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A Hybrid Artificial Neural Network and Particle Swarm Optimization Algorithm for Statistical Downscaling of Precipitation in Arid Region

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Background: Prediction of future climate change is based on output of global climate models (GCMs). However, because of coarse spatial resolution of GCMs (tens to hundreds of kilometers), there is a need to convert GCM outputs into local meteorological and hydrological variables using a downscaling approach. Downscaling technique is a method of converting the coarse spatial resolution of GCM outputs at the regional or local scale. This study proposed a novel hybrid downscaling method based on artificial neural network (ANN) and particle swarm optimization (PSO) algorithm.
Materials and Methods: Downscaling technique is implemented to assess the effect of climate change on a basin. The current study aims to explore a hybrid model to downscale monthly precipitation in the Minab basin, Iran. The model was proposed to downscale large scale climatic variables, based on a feed-forward ANN optimized by PSO. This optimization algorithm was employed to decide the initial weights of the neural network. The National Center for Environmental Prediction and National Centre for Atmospheric Research reanalysis datasets were utilized to select the potential predictors. The performance of the artificial neural network-particle swarm optimization model was compared with artificial neural network model which is trained by Levenberg–Marquardt (LM) algorithm. The reliability of the models were evaluated by using root mean square error and coefficient of determination (R^2).
Results: The results showed the robustness and reliability of the ANN-PSO model for predicting the precipitation which it performed better than the ANN-LM. It was concluded that ANN-PSO is a better technique for statistically downscaling GCM outputs to monthly precipitation than ANN-LM.
Discussion and Conclusions: This method can be employed effectively to downscale large-scale climatic variables to monthly precipitation at station scale.

Keywords: *Artificial neural network (ANN), Climate change, Multi-layer perceptron, Particle swarm optimization (PSO), Statistical downscaling*

1. Background

Human activities are considered as the main reasons for increasing the concentration of CO_2 and other greenhouse gases in the atmosphere, which lead to a changing climate system (1, 2). Global climate models, which describe the climatic patterns by mathematical equations, are the most reliable and efficient tools for studying the effect of climate variation at coarse scale and predicting future climate change are based on the outputs extracted from these models. However, these models fail to represent the local climate variations that take place at finer scales, due to the coarse spatial resolution. During the last decade several downscaling methods have been developed for assessing the GCM large-scale outputs at the local scale (3). Dynamic downscaling and statistical downscaling are considered as the two most common downscaling approaches (4, 5). However, statistical downscaling is one of the most widely used approaches in downscaling large-scale atmospheric parameters to local scale. In general, these methods were developed to recognize quantitative relationship between large-scale climatic predictors and local parameters (4, 6, 7). Statistical downscaling approaches are cheap, easy to use and computationally efficient (7). The application of machine learning methods as statistical downscaling techniques has attracted more attention since the last decade (8, 9, 10). For example, Mendes and Marengo (2010) employed artificial neural network and autocorrelation techniques as a statistical downscaling model for downscaling GCM outputs in the Amazon basin that resulted in an accurate and consistent outcome regarding the reproduction of daily precipitation properties (11). In order to downscale the maximum and minimum daily temperature from GCM outputs to local scale, the accuracy of least-square support vector machine (LS-SVM), multivariate multiple linear regression (MMLR) and multi-site multivariate statistical downscaling (MMSD) approaches were evaluated, the results of which indicated better performance of LS-SVM-based models, compared to other downscaling models (12). In order to predict monthly reservoir inflows, Okkan and Inan (2015) implemented feed forward neural network (FFNN), LSSVM and relevance vector machine (RVM), the result of which showed promising performance of the RVM (13). In addition, Okkan and Kirdemir (2016) utilized ANN and LSSVM, the result of which indicated a good agreement between the observed and predicted monthly precipitation values at meteorological stations (14). Several evolutionary algorithms like unified particle swarm optimization (UPSO) (15), imperialist competitive algorithm (ICA) (16), differential evolution (DE) (17), genetic algorithm (GA) (18), shuffled frog leaping algorithm (SFLA) (19) and pruning algorithm (PA) (20) have also been implemented in order to determine the network parameters such as connecting weights.

Due to water scarcity in the Minab basin (Iran), detailed and accurate precipitation forecast can help water resource managers to utilize more effective and sustainable policies. The current work aims to develop effective and reliable hybrid downscaling model using ANN and particle swarm optimization (ANN-PSO) for downscaling monthly precipitation in this basin by determining the relevant input parameters (predictors) using Pearson correlation analysis and compare its performance with MLP back-propagation neural network-based downscaling model. Reanalysis data from NCEP/NCAR were implemented as large-scale climatic parameters (predictors) to calibrate the approaches and validate the methods.

2. Materials and Methods

2.1. Study area and data collection

As the study location, Minab basin (56° 51' 07" to 57° 53' 00" E and 26° 51' 31" to 28° 30' 25" N) covers an area of 10171 km^2 in the Hormozgan province, Iran (Fig. 1). It has an arid and subhumid climate with an annual average rainfall of 185 mm, 80% of which pours during winter and autumn. The mean monthly maximum and minimum temperature of the region are 42°C and 20°C, respectively. As there was only one meteorological station in the study area, two nearest stations to this basin were also selected for further research support. Table 1 represents the monthly rainfall records of these stations based on the record of the Iranian Meteorological Organization.

