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Seasonal Rainfall Forecasting Using Artificial Neural Network

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Abstract: The rainfall of Khorasan Province, the Northeastern part of Iran, was evaluated from Dec. to May that is included 80% total of annual rainfall in the area under study using artificial neural network. The data of 37 rainfall stations were selected and analyzed over a period of 33 years (1970-2002). The Digital Elevation Model (DEM) was then used to calculate the average rainfall in the area of interest. The relation between variation of synoptic patterns including Sea Surface Temperature (SST), Sea Level Pressure (SLP), the difference of sea level pressure, the difference between sea surface temperature and 1000 hPa surface level, relative humidity at 300 hPa level, geopotential height at 500 hPa level and air temperature at 850 hPa level with mean rainfall of the region were considered. Then the artificial neural network model was trained for 1970-2002 period and rainfall for period of 1993-2002 was predicted. The results showed that artificial neural network method was very successful in predicting rainfall and in more than 70% of years could predict rainfall within acceptable precision. The root mean square error of the model was found to be 41 mm which is considered negligible at yearly level and it is expected that by increasing the number of years of statistical data the precision of the model would increase.

Key words: Khorasan, seasonal rainfall, synoptically patterns, soft computing

INTRODUCTION

Forecasting of the seasonal rainfall is very important to semi-arid area like Khorasan Province in Northeast of Iran. Artificial neural network is an innovative approach to construct computationally intelligent systems that are supposed to possess humanlike expertise within a specific domain, adapt themselves and learn to do better in changing environments and explain how they make decisions. Considering the significance of rainfall in many decision making processes such as water resource management and agriculture, the present study aims to find out the relationship between large-scale climatic signals and regional rainfall using artificial neural network.

McCullagh *et al.* (1995) investigated the use of an Artificial Neural Network (ANN) to estimate the 6 h rainfall over the South-east coast of Tasmania. The results confirm that ANNs have the potential for successful application to the problem of rainfall estimation. Karamouz *et al.* (2004) have used from ANN, fuzzy logic and time series for seasonal rainfall forecasting in the western regions of Iran. In this research, The ANN model displayed a better performance compared to the other models. Nazemosadat and Cordery (2000) used Sea Surface Temperature (SST) for seasonal rainfall variability in the winter (Jan. to Mar.) in the southern regions of Iran. Results showed that rainfall is inversely proportion with Sea Surface Temperature (SST) of the Persian Gulf. Khoshakhlagh (1998) used from correlation between ENSO and rainfall in Iran. Results showed that the Iranian rainfall predictors are strongly related with ENSO.

Suwardi *et al.* (2006) have used of a neuro-fuzzy system for modeling wet season tropical rainfall. The models resulted low values of the RMSE indicated that the prediction models are reliable in representing the recent inter-annual variation of the wet season tropical rainfall.

Lee *et al.* (1998) used RBF (Radial Basis Function) networks and linear regression based on the locational information only for the daily rainfall prediction at 367 locations in Switzerland. Comparison with the observed data revealed that RBF networks produced good predictions while the linear models poor predictions. Maria *et al.* (2005) used ANN and linear regression for

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rainfall forecasting in Sao Paulo State, Brazil. The results show that ANN forecasts were superior to the ones obtained by the linear regression model thus revealing a great potential for an operational suite. Cavazos (2000) used self organization map and ANN for daily rainfall forecasting in Bucharest. Liu and Lee (1999) also used from ANN for short-term rainfall forecasting in Hong Kong region. This neural-based rainfall forecasting system is useful and parallel to traditional forecasts from the Hong Kong observatory. Wong *et al.* (2003) constructed fuzzy rule bases with the aid of SOM (Self-Organization Map) and back propagation neural networks and then with the help of the rule base developed predictive model for rainfall over Switzerland using spatial interpolation. Matayo *et al.* (2000) used Empirical Orthogonal Function (EOF) and simple correlation analysis for seasonal rainfall anomalies over East Africa. Pozo-Vazquez *et al.* (2001) the association among ENSO (El Nino-Southern Oscillation), the Northern Hemisphere Sea Level Pressure (SLP) and temperatures in Europe has been analyzed during the period 1873-1995. Surajit and Manojit (2007) used artificial neural network as a Soft Computing technique to anticipate the average monsoon rainfall over India and results have been compared with those obtained through conventional techniques.

