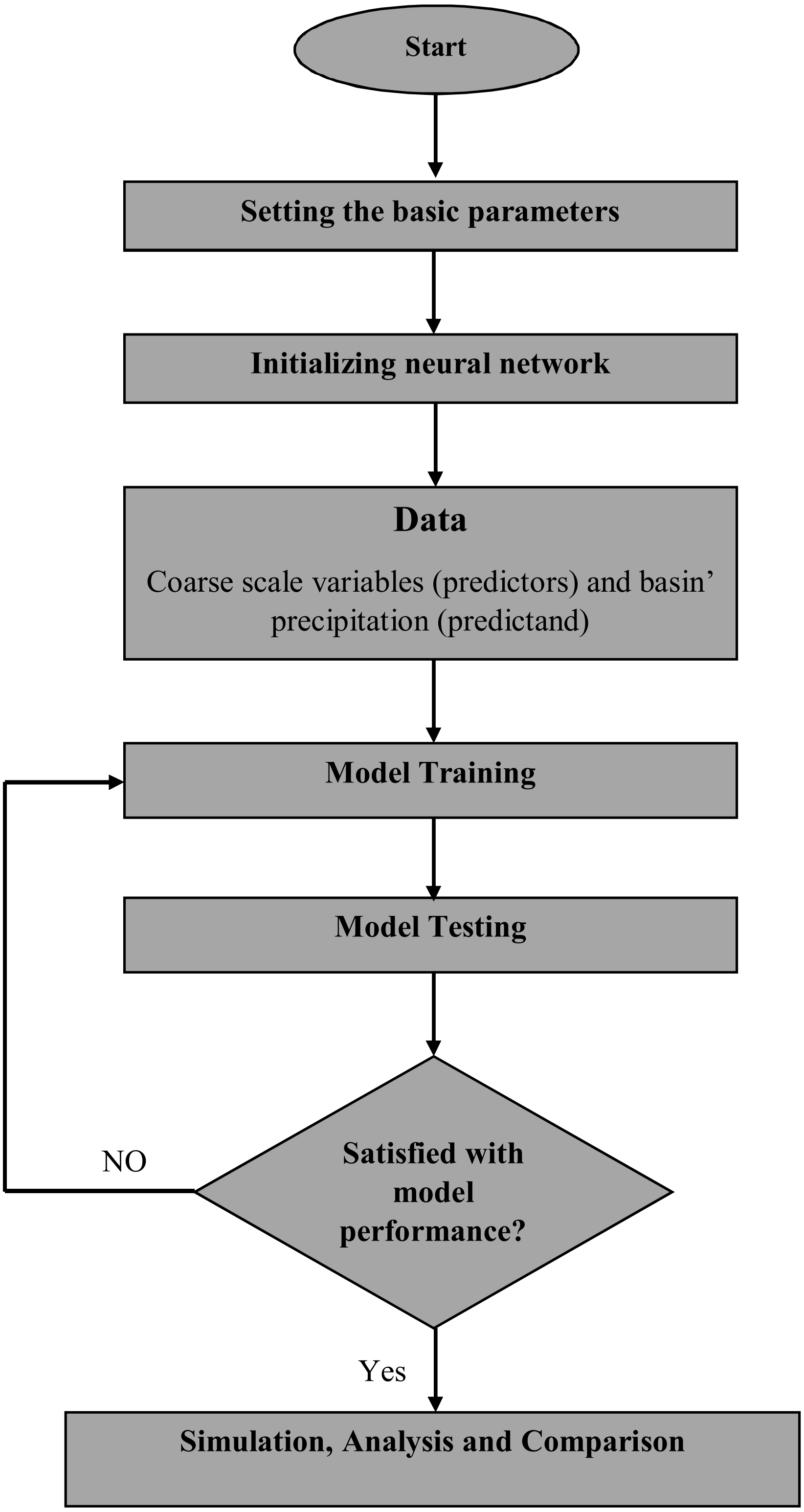

Figure 3. Flowchart of the proposed downscaling model adopted for this study

The Radial Basis Function (RBF)

The RBFs have similar structure to the MLPs by one hidden layer (Haykin, 1999), the RBF simulates the precipitation by a network of Gaussian functions in the hidden layer and linear activation functions in the output layer. Figure 4 shows a typical RBF for the study area. According to Haykin (1999) for training the RBFs, self-organized selection of centre has been selected which includes the following steps:

1. Random selection of initial centre vectors (v_J).
2. Calculation of Euclidean distance for the initial centre vectors.
3. The new centre vector which is closest to the training sample was calculated using the following equation (Equation 2).

$$v_j^{new} = x_j^{old} + \eta * (I_{pi} - v_j^{old}) \tag{2}$$

where P is the training sample, J is the number of centre vector, i and η are the input node and the learning rate, respectively.