Table 1 Meteorological stations in the study area

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

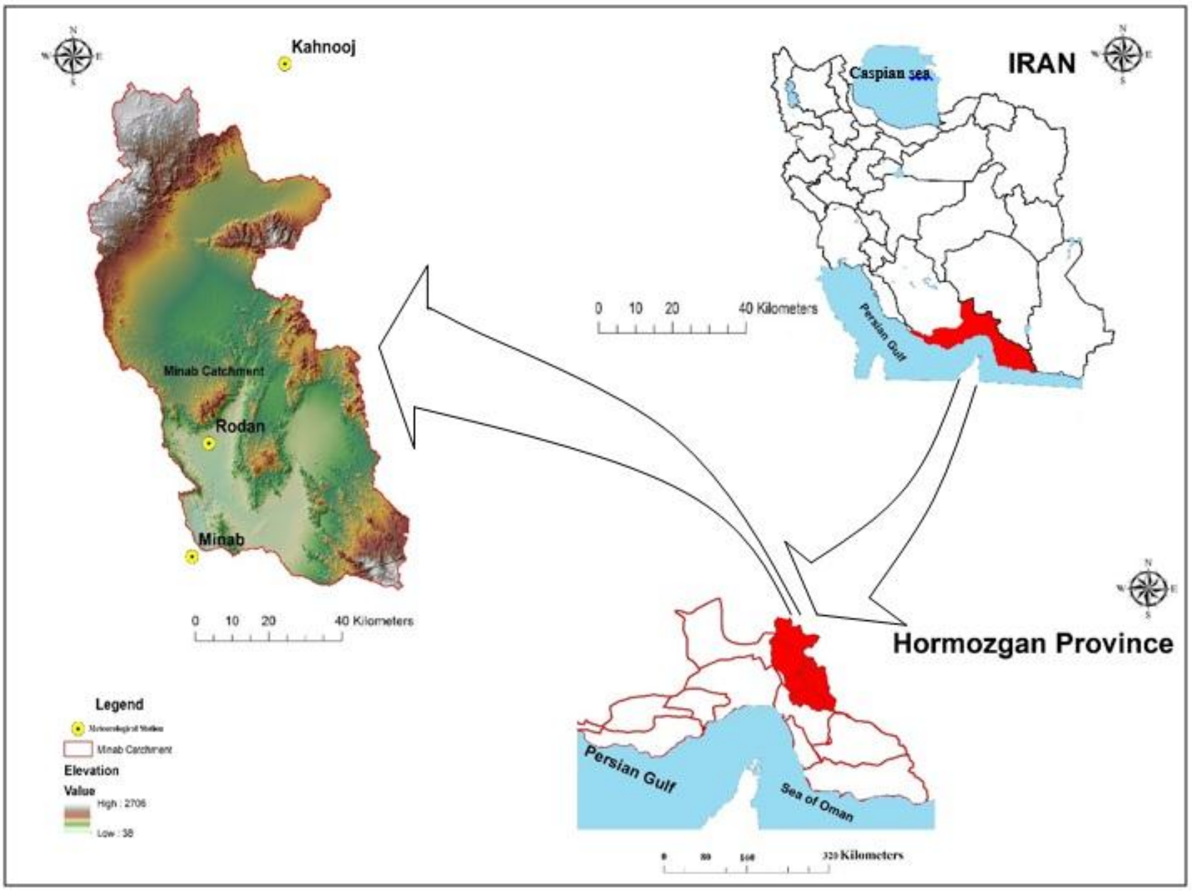

Figure 1 Location map of the study region in Hormozgan Province

2.2. Artificial Neural Network

Based on the biological function of the neurons in human brain, artificial neural networks (ANNs) are an efficient mathematical structure that can capture the non-linearity of the process better than conventional regression approaches (21). Due to good generalization ability of ANNs, a relationship can be found between model inputs and outputs (22). Multilayer feed-forward perceptron (MLP) neural network is reported to be the most popular type of ANN that is utilized in different areas such as water resources and environmental problems. The process of determining the weights of ANN via a reliable algorithm is called training process. In this study, Levenberg–Marquardt (LM) algorithm and particle swarm optimization were implemented to train the ANNs. The LM algorithm, as the modified version of the classic Newton approach for obtaining an optimum solution to the optimization problem, is an efficient learning approach for multi-layer feed-forward networks (23) has been successfully applied in different studies (24). In this method, an approximation to the Hessian matrix is used based on the Eq. 1.

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

Where, x is the neural network weights, J represents the performance criteria Jacobian matrix and μ and e are regarded as a learning process parameter and a residual error vector, respectively. Figure 2 displays a typical MLP feed-forward network for this study with one hidden layer. The user defined parameters utilized in ANN model is presented in Table 2.

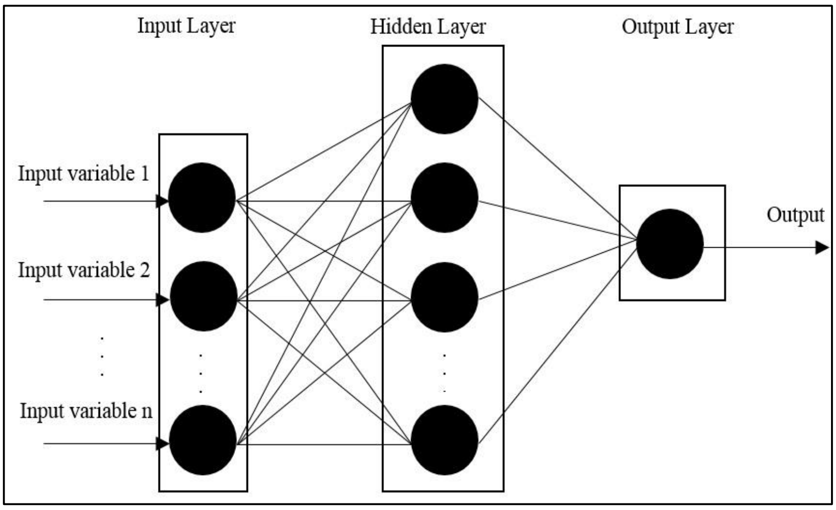

Figure 2 A schematic architecture of the feed-forward three-layer ANN for the study area