MATERIALS AND METHODS

Study area: The area of this study is Khorasan Province in North east of Iran in Fig. 1. Total precipitation from December to May over a period of 33 yeas (1970-2002) was selected as data of our interest in this research.

Data of 37 stations including four Synoptic, five climatology and 28 rain gauges (all belong to Iranian Meteorological organization) were selected for each year.

Calculating of local average rainfall: Digitizes Elevation model is used to get the amount of local average rainfall. The following steps were taken to obtain the time series of average regional rainfall:

- Making input files for the Arc GIS software
- Obtaining the relation between rainfall and elevation using regression model
- Obtaining digitized map of area under study
- Analyzing and drawing annual spatial changes of rainfall in the region
- Obtaining the values of annual average rainfall in the region under study
- Making time series of rainfall in the region under study

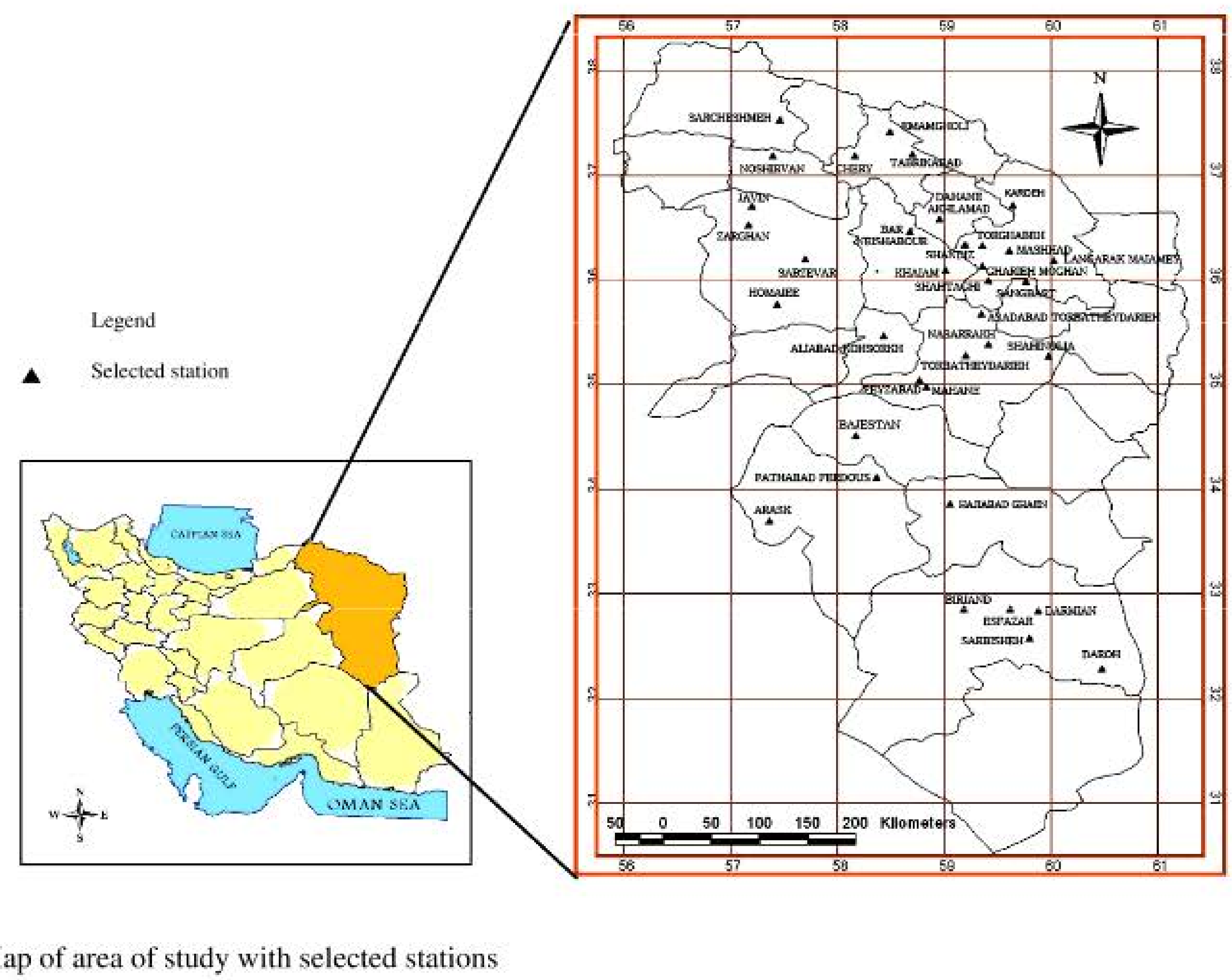

Fig. 1: Map of area of study with selected stations

Table 1: Name and properties of selected stations in the area under study

Station name	Longitude (°E)	Latitude (N)	Elevation	Rainfall (from Dec. to May)
Arask	57 23	33 42	1240.0	107.5
Asad Abad Torbat	59 21	35 39	1770.0	192.0
Asfazar	59 38	32 52	2030.0	198.5
Emam Gholi	58 31	37 25	1650.0	289.9
Bar Neyshabur	58 42	36 29	1520.0	293.7
Bajestan	58 11	34 31	1370.0	160.8
Barsalan	58 29	36 55	1660.0	279.5
Birjand	59 12	32 52	1491.0	161.2
Tabarok Abad	58 43	37 11	1450.0	205.6
Torbat Heydarieh	59 13	35 16	1450.0	255.7
Javin	57 13	36 42	1050.0	127.0
Chery	58 11	37 11	1330.0	308.0
Haji Abad Ghaen	59 04	33 52	1460.0	130.9
Khayam	59 01	36 05	1230.0	226.9
Daramiyan	59 54	32 50	2000.0	178.9
Daruh	60 30	32 17	1156.0	115.1
Dahaneh Akhlomad	58 58	36 35	1350.0	194.0
Zarghan	57 12	36 31	1370.0	245.3
Sabzevar	57 43	36 12	977.6	178.8
Sarbisheh	59 49	32 34	1900.0	209.8
Sarbishmeh	57 29	37 33	1100.0	311.9
