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Evaluating the Performance of Artificial Neural Network Model in Downscaling Daily Temperature, Precipitation and Wind Speed Parameters

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ABSTRACT: Numerous studies yet have been carried out on downscaling of the large-scale climate data using both dynamical and statistical methods to investigate the hydrological and meteorological impacts of climate change on different parts of the world. This study was also conducted to investigate the capability of feed-forward neural network with error back-propagation algorithm to downscale the provincial segmentation of Iran (30 provinces) on a daily scale. This model was proposed for the downscaling daily temperature, precipitation and wind speed data, and it was calibrated and verified by using the daily outputs derived from the National Center for Environmental Prediction (NCEP) database including air temperature, air pressure, absolute and relative air humidity, wind speed and direction, and data for the base period (1982-2001) at the selected synoptic station in each province. Correlation and root mean square error (RMSE) coefficients were used to analyze the performance of the proposed models. These criteria indicated the high accuracy of the proposed models in downscaling of daily temperature parameter rather than precipitation and wind speed parameters.

Key words: Climate, Downscaling, Neural network (NN), Iran

INTRODUCTION

Undoubtedly, climate change is one of the most important challenges for the current climate conditions, which occurs on a global scale and has a profound effect on all countries, especially their water resources (Matondo, 2004). Climate change can lead to rise of temperature, changes in rainfall pattern and decrease or increase of rainfall in various seasons. It can also affect the available water resources, so that some areas may face with runoff reduction or peak flow in early spring, and flow limit values (floodwater and drought) may also be further intensified (Dibike *et al.,* 2004; Houghton *et al.,* 2000; Motiee,2009; Samadi,2012). Complex models, known as Global Climate Models (GCMs), are used to study the climate system and its global-scale changes. These models mathematically simulate the physical behavior of the Earth, atmosphere and ocean system (Mendes *et al.,* 2010). The main problems in utilization of GCM outputs are their low resolution and, particularly, spatial large-scaleness of their computational cells in proportion to the study area, which require them to be downscaled through appropriate methods (Xu C y,1999; Boosik et al,2009). There are many different methods for the downscaling, but it is not yet quite evident that which method has the capability to reproduce more realistic data (Hoai *et al.,* 2011). The following are some of the related studies on application of neural network for the downscaling of climate variables.

(Sailor *et al.,* 2000) used feed-forward neural network and error back-propagation algorithm with a sigmoid transfer function to predict future wind speed

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over three regions in the United Sates (one in Texas and two in California). The studied large-scale climate variables were temperature, pressure and mean sea level (MSL), sea surface specific humidity and 700 and 850 hPa geo-potential heights, high-altitude wind, etc. The results of their study indicated a wind speed decrease of 0.4% and 0.8% over the two regions in California, and a wind speed increase of 2.7% over the other region in Texas on an annual scale (Xu, 1999). Boosik et al. (2009), in another study, used the large-scale outputs from the Third Generation Coupled Global Climate Model (CGCM3), including precipitation, sea surface pressure, near-surface temperature, etc., as inputs to the feed-forward neural network with error back-propagation algorithm, and predicted the precipitation and pressure on a regional scale (Christensen *et al.,* 2005). Moreover, (Mendes *et al.,* 2010) and (Hoai *et al.,* 2011) studied the performance of feed-forward neural network with error back-propagation algorithm and hyperbolic tangent transfer function in downscaling daily precipitation over the Amazon Basin and central Vietnam. Finally, they compared the performance of neural network model to that of the statistical autocorrelation and linear regression models. The obtained results revealed that the neural network model outperforms the statistical autocorrelation and linear regression models (IPCC, 2007; Sailor *et al.,* 2000). The results obtained by (Chadwick *et al.,* 2011), also, indicate the outperformance of multilayer perceptron (MLP) neural network model in downscaling of temperature rather than precipitation (Coulibaly, 2000). (Samadi *et al.,* 2012), compared the performance of Statistical Downscaling Model (SDSM) to that of Time Lagged Feed-forwarded Network (TLFN) in order to downscale the large-scale temperature and precipitation parameters derived from HadCM3 (Hadley Centre Coupled Model, version 3) in Karkheh catchment located in western Iran. Notably, the coefficient of determination of neural network in their study was 0.7 for precipitation and 0.91 for temperature, and fitted well with hyperbolic tangent transfer function giving the most appropriate result.