Table 2 The selected parameters for the proposed downscaling model

Number of layers	3
Neurons	Inputs: 4 Hidden: 20 Output: 1
Number of iteration	1000
Activation function in hidden layer	Tangent sigmoid
Activation function in output layer	Pure linear
Learning rule	Levenberg-Marquardt

2.3. Particle Swarm Optimization

Particle swarm optimization (PSO) has been proposed by Eberhart and Kennedy (25) as a global optimization algorithm for the problems in which a point or surface represents the best solution in a multi-dimensional space. PSO is based on a set of random particles (potential solutions) with random velocities and positions. Particles are absorbed by the position of the best fitness historically obtained by their experience (local best) and by the best among the neighbors of each particle (global best) (26). Each particle is able to search based on both local and global best. New velocity of each particle is determined based on distance from personal best and global best position. In the next iteration, random weights are determined to personal best and global position velocities to create a new value for the particle velocity (26). PSO is regarded as an efficient algorithm to determine the global optimum with a large probability and high convergence rate (27). Therefore, this method was implemented to train the MLP models in the current study.

2.4. Training using particle swarm optimization

As already mentioned, PSO algorithm is utilized for training the network to obtain a set of weights which minimizes the training error and the fitness function should be the mean square error of the network with the training data set.

Eqs. 2 and 3 were used to train the network by PSO:

$$V_i^{t+1} = \omega V_i^t + c_1 r_1^t (P_i^t - X_i^t) + c_2 r_2^t (P_g^t - X_i^t) \quad (2)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (3)$$

Where, V_i^t represents the velocity vector at iteration *t*, r_1 and r_2 indicate random numbers in the range from 0 to 1, c_1 and c_2 are regarded as learning factors and positive constants. Eq. 2 was employed to calculate the new velocity of the particle based on its previous velocity and the distance of its current position from the best experiences both individually and as a group. P_i^t denotes the best position of particle *i*, and P_g^t represents the global best position in the swarm until iteration *t*, X_i^t refers to the position vector for the particle *i* and ω represents the inertia weight. Figure 3 illustrates the basic PSO procedure in optimizing ANN.

2.5. Evaluation criteria

Coefficient determination (R^2) and root mean square error (RMSE) were used to assess the performance of the two ANN models developed in this study. In order to obtain these two evaluation criteria, Eqs. 4 and 5 were used:

1) Root-mean-square error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad (4)$$

2) Coefficient of determination (R^2)

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i - \overline{O}_i\right)\cdot\left(P_i - \overline{P}_i\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - \overline{O}_i\right)\cdot\sum_{i=1}^{n}\left(P_i - \overline{P}_i\right)} \quad (5)$$

Where, P_i and O_i represnet the simulated and observed values, respectively, and *n* indicates the total number of data.