Sangbast	59 47	35 59	1500.0	192.9
Shandiz	59 13	36 20	1830.0	220.2
Shah Taghi	59 26	35 58	1450.0	191.6
Shahin Olya	59 59	35 16	1620.0	265.6
Torghabeh	59 22	36 19	1360.0	249.2
Ali Abad Kuhe Sorkh	58 27	35 27	1765.0	221.0
Fath Abad Ferdows	58 23	34 07	1840.0	220.7
Fayz Abad Kashmar	58 47	35 01	910.0	183.0
Ghariyeh Moghan	59 22	36 08	1900.0	331.8
Kardeh	59 39	36 40	990.0	207.0
Langarak Miyamay	60 03	36 10	850.0	206.9
Mahaneh	58 51	34 59	950.0	140.2
Mashhad	59 38	36 16	999.2	232.4
Nasrokh	59 26	35 23	2130.0	303.2
Nushirvan	57 25	37 10	1420.0	249.7
Homaie	59 42	35 45	1337.0	194.2

Data collection: The data used in this study are:

- Thirty seven rainfall station data for the seasonal rainfall (Dec.-May) were obtained from Iranian Meteorological organization. All of these stations are in the Eastern north region of Iran. Properties of these stations have shown in Table 1
- Large-scale ocean and atmospheric circulation variables such as Sea Surface Temperature (SST), Sea Level Pressure (SLP), the difference sea level pressure, the difference sea surface temperature between surface and 1000 hPa level, relative humid at 300 hPa level, geopotential height at 500 hPa level, air temperature at 850 hPa level during months (June-Nov.). These data were obtained from NCEP/NCAR Re-analysis data. These data sets span the period of 1948-current, covering the globe on a 2.5×2.5 grid and available at http://www.cdc.noaa.gov National Oceanic and Atmospheric Administration (NOAA) website
- Standard ENSO indices: $NINO_3$, NINO1+2, Southern Oscillation Index (SOI) Available at http://www.cdc.noaa.gov
- Indian Ocean Dipole (IOD) index (Saji *et al*., 1999). This is an index based on SST anomaly difference between the Eastern and Western tropical Indian Ocean. The index, its impact on the adjoining continental rainfall, interactions with El Nino Southern Oscillation (ENSO) and teleconnections can all be obtained from the IOD home page http://www.jamstec.go.jp/frsgc/research/d1/iod/