In general, it should be noted that parameters such as sea surface specific humidity and 500 hPa geo-potential height, near-surface wind speed, 850 hPa geo-potential heights and also mean temperature at 2 m are considered to be the most important inputs in majority of downscaling methods. It is noteworthy that all of these studies are relying on an assumption that the relationships between large-scale variables and observational data remain unchanged for the base and future periods, which can make serious errors in future predictions.

In this study, temperature, precipitation and wind speed values pertaining to the whole 30 provinces of Iran were considered in order to investigate the impact of climate change on meteorological parameters of the country. Subsequently, the appropriate models were identified after downscaling of the parameters on a daily scale with the help of neural network model.

MATERIALS & METHODS

This study aims to downscale the climate parameters (temperature, precipitation and wind speed) in Iran provincial segmentation. For this purpose, the synoptic stations with a suitable statistical period at each province were selected at the first step. Then, Iran provincial segmentation map was interpolated onto the gridded NCEP database map in order to adjust the large-scale atmospheric GCM outputs to the provincial segmentation. In this procedure the intended computational cells were specified, and those related to the large-scale parameters of each province were selected according to the location of each synoptic station. Demonstrates the interpolation of Iran map onto the gridded large-scale climate model. As previously mentioned, in this study, the daily statistics related to the large-scale climate models for the base period were extracted from their database websites (www.cccsn.ca) using the exact coordinates of the given regions. Large-scale variables (predicators) derived from NCEP database, which were used as inputs to neural network models for the base period in this study, are presented in Table 1.

After specifying the computational cells corresponding to each province, it was attempted to establish a downscaling model. Considering a host of studies on downscaling, some of which were discussed earlier in the introduction, the large-scale climate variables involved in the downscaling of temperature, precipitation and wind speed parameters were determined in this study (Table 1). Afterwards, the best performing network for each province was determined through designing various neural networks and evaluating their performances. Feed-forward networks account for about 90% of the networks mostly applied in different fields Goasian *et al.,* 2003). The general architecture of this neural network includes three layers: input, hidden and output. Since the number of neurons placed in the input layer must be matched with the input dimension of each input pattern, the size of input layer depends on the dimension of input data. Likewise, the number of neurons placed in the output layer

Table 1. NCEP large-scale variables (predicators)

No.	Predictors	Description
1	ncepmslp	Mean sea level pressure
2	ncepp__f	surface Geostrophic air flow velocity
3	ncepp__u	surface Zonal velocity component
4	ncepp__v	surface Meridional velocity component
5	ncepp__z	surface Vorticity
6	ncepp_th	surface Wind direction
7	ncepp_zh	surface Divergence
8	ncepp5_f	500 hPa height Geostrophic air flow velocity
9	ncepp5_u	500 hPa height Zonal velocity component
10	ncepp5_v	500 hPa height Meridional velocity component
11	ncepp5_z	500 hPa height Vorticity
12	ncepp5th	500 hPa height Wind direction
13	ncepp5zh	500 hPa height Divergence
14	ncepp8_f	850 hPa height Geostrophic air flow velocity
15	ncepp8_u	850 hPa height Zonal velocity component
16	ncepp8_v	850 hPa height Meridional velocity component
17	ncepp8_z	850 hPa height Vorticity
18	ncepp8th	850 hPa height Wind direction
19	ncepp8zh	850 hPa height Divergence
20	ncepp500	500 hPa geopotential height
21	ncepp850	850 hPa geopotential height
22	ncepr500	Relative humidity at 500 hPa height
23	ncepr850	Relative humidity at 850 hPa height
24	nceprhum	Near surface relative humidity
25	ncepshum	Near surface specific humidity
26	nceptemp	Mean temperature at 2 m