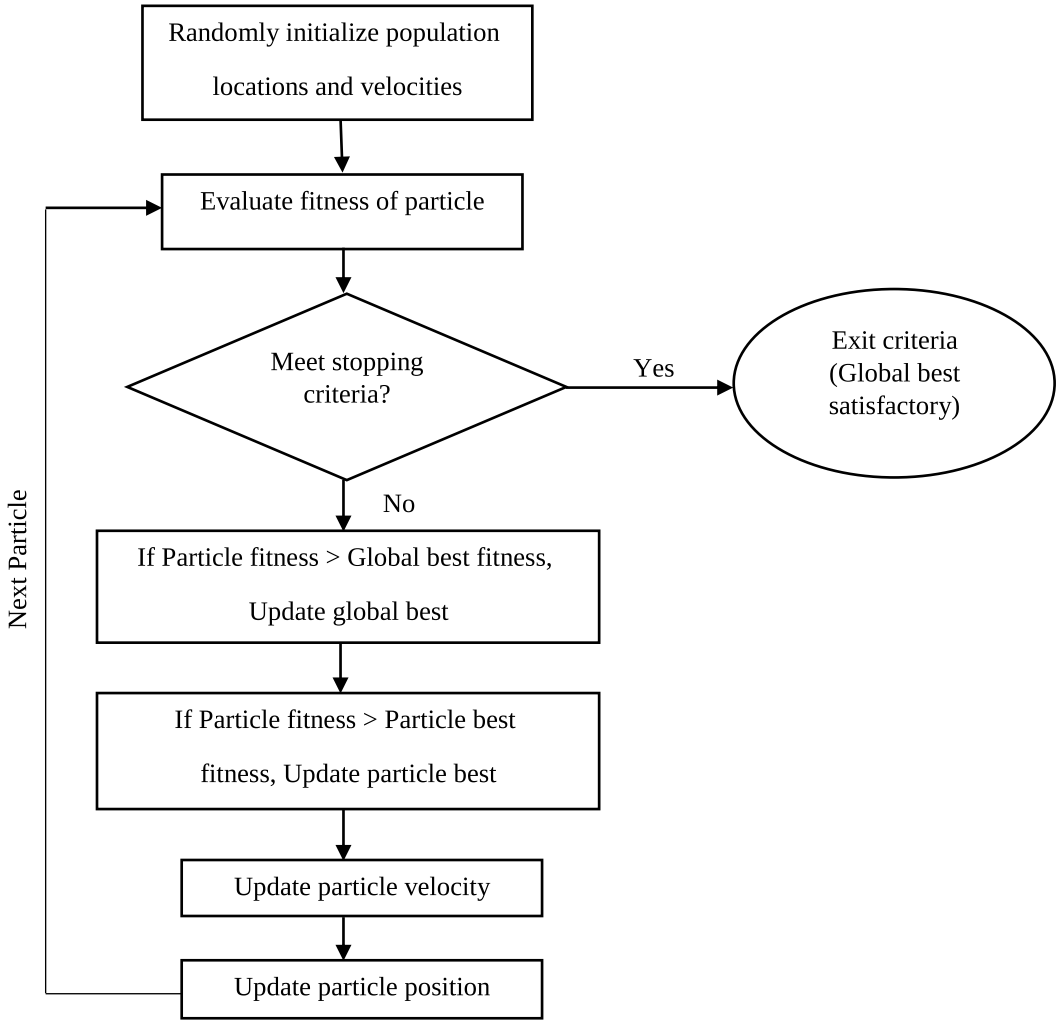

Figure 3 A basis flowchart for PSO algorithm (28)

3. Results

In the current study, NCEP/NCAR reanalysis data set prepared by National Centers for Environmental Prediction was implemented to select the predictors (29). This data set have different time resolutions from hours to a month to represent climatic conditions at different levels of the atmosphere, which are available from 1948 till now with a spatial resolution of 2.5° * 2.5°. NCEP/NCAR reanalysis data set archive has been utilized in several statistical downscaling studies (30, 31, 32). The selection of large-scale climatic variables (predictors) from the NCEP/NCAR data set is regarded as an important process. However, among the reanalysis data set for each station in National Center for Environmental Prediction and National Center for Atmospheric Research (NCEP/NCAR), the most relevant large scale atmospheric parameters were selected via the Pearson correlation analysis (6, 33). The best set of predictors, which have good correlation coefficient are mean sea level pressure (slp), 500 hPa geopotential height (hgt), 850 hPa geopotential (hgt), precipitation (prate), 500 hPa relative humidity (rhum) and air temperature (2m) with R = 0.692, 0.678, 0.661, 0.639, 0.599 and 0.586, respectively.

Table 3 represents the final optimum large scale atmospheric variables of the NCEP/NCAR dataset which were employed in the current study. For downscaling models in each station, some predictors such as Mean sea level pressure, 500 hPa specific humidity, precipitation, air temperature, 500 hPa and 850 hPa geopotential heights were used in this study and the mean precipitation of the Minab basin was considered as the predictant (Table 3).

Two soft-computing approaches were developed to build a model to downscale monthly precipitation in the Minab basin. Based on the first approach, ANN model was trained by LM algorithm. In this model, sigmoid and linear transfer functions are applied in the hidden and output layer, respectively. Regarding the second approach, PSO was utilized as a neural network optimization algorithm and the mean square error utilized as a cost function in this model. The main purpose of implementing PSO is to minimize the cost function. The first 80% of the predictor and observed precipitation data were implemented to calibrate the model and the rest of the obtained data was used for validating the model. The root mean square error (RMSE) and coefficient of determination (R^2) were used to evaluate the model performances in calibration and validation. Further, trial and error process was implemented to determine the optimum structure of ANN-PSO and ANN-LM models including the number of hidden layers, the number of iterations and the number of the nodes in the hidden layers for gaining precise output (34, 35). Finally, the ANN-LM was utilized with the same data sets used in the ANN-PSO in order to assess the performance of the ANN-PSO model.

Table 3 **Optimal combination of large scale climatic predictors utilized in the ANN-PSO and ANN-LM models in each station with their respective elevations**

Station	Large scale parameters
Kahnooj	Mean sea level pressure (hPa), 500 hPa geopotential, 850 hPa geopotential, precipitation (kgm^{-2})
Roudan	Mean sea level pressure (hPa), 500 hPa geopotential, 500 hPa relative humidity (%), precipitation (kgm^{-2})
Minab	Mean sea level pressure (hPa), 500 hPa geopotential, air temperature (2m) (°C), precipitation (kgm^{-2})

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**

Stations	Methods	Training phase		Testing phase	
		RMSE	R^2	RMSE	R^2
Kahnooj	ANN-PSO	22.3	0.719	14.3	0.704
	ANN-LM	23.5	0.683	15.6	0.654
Roudan	ANN-PSO	21.4	0.758	20.69	0.691
	ANN-LM	23.3	0.698	20.9	0.677
Minab	ANN-PSO	23.72	0.752	19.07	0.675
	ANN-LM	26.6	0.681	19.2	0.639

The values of R^2 and RMSE at each station are presented in Table 4. The R^2 for the ANN-PSO model ranged from 0.719 to 0.758 for the training data set and from 0.675 to 0.704 for the testing data set. Similarly, RMSE ranged from 21.4 mm to 23.72 mm for the training data set and from 14.3 mm to 20.69 mm for the testing data set. For the training data set, the R^2 ranged from 0.681 to 0.698 for the ANN-LM model while it ranged from 0.639 to 0.677 for the testing data set. In addition, RMSE ranged from 23.3 mm to 26.6 mm for the training data set while it ranged from 15.6 mm to 20.9 mm for the testing data set. The most appropriate ANN-PSO models for Kahnooj, Roudan and Minab stations had a testing RMSE of 14.3 mm, 20.69 mm and 19.07 mm, respectively (Table 4), which indicated the superiority of the best ANN-PSO model to the best ANN-LM model, which had a testing RMSE of 15.6 mm, 20.9 mm and 19.2 mm for the mentioned stations. As shown in Table 4, the best ANN-PSO models had a testing R^2 of 0.7049, 0.6914 and 0.675 for Kahnooj, Roudan and Minab, respectively, which were more efficient, in comparison to the best ANN-LM models, involving a testing R^2 of 0.654, 0.677 and 0.639 for the mentioned stations. The higher R^2 value indicates that the ANN-PSO model is more precise, comapred to ANN-LM model.