Identification of predictors: The aim of identification of predictors is to identify predictors for Khorasan Province seasonal rainfall, which can then be used in forecast models. The two main requirements for any useful predictors are good relationship with the seasonal rainfall and reasonable lead-time (i.e., months to season). The earlier research indicated that seasonal rainfall in the region is strongly correlated with predictors. So, the first step is to look for relationship with standardized predictors during the season (June-Nov.) and follow up with correlation's between the rainfall and large-scale ocean-atmospheric variables (SST, SLP and so on). This approach of correlation with large-scale ocean-atmospheric circulation variables used to identify predictors for seasonal rainfall forecasting in the Northern East of Iran.

Correlation with large-scale variables: The predictors' large-scale aspects and also the seasonal rainfall correlation with predictors such as SST, SLP and etc. were checked during pre-season rainfall (June-Nov). In this research, the correlations that are significant at 95% confidence level have been selected. Figure 2 show properties of selected points which have used for relation between rainfall and remote linkage controlling.

Predictor selection: Based on the correlations with indices and the correlation with large-scale variables, predictors with high correlations to the seasonal rainfall were identified. With this criterion, the selected predictors parameters are:

Standardized pressure of Aden gulf (x_1), South of Persian Gulf (x_2), North of Red Sea (x_3), South of Red Sea (x_4), The difference of pressure standardized between Adriatic Sea and south of Persian Gulf (x_5). Aral Lake and North of Caspian Sea (x_6), South of Persian Gulf and Arab Sea (x_7), Oman Sea and South of Persian Gulf (x_8), South of Persian Gulf and South of Red sea (x_9), The standardized sea surface temperature of Siberian network (x_{10}), The difference of temperature standardized between sea surface and the 1000 mb level of the Island network (x_{11}).