should be equal to the number of outputs. No criterion exists to specify the number of neurons at the hidden layer, and typically it is done by trial and error so that the network gives a reasonable response. The method commonly used to determine the number of neurons in a neural network is that, primarily, one neuron is selected to represent the number of neurons at the middle layer, and then the network is trained to produce the results. Afterwards, the number of neurons is gradually increased to the extent that no significant change is noticed in the network results even by further neuron increasing. The number of neurons at this stage would represent their desired number in the middle layer. The feed-forward neural network with error back-propagation algorithm was used in the present study (Chadwick *et al.*, 2011). Generally, this study used a combination of various inputs derived from the large-scale climate variables presented in Table 1 for downscaling the temperature, precipitation and wind speed parameters over each province on a daily scale. Inputs to the neural network were, in fact, the large-scale climate variables derived from the NCEP database, while the outputs were daily temperature, daily precipitation and daily wind speed. All the daily variables were studied separately, and the best performing networks were selected by varying the number of neurons at the hidden layer, varying the number of time-lags at the input layer and using the transfer function and different training. The designed network should have been evaluated for its performance. For this purpose, the correlation coefficient (ρ) and root mean square error (RMSE) criteria are used and defined as (ASCE, 2000):

Correlation coefficient (ρ)

$$\rho = \frac{\frac{1}{n}\sum_{m=1}^{n}(X_s-\mu_s)(X_0-\mu_0)}{\sigma_s \times \sigma_0} \quad (1)$$

Root mean square error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{m=1}^{n}(X_s-X_0)^2}{n}} \quad (2)$$

Where X_s is simulated data, X_0 is observational data, μ is data mean, σ is standard deviation of data, and n is number of the data. ρ value, ranging from 0 to 1, represents a linear relationship between simulated and observational data. The closer the ρ value is to 1, the stronger the linear relationship between the two variables. Since the correlation coefficient shows only behavioral pattern of two data sets, another criterion such as RMSE is also used. The RMSE, ranging from 0 to 1, with smaller values indicates a less difference between simulated and observational data and thereby a better model fit.

RESULTS & DISCUSSION

Considering a large number of studies on downscaling by ANN, some of which were discussed earlier in the introduction, the large-scale climate variables having a key role in the downscaling of temperature, precipitation and wind speed parameters were identified in this study. The designed networks were verified by the large-scale climate data for the base period and by the synoptic stations statistics for the corresponding period, and finally the best performing network for each province was determined according to error assessment criteria.

The feed-forward neural network with error back-propagation algorithm is used in this study. As previously mentioned, this type of network is capable of approximating all the given functions with any degree of accuracy. The number of neurons at the hidden layer is specified by trial and error. Mean squared error (MSE) is the target function of the model. Characteristics of the best performing networks in each province have also been presented in Tables 2, 3 and 4. As can be seen, the input columns in these tables are tagged with the row number of variables in Table 1. In fact, the large-scale climate parameters for the base period are inputs to these networks, while the mean daily temperature, precipitation and wind speed at the selected synoptic station in the given province are outputs from them. It should be noted that the hidden layer activation function was a hyperbolic tangent type and the output layer was linear in all of the selected networks, and after data classification the best performances of 70 and 30% were respectively observed during training and testing of the networks.

Indicates the statistical period for the selected synoptic stations in all provinces. In all the studied networks, the appropriate classification was used for network training and testing. Furthermore, the best combination of the large-scale climate parameters, as inputs, was selected to be used for the downscaling of daily temperature, daily precipitation and daily wind speed parameters. Tables 2 to 4 present the structure of the best performing network as well as the best combination of the large-scale climate inputs in each province. According to the results, mean temperature at 2 m, pressure on the Earth surface, near surface specific humidity, 500 and 850 hPa geopotential heights and wind speed were found to be the most effective large-scale climate parameters used as inputs in all of the selected networks. The results from Tables 3-5, also, indicate the high performance of ANN model in downscaling of temperature rather than precipitation and wind speed. As can be seen, the mean value for the correlation coefficient of daily temperature is 0.98 which is higher than that of daily precipitation (0.73) and daily wind speed (0.72) parameters, indicating the high accuracy of the daily temperature downscaling model. Notably, the studied synoptic station at Mazandaran did not show a good performance in downscaling of daily wind speed through all of the studied networks. The same was also applied to downscaling of daily precipitation at East Azerbaijan synoptic station. However, it was concluded that the feed-forward neural network with error back-propagation algorithm had a good performance in downscaling of the daily meteorological parameters at all of the provinces in Iran.