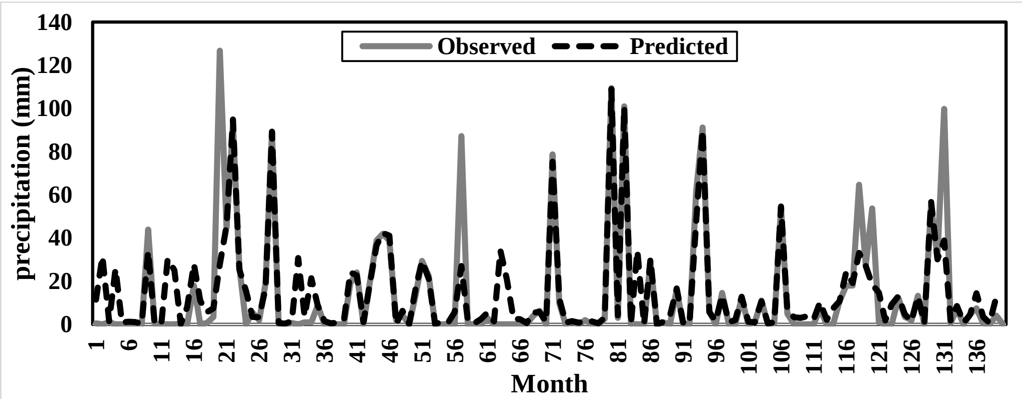

Figure 4 Comparison of the ANN-PSO estimated daily precipitation with the observed daily precipitation in the testing period at Kahnooj station

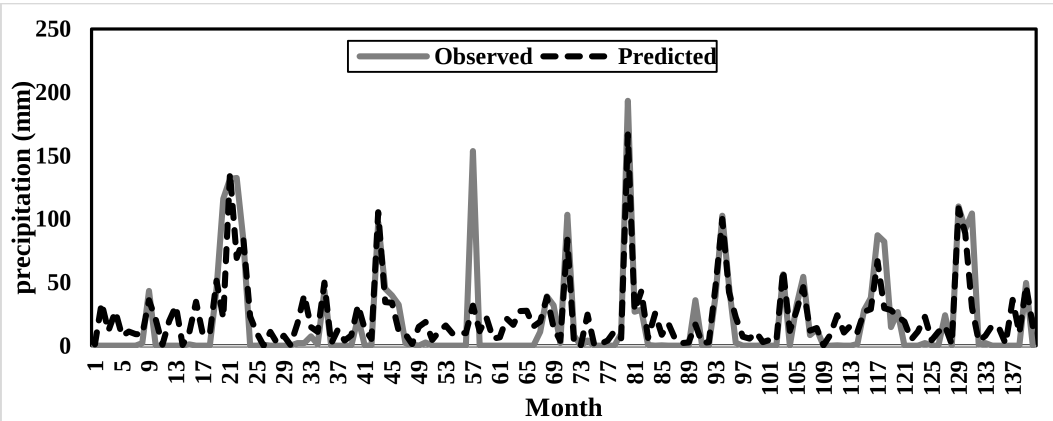

Figure 5 Comparison of the ANN-PSO estimated daily precipitation with the observed daily precipitation in the testing period at Roudan station

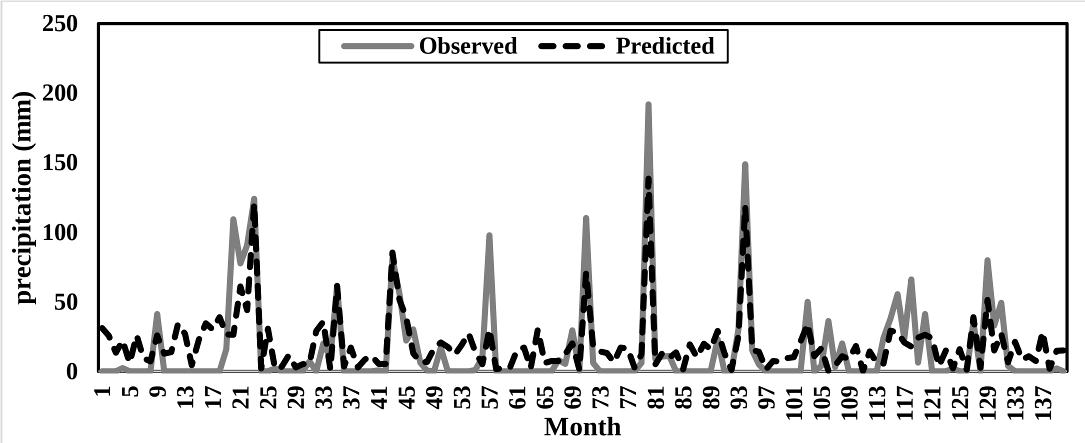

Figure 6 Comparison of the ANN-PSO estimated daily precipitation with the observed daily precipitation in the testing period at Minab station