4. The above mentioned steps were continued until no considerable change was observed for the centre vector.
5. Calculation of spread parameter and output layer weights.
6. Assessment of mean square error (MSE) value for training sample.
7. The phases were carried out for a certain number of iteration.

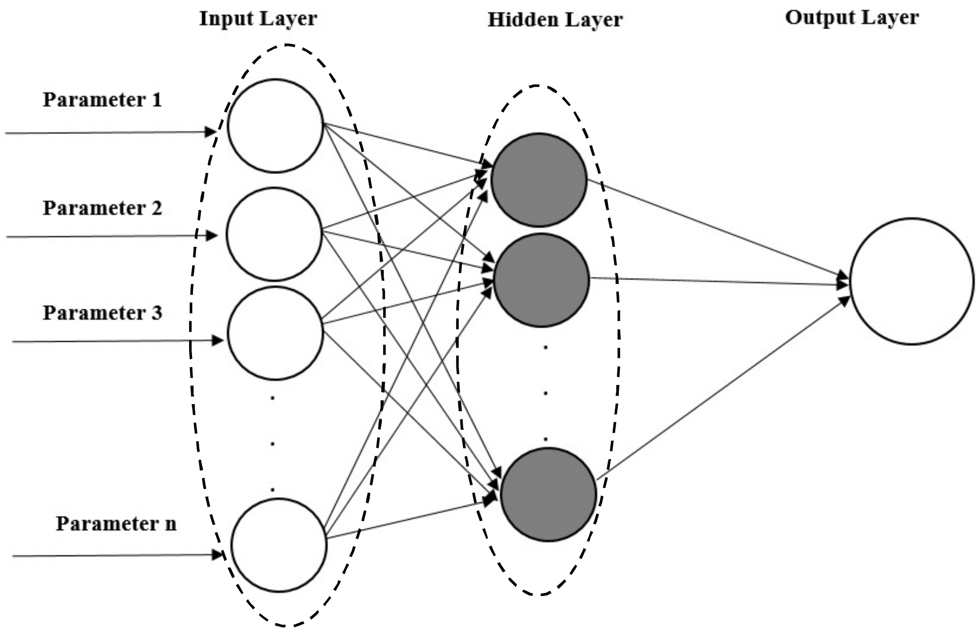

Figure 4. Schematic architecture of proposed RBF model.

Evaluation Criteria

In this research, three statistical indicators were used in order to assess the effectiveness of the two artificial neural network models developed. The assessment indicators include coefficient determination (R^2), root mean square error (RMSE) and Nash-Sutcliffe (NS) which are obtained from the following equations:

1) Root-mean-square error (RMSE) (Kim and Kim, 2008)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \tag{3}$$

2) Coefficient of determination (R^2) (Mohammadian *et al.,* 2016)

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\left(P_i - \overline{P_i}\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\sum_{i=1}^{n}\left(P_i - \overline{P_i}\right)} \tag{4}$$

3) Nash-Sutcliffe (NS): the optimal value is 1, refers to the perfect fit (Vernieuwe *et al.,* 2005).

$$NS = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O}_i)^2} \quad (5)$$

where the simulated and observed values are P_i and O_i respectively, the total number of test data is given by n and $\overline{O}_i$ is mean of observational values.

Results and Discussion

In this study the required information such as the monthly reanalysis data were obtained from the National Center for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) and precipitation (predictand) data at the selected stations were employed in the calibration and validation periods of the downscaling tools. The NCEP/NCAR reanalysis data set is outputs of a global circulation model (GCM) (Kalnay *et al.,* 1996) and many studies have utilized this data for the calibration and validation of their statistical downscaling models (Gautam *et al.,* 2014; Yang *et al.,* 2016). In a statistical downscaling, mathematical relationship between predictors and predictand is essential to convert GCM outputs to catchment scale. As mentioned before, in this research, predictor parameters were extracted from NCEP/NCAR data at the selected meteorological stations. The downscaling models were developed through employing the MLP and RBF approaches. In order to gain the optimum climatic parameters from the probable predictors, the Pearson correlation (Pearson, 1895) coefficient was utilized (Anandhi *et al.,* 2008; Sachindra *et al.,* 2013). The final optimum large scale atmospheric variables of the NCEP/NCAR dataset which were employed in this research are presented in Table 2. The predictors combination applied for the downscaling models consisted of Mean sea level pressure, 500 hPa specific humidity, precipitation, air temperature, 500 hPa and 850 hPa geopotential heights.