Table 2. Results of the selected neural network models for the downscaling of mean temperature in all provinces of Iran

No.	Province	Model structure	Inputs' No.	Period		Training		Testing	
				Training	Testing	P	RMSE	ρ	RMSE
1	East Azerbaijan	9-8-1	1,3,5,9,19,20,21,25,26	1982-1988	1989-1991	0.98	1.9	0.98	1.7
2	West Azerbaijan	9-5-1	1,3,5,9,19,20,21,25,26	1992-1998	1999-2001	0.98	1.9	0.98	2
3	Ardabil	9-4-1	1,3,5,9,19,20,21,25,26	1987-1993	1994-1996	0.97	2.08	0.97	1.9
4	Gilan	9-9-1	1,3,5,9,19,20,21,25,26	1982-1988	1989-1991	0.97	1.7	0.97	1.6
5	Zanjan	9-4-1	1,3,5,9,19,20,21,25,26	1992-1998	1999-2001	0.98	1.8	0.98	1.7
6	Qazvin	9-6-1	1,3,5,9,19,20,21,25,26	1992-1998	1999-2001	0.98	1.6	0.98	1.4
7	Kermanshah	9-8-1	1,3,5,9,19,20,21,25,26	1992-1998	1999-2001	0.98	1.43	0.98	1.45
8	Markazi	9-5-1	1,3,5,9,19,20,21,25,26	1995-May 1999	Jun. 1999-2001	0.98	1.7	0.98	1.7
9	Hamadan	7-6-1	1,3,5,20,21,25,26	1992-1998	1999-2001	0.97	2.05	0.98	1.7
10	Tehran	9-8-1	1,3,5,9,19,20,21,25,26	1982-1988	1989-1991	0.98	1.6	0.98	1.6
11	Qom	9-8-1	1,3,5,9,19,20,21,25,26	1992-1998	1999-2001	0.98	1.8	0.98	1.7
12	Mazandaran	9-9-1	1,3,5,9,19,20,21,25,26	1986-1992	1993-1995	0.97	1.7	0.97	1.8
13	Isfahan	9-6-1	1,3,5,9,19,20,21,25,26	1982-1988	1989-1991	0.99	1.5	0.99	1.4
14	Chahar Mahaal and Bakhtiari	7-9-1	1,3,5,20,21,25,26	1982-1988	1989-1991	0.97	2.01	0.98	1.7
15	Yazd	9-7-1	1,3,5,9,19,20,21,25,26	1992-1998	1999-2001	0.98	1.6	0.98	1.65
16	Fars	9-7-1	1,3,5,9,19,20,21,25,26	1986-1992	1993-1995	0.99	1.2	0.99	1.3
17	Kohgiluyeh and Boyer-Ahmad	9-10-1	1,3,5,9,19,20,21,25,26	1992-1998	1999-2001	0.99	1.18	0.99	1.22
18	Ilam	9-10-1	1,3,5,9,19,20,21,25,26	1992-1998	1999-2001	0.99	1.14	0.99	1.13
19	Bushehr	9-8-1	1,3,5,9,19,20,21,25,26	1992-1998	1999-2001	0.98	1.2	0.98	1.27
20	South Khorasan	9-10-1	1,3,5,9,19,20,21,25,26	1992-1998	1999-2001	0.98	1.38	0.98	1.35
21	Razavi Khorasan	9-5-1	1,3,5,9,19,20,21,25,26	1982-1988	1989-1991	0.98	1.53	0.99	1.32
22	North Khorasan	9-8-1	1,3,5,9,19,20,21,25,26	1982-1988	1989-1991	0.98	1.54	0.98	1.67
23	Khuzestan	9-5-1	1,3,5,9,19,20,21,25,26	1982-1988	1989-1991	0.99	1.22	0.99	1.28
24	Semnan	9-9-1	1,3,5,9,19,20,21,25,26	1982-1988	1989-1991	0.99	1.35	0.99	1.36
25	Sistan and Baluchestan	9-10-1	1,3,5,9,19,20,21,25,26	1982-1988	1989-1991	0.98	1.5	0.98	1.5
26	Kurdistan	9-8-1	1,3,5,9,19,20,21,25,26	1982-1988	1989-1991	0.96	2.6	0.97	2.7
27	Kerman	9-7-1	1,3,5,9,19,20,21,25,26	1992-1998	1999-2001	0.97	1.7	0.98	1.54
28	Golestan	7-5-1	1,3,5,20,21,25,26	1992-1998	1999-2001	0.98	1.56	0.98	1.71
29	Lorestan	9-5-1	1,3,5,9,19,20,21,25,26	1986-1992	1993-1995	0.98	1.55	0.98	1.57
30	Hormozgan	7-7-1	1,3,5,20,21,25,26	1992-1998	1999-2001	0.98	1.232	0.98	1.27