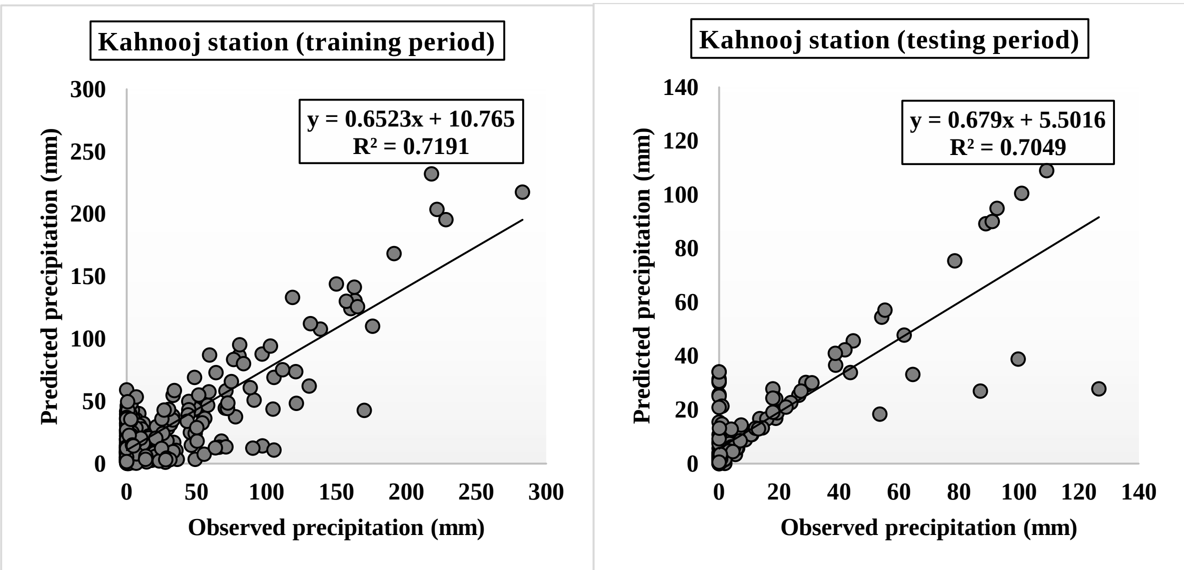

Figure 7 Scatter plots of the observed and downscaled precipitation for training and testing phases at Kahnooj station

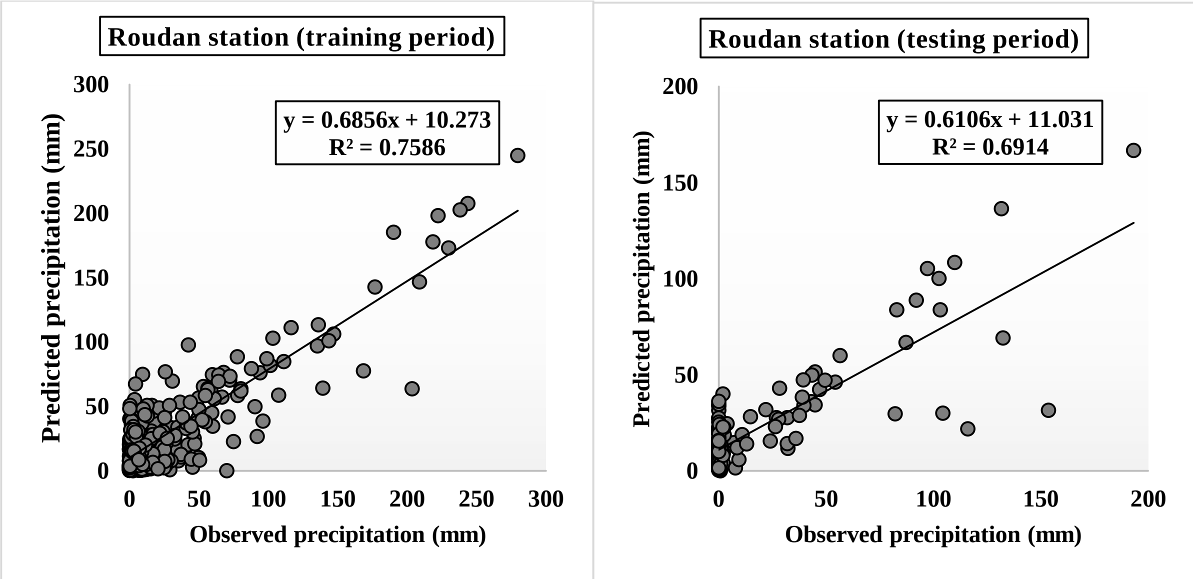

Figure 8 Scatter plots of the observed and downscaled precipitation for training and testing phases at Roudan station