Table 2. Optimal combination of large scale climatic predictors utilized in the MLP and RBF models in each station

Station	Large scale parameters
Kahnooj	Mean sea level pressure, 500 hPa Geopotential, 850 hPa Geopotential, precipitation
Rodan	Mean sea level pressure, 500 hPa Geopotential, 500 hPa Specific humidity, precipitation
Minab	Mean sea level pressure, 500 hPa Geopotential, air temperature (2m), precipitation

The first 80% of the predictor and precipitation data were allocated for the model calibration and the rest of the obtained data for the period of 2003-2015 was allocated for the model validation. The performance of models in calibration and validation was assessed using the root mean square error (RMSE), Nash-Sutcliffe (NS) and coefficient of determination (R^2). The optimum structure of MLP and RBF models including number of hidden layers, number of iterations and the number of the nodes in the hidden layers were specified using trial and error process for gaining precise and accurate outputs (Mohanty *et al.,* 2010; Daliakopoulos *et al.,* 2005). The activation function of the hidden layer and output layer were set as logsig and linear, respectively (Table 3).

Table 4 gives the performance evaluation of MLP and RBF models through the R^2, RMSE and NS criteria. The best MLP models for Kahnooj, Rodan and Minab stations had a testing RMSE of 15.64 mm, 20.94 mm and 19.29 mm respectively (Table 4), and proved to be superior to the best RBF model, which had a testing RMSE of 17.26 mm, 24.21 mm and 21.16 mm for the mentioned stations. The lower RMSE values show that the best MLP model indicated slight differences between the observed and the downscaled precipitation at mentioned sites.

Table 3. The optimal parameters for the proposed downscaling models

RBF		MLP	
Number of layers	3	Number of layers	3
Neurons	Inputs: 4 Hidden: 25 Output: 1	Neurons	Inputs: 4 Hidden: 25 Output: 1
-	-	Number of iteration	250
Activation function	Sigmoid	Activation function in hidden layer Activation function in output layer	Logsig linear
Learning rule	-	Learning rule	Levenberg-Marquardt

Table 4. Statistical parameters of model performance metrics in terms of RMSE and R^2 for the different soft computing models tested in all the stations.

Station	Model	Training phase			Testing phase		
		RMSE (mm)	Nash-Sutcliffe	R^2	RMSE (mm)	Nash-Sutcliffe	R^2
Kahnooj	MLP	23.52	0.67	0.68	15.64	0.64	0.65
	RBF	24.53	0.64	0.65	17.26	0.56	0.57
Rodan	MLP	23.37	0.69	0.7	20.94	0.66	0.68
	RBF	25.22	0.64	0.65	24.21	0.55	0.56
Minab	MLP	26.65	0.67	0.68	19.29	0.62	0.64
	RBF	28.51	0.62	0.63	21.16	0.55	0.56

For Kahnooj, Rodan and Minab stations, in the testing phase, the MLP model obtained the best NS statics of 0.64, 0.66 and 0.62 respectively (Table 4) which indicate that the overall quality of estimation of the MLP model is better than the RBF model according to NS.

The best MLP models for Kahnooj, Rodan and Minab had a testing R^2 of 0.65, 0.68 and 0.64 respectively (Table 4), and were more efficient compared to the best RBF models, which had a testing R^2 of 0.57, 0.56 and 0.56 for mentioned stations. The higher R^2 value reveals that the MLP model has outperformed the RBF model in both the training (calibration) period as well as in the testing (validation) period. In the validation period, the RBF model efficiency is less than 60% while the MLP model efficiency is 60%, which is a significant improvement over the RBF model results.