Table 3. Results of the selected neural network models for the downscaling of mean precipitation in all provinces of Iran

No.	Province	Model structure	Inputs' No.	Period		Training		Testing	
				Testing	Training	ρ	RMSE	ρ	RMSE
1	East Azerbaijan								
2	West Azerbaijan	22-5-2-1	Lag (1,5,7,20,21,22,23,26),2lag(24,25)	1995-1999	2000-2001	0.68	1.58	0.77	1.14
3	Ardabil	15-7-1-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1987-1993	1994-1996	0.6	2.7	0.66	2.23
4	Gilan	15-19-2-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1992-1998	1999-2001	0.81	6.3	0.71	9.5
5	Zanjan	15-10-2-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1994-1998	1999-2000	0.71	1.92	0.76	2.26
6	Qazvin	15-7-1-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1982-1988	1989-1991	0.74	2.5	0.72	2.6
7	Kermanshah	15-8-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1992-1998	1999-2001	0.7	3.2	0.7	2.6
8	Markazi	15-5-4-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1995- Mar. 1999	Apr.1999-2000	0.77	1.5	0.71	3.2
9	Hamadan	15-13-1-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1982-1988	1989-1991	0.67	2.4	0.68	1.85
10	Tehran	15-11-1-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1982-1995	1996-2001	0.71	1.95	0.7	1.58
11	Qom	15-2-1-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1992-1998	1999-2001	0.67	1.43	0.71	1.8
12	Mazandaran	30-8-1-1	2 lag (1,5,7,20,21,22,23,24,25,26)	1984-Feb.1988	Mar.1988-1989	0.85	3.47	0.65	5.65
13	Isfahan	15-13-2-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1996- Feb. 2000	Mar. 2000-2001	0.8	1.2	0.7	1.2
14	Chahar Mahaal and Bakhtiari	15-11-1-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1992-1998	1999-2001	0.78	2.43	0.76	2.02
15	Yazd	10-9-1-1	1,5,7,20,21,22,23,24,25,26	1994- Feb.1998	Mar. 1998-1999	0.7	0.68	0.7	1.55
16	Fars	15-5-1-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1982-1995	1996-2001	0.73	3.4	0.67	2.97
17	Kohgiluyeh and Boyer-Ahmad	15-13-1-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1992-1998	1999-2001	0.86	4.69	0.77	6.83
18	Ilam	15-18-2-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1987- Jun. 1997	Jul. 1997-2001	0.7	4.8	0.7	3.8
19	Bushehr	10-18-1-1	1,5,7,20,21,22,23,24,25,26	1990-1994	1995-1996	0.92	1.5	0.77	4.3
20	South Khorasan	15-6-1-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1982-1995	1996-2001	0.7	1.63	0.67	1.21
21	Razavi Khorasan	10-10-2-1	1,5,7,20,21,22,23,24,25,26	1992-1998	1999-2001	0.74	2.12	0.71	1.58
22	North Khorasan	10-15-2-1	1,5,7,20,21,22,23,24,25,26	1989-1993	1994-1995	0.64	1.94	0.65	1.61
23	Khuzestan	15-15-1-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1992-1998	1999-2001	0.8	2.91	0.7	2.35
24	Semnan	15-15-2-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1992-1998	1999-2001	0.79	1.48	0.68	1.41
25	Sistan and Baluchestan	10-3-1	1,5,7,20,21,22,23,24,25,26	May 1988-Jun. 1992	Jul. 1992-Apr. 1994	0.74	1.08	0.72	1.03
26	Kurdistan	15-6-1-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1982-1988	1989-1991	0.71	3.28	0.66	3.93
27	Kerman	15-11-2-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1993- Apr. 1999	May 1999-2001	0.79	1.37	0.67	1.57
28	Golestan	10-17-1-1	1,5,7,20,21,22,23,24,25,26	1984-Feb.1988	Mar.1988-1989	0.68	3.2	0.7	3.1
29	Lorestan	15-8-1-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1982-1995	1996-2001	0.8	2.99	0.76	3.3
30	Hormozgan	15-5-2-1	1,3,4,7,9,13,15,19,20,21,22,23,24,25,26	1992-1998	1999-2001	0.91	1.9	0.91	0.98