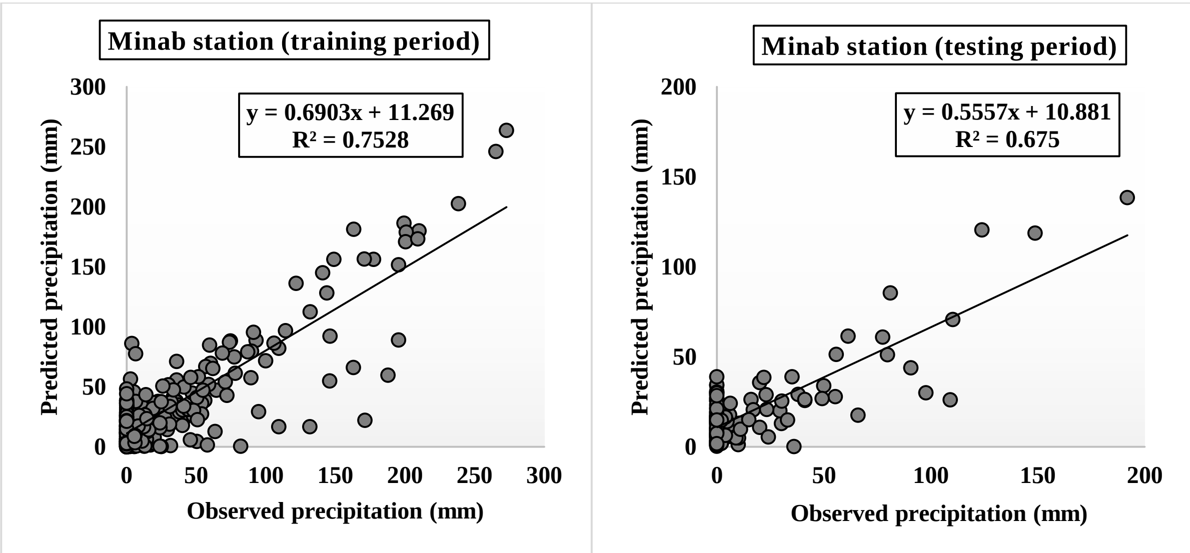

Figure 9 Scatter plots of the observed and downscaled precipitation for training and testing phases at Minab station

Figures 4 to 6 illustrate the observed and downscaled precipitation for the three stations during the testing period for ANN-PSO models. Regarding the results of these figures and Table 4, the model performance was superior for the ANN-PSO model, as indicated by greater R^2 and lower RMSE values, compared with those for the ANN-LM model. Figures 7 to 9 display scatter plots of the predicted and observed data during the training and testing periods phase at the Kahnooj, Roudan and Minab for ANN-PSO model. Scatter plots between the observed and predicted precipitation are implemented as a useful visual aid to assess the accuracy of a model. The model is more efficient when the scatter points are closer to the line of the best fit. As shown in Table 4, the ANN-PSO model has scattered less around the best fit line, compared to the ANN-LM models for all stations. Comparison of model efficiency coefficient (R^2) between the ANN-PSO model and the ANN-LM model, presented in Figures 7 to 9, reveals that the ANN-PSO model has outperformed the ANN-LM model in both the training (calibration) period and in the testing (validation) period. In the validation period, the ANN-PSO model has higher efficiency than the ANN-LM model for all stations, which indicates a significant improvement over the ANN-LM model results. In conclusion, the best ANN-PSO model provided more accurate results at three sites under study, in comparsion to the ANN-LM model for forecating precipitation.

4. Discussion and Conclusion

Various artificial intelligence methods have been used (e.g., ANN, SVM, GP) for downscaling GCM outputs (36, 37, 38, 39, 40, 41). Fistikoglu and Okkan (4) applied ANN model in estimating monthly precipitation and they found R^2 value as 0.64; Hashmi *et al.* (5) used gene expression programming for modeling watershed precipitation and they found R^2 of 0.5 in the test period. Sachindra *et al.* (33) used SVM for modeling catchment stream flow and found R^2 of 0.65 in the test period. It is clear from the Table 4 that the ANN-PSO and ANN-LM generally provided accurate results in modeling precipitation with respect to R^2 criteria. For the ANN-PSO model, the R^2 values are higher than 0.65 in the testing phase for all stations, showing better performance compared with the previous studies. It shows robustness and accuracy of the ANN-PSO-based model to downscaling GCM outputs to monthly precipitation.

In the current study, a comparative statistical downscaling analysis was undertaken to evaluate the ANN-PSO based as a statistical downscaling tool. Monthly precipitation time series of the Minab basin in Iran were downscaled using ANN-PSO. The ANN-LM model results were utilized as a benchmark for analyzing the downscaled results of the ANN-PSOmodel. A comparison was made between the estimates provided by the ANN-PSO model and the ANN-LM with respect to root mean square error, determination coefficient, time variation and scatter plot graphs. Based on the results, the training and the testing period of each station indicated that ANN-PSO can be utilized to downscale the NCEP/NCAR data set to station scale. Furthermore, ANN, coupled with PSO, consistently performed better, compared to ANN-LM model for downscaling coarse-scale climatic variables to monthly precipitation in the study area. This method proved to be more reliable in regenerating monthly precipitation time series, especially for future climate change assessment at the basin scale. Therefore, this model can be implemented to identify the optimal strategies that can allow for the sustainable management of the water resources in the Minab basin under the future climate.

Conflict of Interest

The authors declare that there is no conflict of interests regarding the publication of this manuscript.

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Authors' Contributions

All authors were involved in all stages of the article.