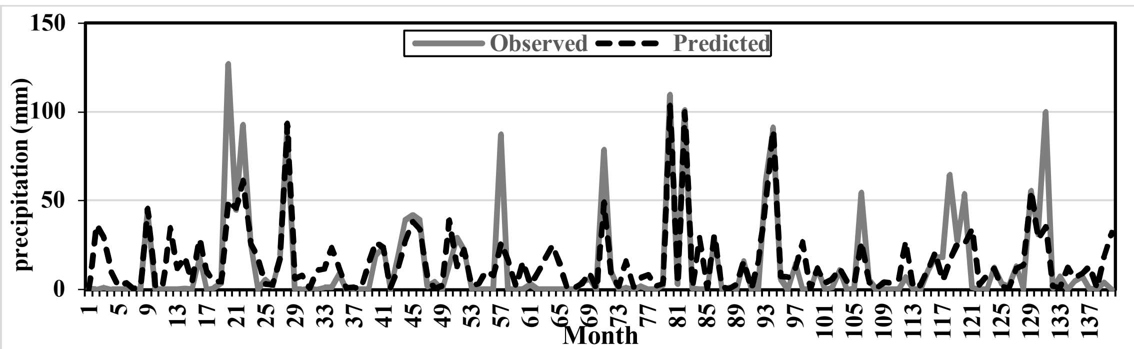

Figure 5. Comparison of the MLP estimated daily precipitation with the observed daily precipitation in the testing period at Kahnooj station.

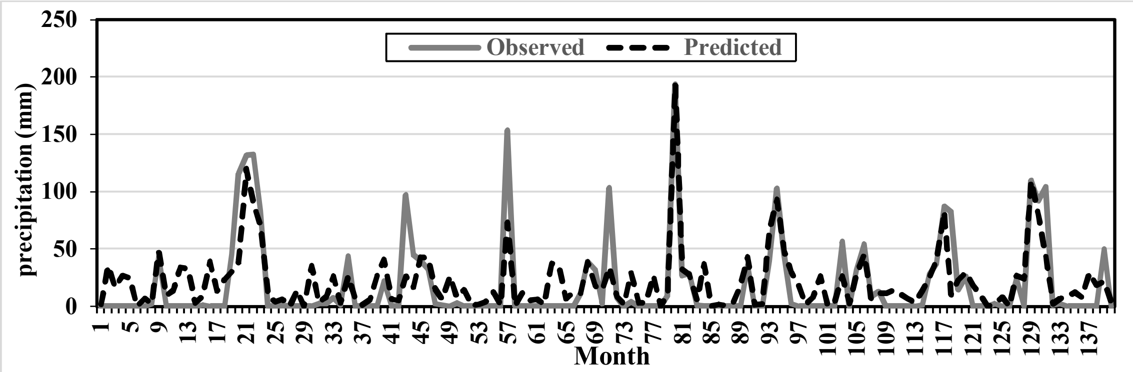

Figure 6. Comparison of the MLP estimated daily precipitation with the observed daily precipitation in the testing period at Rodan station.

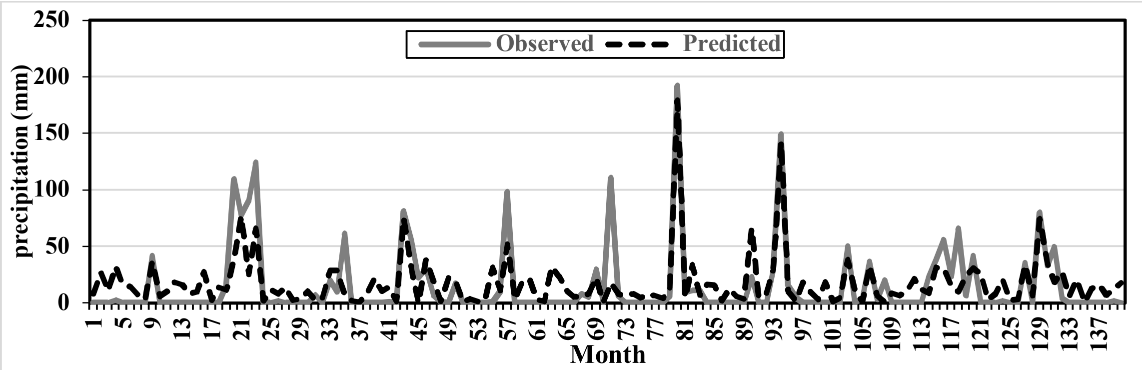

Figure 7. Comparison of the MLP estimated daily precipitation with the observed daily precipitation in the testing period at Minab station.