Table 4. Results of the selected neural network models for the downscaling of mean wind speed in all provinces of Iran

No.	Province	Model structure	Inputs' No.	Period		Training		Testing	
				Testing	Training	ρ	RMSE	ρ	RMSE
1	East Azerbaijan	16-19-1	1,2,3,4,5,6,7,8,13,14,19,20,21,24,25,26	1982-1988	1989-1991	0.77	2.3	0.77	2.22
2	West Azerbaijan	18-10-2-1	1,2,3,4,5,6,7,8,13,14,19,20,21,22,23,24,25,26	1994-1998	1999-2000	0.77	1.45	0.68	2.9
3	Ardabil	18-13-1-1	1,2,3,4,5,6,7,8,13,14,19,20,21,22,23,24,25,26	1992-1998	1999-2001	0.8	1.83	0.72	2.32
4	Gilan	16-7-2-1	1,2,3,4,5,6,7,8,13,14,19,20,21,24,25,26	1996-1999	2000-2001	0.74	1.73	0.72	1.73
5	Zanjan	14-13-2-1	1,2,3,4,5,6,7,8,13,14,19,20,21,26	1989-1993	1994-1995	0.62	1.64	0.6	1.77
6	Qazvin	18-6-1	1,2,3,4,5,6,7,8,13,14,19,20,21,22,23,24,25,26	1984-Apr. 1990	May1990-1992	0.64	2.08	0.7	1.77
7	Kermanshah	17-6-1	1,2,3,4,5,6,7,8,13,14,19,20,21,22,23,24,25	1992-1998	1999-2001	0.72	1.77	0.74	1.74
8	Markazi	14-5-2-1	1,2,3,4,5,6,7,8,13,14,19,20,21,26	1995-Jun.1999	Jul.1999-2001	0.7	2.73	0.67	2.74
9	Hamadan	16-8-1-1	1,2,3,4,5,6,7,8,13,14,19,20,21,24,25,26	1992-1998	1999-2001	0.74	1.77	0.73	2.31
10	Tehran	17-16-1	1,2,3,4,5,6,7,8,13,14,19,20,21,22,23,24,25	1982-1995	1996-2001	0.73	2.2	0.73	2.2
11	Qom	18-10-1	1,2,3,4,5,6,7,8,13,14,19,20,21,22,23,24,25,26	1987-Jun.1997	Jul.1997-2001	0.73	2.15	0.70	2.1
12	Mazandaran								
13	Isfahan	16-12-1-1	1,2,3,4,5,6,7,8,13,14,19,20,21,24,25,26	1994-May 1999	Jun.1999-2001	0.78	1.55	0.74	1.74
14	Chahar Mahaal and Bakhtiari	16-13-1-1	1,2,3,4,5,6,7,8,13,14,19,20,21,24,25,26	1982-1988	1989-1991	0.76	1.51	0.72	1.47
15	Yazd	18-13-1-1	1,2,3,4,5,6,7,8,13,14,19,20,21,22,23,24,25,26	1992-1998	1999-2001	0.55	2.2	0.67	2.08
16	Fars	18-13-2-1	1,2,3,4,5,6,7,8,13,14,19,20,21,22,23,24,25,26	Jun.1985-1996	1997-2001	0.7	1.53	0.7	1.76
17	Kohgiluyeh and Boyer-Ahmad	18-13-2-1	1,2,3,4,5,6,7,8,13,14,19,20,21,22,23,24,25,26	1989-Jul. 1994	Aug. 1994-1996	0.65	1.31	0.61	1.6
18	Ilam	18-6-2-1	1,2,3,4,5,6,7,8,13,14,19,20,21,22,23,24,25,26	1995-Jun.1999	Jul.1999-2001	0.71	1.88	0.73	1.94
19	Bushehr	18-9-1	1,2,3,5,6,7,8,13,14,19,20,21,22,23,24,25,26	1982-1995	1996-2001	0.79	2.33	0.79	2.19
20	South Khorasan	13-2-1	1,2,3,5,6,7,8,14,20,21,24,25,26	1992-1998	1999-2001	0.71	2.1	0.76	2.4