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ABBREVIATIONS	
ANN	Artificial Neural Network
DE	Differential Evolution
FFNN	Feedforward neural network
GA	Genetic algorithm
GCM	Global Climate Model
hPa	Hectopascal
ICA	Imperialist competitive algorithm
LM	Levenberg–Marquardt
LS-SVM	Least Square-Support Vector Machine
MLP	Multilayer perceptron
NCAR	National Center for Atmospheric Research
NCEP	National Center for Environmental Prediction
PSO	Particle swarm optimization
PA	Pruning algorithm
RCM	Regional climate model
RMSE	Root mean square error
RVM	Relevance vector machine
R^2	Coefficient of determination
SDSM	Statistical downscaling model
SFLA	Shuffled frog leaping algorithm
SVM	Support Vector Machine
UPSO	Unified particle swarm optimization

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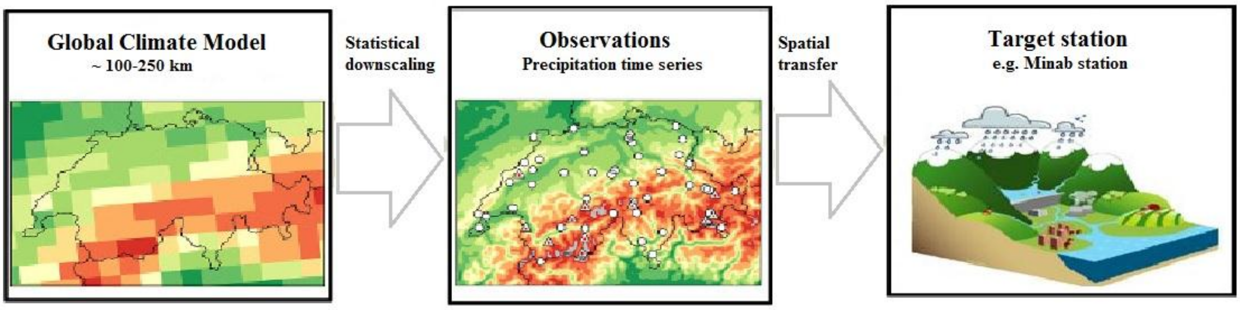
GRAPHICAL ABSTRACT



HIGHLIGHTS

The ability of an optimized ANN based on PSO is investigated for downscaling monthly precipitation in the Minab basin.

- The explanatory large-scale atmospheric variables (predictors) were selected among NCEP/NCAR reanalysis data set based on Pearson correlation analysis.

- The ANN-PSO based downscaling model outperformed the ANN model with regard to precipitation downscaling for all stations.

- The hybrid models increase the RMSE accuracy of the ANN model by 8.5% for Kahnooj station, 1.2% for Roudan station and 1.1% for Minab station.

مدل ترکیبی شبکه عصبی مصنوعی و الگوریتم بهینه‌سازی ازدحام ذرات جهت ریزمقیاس‌نمایی آماری بارش در ناحیه خشک

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مقدمه: پیش‌بینی تغییر اقلیم در سال‌های آتی براساس خروجی‌های مدل‌های جهانی اقلیمی می‌باشد. با توجه به اینکه این مدل‌ها بزرگ مقیاس هستند، نتایج آنها باید با استفاده از یک روش ریز مقیاس‌گردانی به متغیرهای هواشناسی و هیدرولوژیکی در مقیاس محلی تبدیل شوند. در واقع ریز مقیاس‌گردانی، روشی برای برگرداندن خروجی‌های درشت مقیاس مدلهای جهانی اقلیمی در سطح منطقه‌ای یا محلی می‌باشد. در این تحقیق یک روش نوین ریز مقیاس‌گردانی ترکیبی براساس شبکه عصبی مصنوعی و الگوریتم ازدحام ذرات ارایه شده است.

مواد و روش‌ها: برای ارزیابی اثر تغییر اقلیم بر حوزه آبریز، یک فن ریز مقیاس‌گردانی مورد استفاده قرار گرفته است. هدف این تحقیق، ارزیابی عملکرد یک مدل ترکیبی برای ریز مقیاس‌گردانی آماری بارش ماهانه در حوزه آبریز میناب در ایران می‌باشد. مدل پیشنهاد شده جهت ریز مقیاس‌گردانی متغیرهای بزرگ مقیاس جوی، براساس شبکه عصبی مصنوعی است که با استفاده از الگوریتم ازدحام ذرات، بهینه‌سازی گردیده است. این الگوریتم جهت تعیین وزن‌های اولیه شبکه عصبی بکار گرفته شده است. داده‌های بزرگ مقیاس جوی باز آنالیز شده NCEP/NCAR، جهت انتخاب پیش‌بینی کننده‌ها انتخاب گردیده‌اند. جهت ارزیابی دقت مدل‌ها از جذر میانگین مربعات خطا و ضریب تبیین استفاده شده است. عملکرد مدل ترکیبی با مدل شبکه عصبی که با استفاده از الگوریتم لونبرگ-مارکوات آموزش دیده است، مقایسه گردید.

نتایج: نتایج این تحقیق حاکی از دقت و قابلیت اطمینان مدل ترکیبی شبکه عصبی و لگوریتم ازدحام ذرات در پیش‌بینی بارش می‌باشد که دارای عملکرد بهتری نسبت مدل شبکه عصبی و الگوریتم لونبرگ-مارکوات می‌باشد. در نتیجه مدل ترکیبی، روشی کارآمد برای ریز مقیاس گردانی آماری خروجی مدل‌های جهانی اقلیمی به بارش ماهانه می‌باشد.

بحث و نتیجه‌گیری: روش ارایه شده را می‌توان به طور موثری در ریز مقیاس‌گردانی متغیرهای آب و هوایی بزرگ مقیاس به بارش ماهانه در مقیاس ایستگاهی بکار گرفت.

کلمات کلیدی: بهینه‌سازی ازدحام ذرات، پرسپترون چندلایه، تغییر اقلیم، ریزمقیاس گردانی آماری، شبکه عصبی مصنوعی