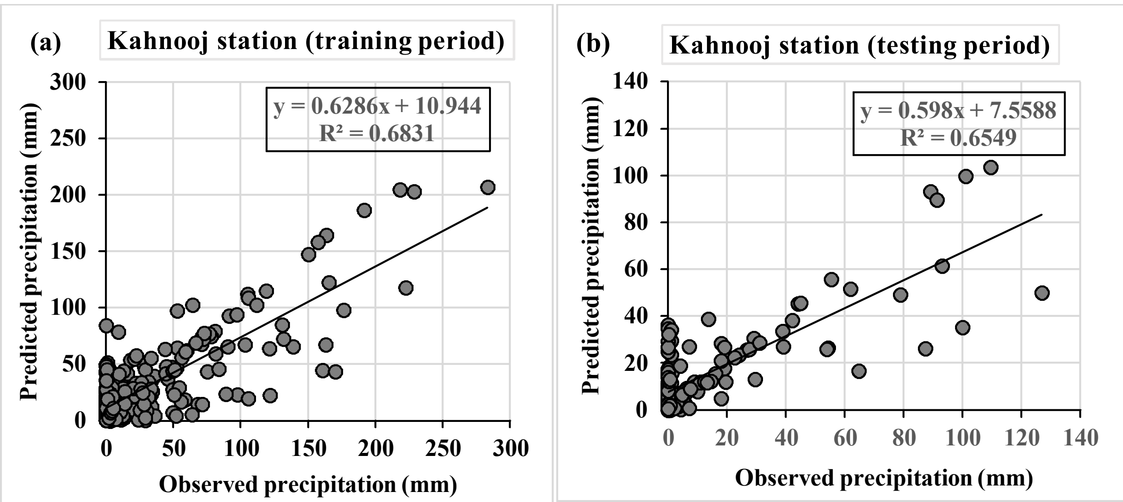

Figure 8. Scatter plots of observed and downscaled precipitation for **a** training and **b** testing phases at Kahnooj station

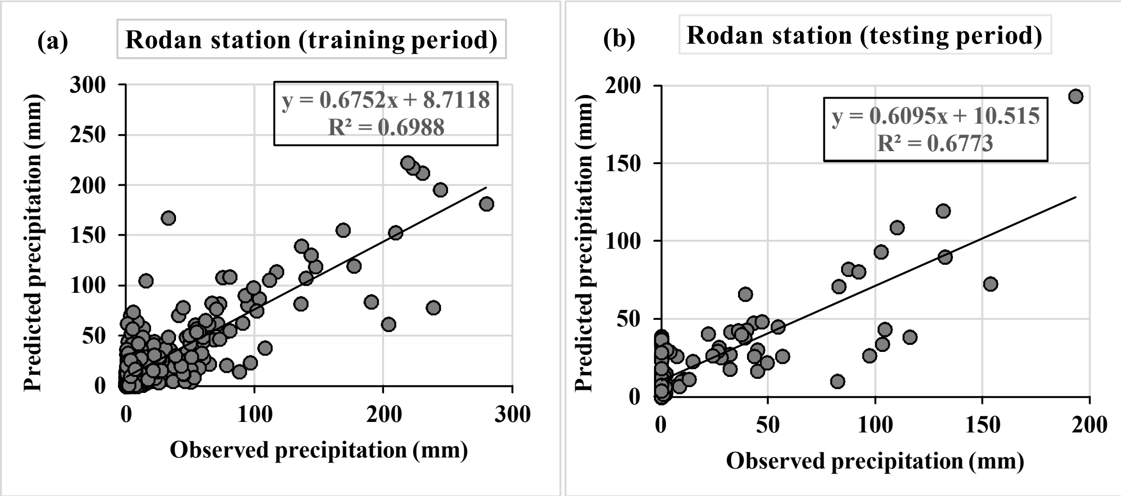

Figure 9. Scatter plots of observed and downscaled precipitation for **a** training and **b** testing phases at Rodan station