21	Razavi Khorasan	14-14-1	1,2,3,5,6,7,8,14,19,20,21,24,25,26	Aug. 1994-Aug. 1999	Sep. 1999-2001	0.75	1.65	0.71	1.9
22	North Khorasan	16-12-2-1	1,3,4,5,6,7,8,14,19,20,21,22,23,24,25,26	1992-1998	1999-2001	0.8	2.83	0.73	3.07
23	Khuzestan	16-14-2-1	1,2,3,4,5,6,7,8,13,14,19,20,21,24,25,26	1996-1999	2000-2001	0.8	1.8	0.8	1.86
24	Semnan	16-13-1-1	1,2,3,4,5,6,7,8,13,14,19,20,21,24,25,26	1996-1999	2000-2001	0.77	1.41	0.75	2.06
25	Sistan and Baluchestan	15-14-1-1	1,2,3,4,5,6,7,8,13,14,19,20,21,24,25	1982-1988	1989-1991	0.83	2.16	0.8	2.2
26	Kurdistan	16-19-1-1	1,2,3,4,5,6,7,8,13,14,19,20,21,24,25,26	1994-May 1999	Jun. 1999-2001	0.74	2.2	0.72	2.7
27	Kerman	18-11-1-1	1,2,3,4,5,6,7,8,13,14,19,20,21,22,23,24,25,26	1992-1998	1999-2001	0.8	2.27	0.78	1.68
28	Golestan	15-14-1-1	1,2,3,4,5,6,7,8,14,20,21,22,23,24,25	1988-Feb. 1992	Mar. 1992-1993	0.7	0.93	0.63	1.04
29	Lorestan	14-20-1	1,2,3,4,5,6,7,8,13,14,19,20,21,26	1991-Jul. 1996	Aug. 1996-1998	0.72	1.4	0.65	3.3
30	Hormozgan	18-18-1-1	1,2,3,4,5,6,7,8,13,14,19,20,21,22,23,24,25,26	1995-Jun.1999	Jul. 1999-2001	0.81	1.03	0.7	1.33

CONCLUSION

In this study, the ability of ANN model to downscale the large-scale climate parameters at Iran provincial segmentation was evaluated. For this purpose, first a synoptic station with a suitable statistical period was selected in each province, and then different networks were examined using a combination of various inputs. The inputs were, in fact, the large-scale climate variables. Moreover, it was found that mean temperature at 2 m, pressure on the Earth surface, near surface specific humidity, 500 and 850 hPa geopotential heights and wind speed were found to be the most effective large-scale climate parameters as inputs in all of the selected networks. The obtained results indicated the high potential of feed-forward neural network with error back-propagation algorithm for downscaling of temperature rather than precipitation and wind speed parameters. Using this network, the mean correlation coefficient for daily temperature was 0.98, while the mean correlation coefficients for daily precipitation and daily wind speed were 0.73 and 0.72, respectively.

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