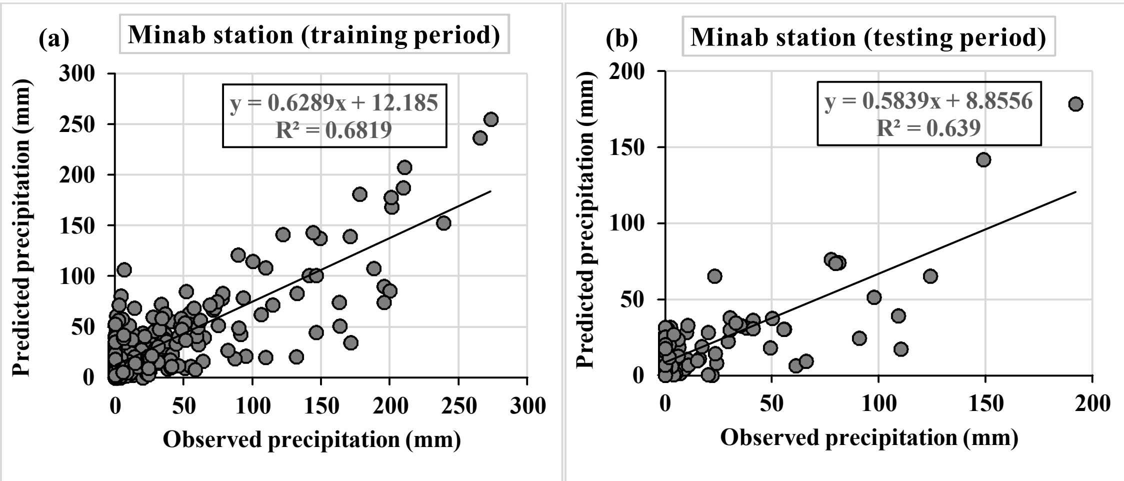

Figure 10. Scatter plots of observed and downscaled precipitation for **a** training and **b** testing phases at Minab station

Figures 5 to 7 compare the observed and downscaled precipitation during the testing phase at the Kahnooj, Rodan and Minab siterespectively for the best MLP models. Figures indicate that MLP models have better performance in predicting the peak values compared with RBFs. The RBF models forecast approximatly the general behavior of the measured data with good accuracy; however, the peak of precipitation values could not be acceptably predicted by RBF models. Figures 8 to 10 are scatter plots comparing the observed and downscaled precipitation using the best MLP model during the the testing period at the Kahnooj, Rodan and Minab stations repectively. This figure further emphasizes the better performance of the MLP model over the RBF model. In both the model calibration phase, as well as in the model validation phase, the MLP simulated data show more agreement with the observed data than the RBF simulated data. Overall, it can be concluded that the best MLP model at three study sites provided more accurate results than the RBF model for monthly precipitation forecasting.

Based on previous studies, Coulibaly (2004) applied genetic programming for modelling maximum and minimum temperatures based on coarse-scale climatic parameters. The results of this study showed better performance of GP model compared with multiple linear regression (MLR) in downscaling daily minimum temperature. Mendes and Marengo (2010) developed downscaling models using artificial neural network (ANN) and autocorrelation techniques in the Amazon Basin. The results of this study indicated that the ANN as well as the autocorrelation model both provided a very good fit to the data. In another study, Hashmi *et al.* (2011) used Gene Expression Programming (GEP) and SDSM for statistical downscaling of precipitation at the Clutha River watershed of New Zealand. The results of this study showed that in the validation period, the SDSM model efficiency is less than 40% while the GEP model efficiency is 50%, which is a significant improvement over the SDSM model results. In another study, George *et al.* (2015) applied local polynomial regression, multiple linear regression and artificial neural network to predict he rainfall in the catchment of Idukky reservoir in Kerala, India. As shown in the study, the local polynomial regression offered a better performance in forecasting the rainfall in this basin.

Conclusions

In this study, the most explanatory climatic variables for an accurate downscaling of monthly precipitation at the selected meteorological stations in the Minab basin among NCEP/NCAR reanalysis parameters were determined using the Pearson correlation analysis. The mean precipitation of the Minab basin was considered as the predictand. The Pearson correlation indicated that the optimum NCEP/NCAR parameters as the Mean sea level pressure, 500 hPa specific humidity, precipitation, air temperature, 500 hPa and 850 hPa geopotential heights.

The statistical downscaling models for the three meteorological stations analyzed by using MLP and RBF approaches. The MLP and RBF models were compared with each other at three stations. The comparison of the results demonstrated that MLP model performed better than the RBF model. Additionally, the training and the testing phases of each station revealed that MLP can be utilized to downscale NCEP/NCAR data set to station scale. Hence, the presented MLP can be reliably used for downscaling the coarse spatial resolution of GCMs for getting the future projections of precipitation in the Minab basin.

Overall, this resaearch proposed the application of soft computing methodologies that are constructive in assessment of climate change impacts in the basin scale. Thus, the proposed approaches can be employed to generate more accurate input parameters which are essential in water resources management and planning to tackle the related problems.

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