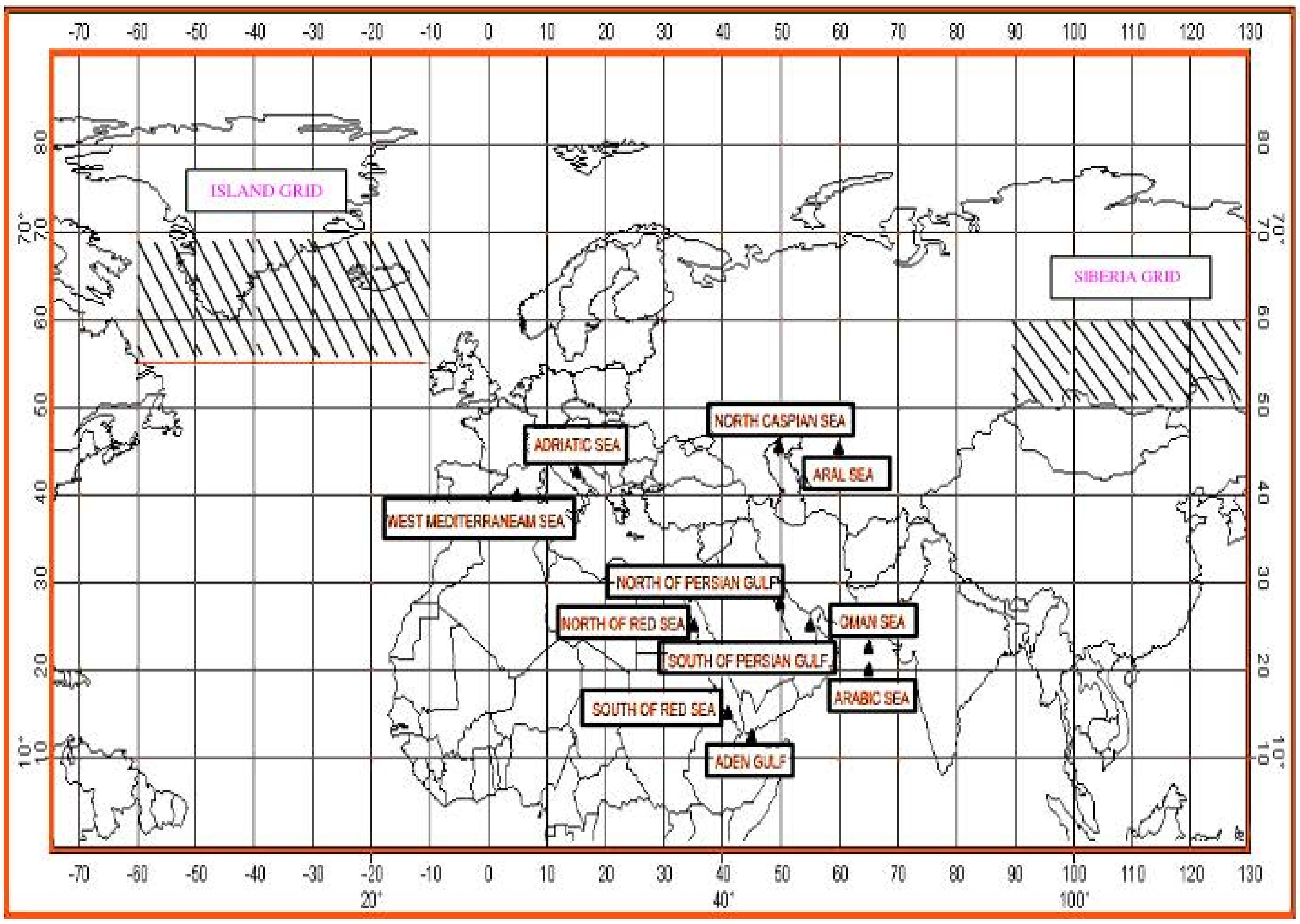

Fig. 2: Name and coordinates that have used for relation between rainfall and remote linkage controlling

The factor analysis of the relative humidity in the index area of factor 1 in a 5×5 degree networks (x_{12}). These regions have shown in Fig. 3.

Time series of rainfall and selected predictors that are used for relation between rainfall and Remote linkage controlling that mentioned above have shown in Table 2.

THE STRUCTURE OF ARTIFICIAL NEURAL NETWORKS

Artificial neural networks were first introduced in 1943 by McCulloch *et al*. (1995). Later, with the development of back propagation algorithm for feed forward networks the application of neural network entered a new stage (Mahdizadeh, 2004).

Like natural neural networks, artificial neural networks are made up of parts called neural cells. As in natural neural networks where some cells are responsible for receiving the external stimulus, some for processing and some for the transfer of response to the intended part, in artificial neural networks, too, some cells receive the data of the problem, some process the data and some provide the solution to the problem. Thus, every neural network is made up of the input layer, the hidden layer and the output layer, with the three layers connected by means of connectors of different weights. In all neural networks, there is one input layer, one output layer and several hidden layers (Mahdizadeh, 2004). Figure 4 shows the structure of one kind of such networks (Mohammadi and Misaghi, 2003).

Figure 5 shows the model of a multi-input neuron (Christodoulou and Georgiopoulos, 2001). The three elements of a multi-input neuron are the following:

A) The set of synapses each specified with a certain weight. As it is shown in the Fig. 5, the neuron k with the output x_k is connected to the intended neuron j through a proper weight connector called w_{jk}. The effect of the neuron k on the neuron j is calculated through $x_k.w_{jk}$. If the neuron k is active and w_{jk} is positive (excitatory synapse), the neuron k will have a positive effect on the neuron j. On the other hand, if the neuron k is active, but w_{jk} is negative (inhibitory synapse), the neuron k will have

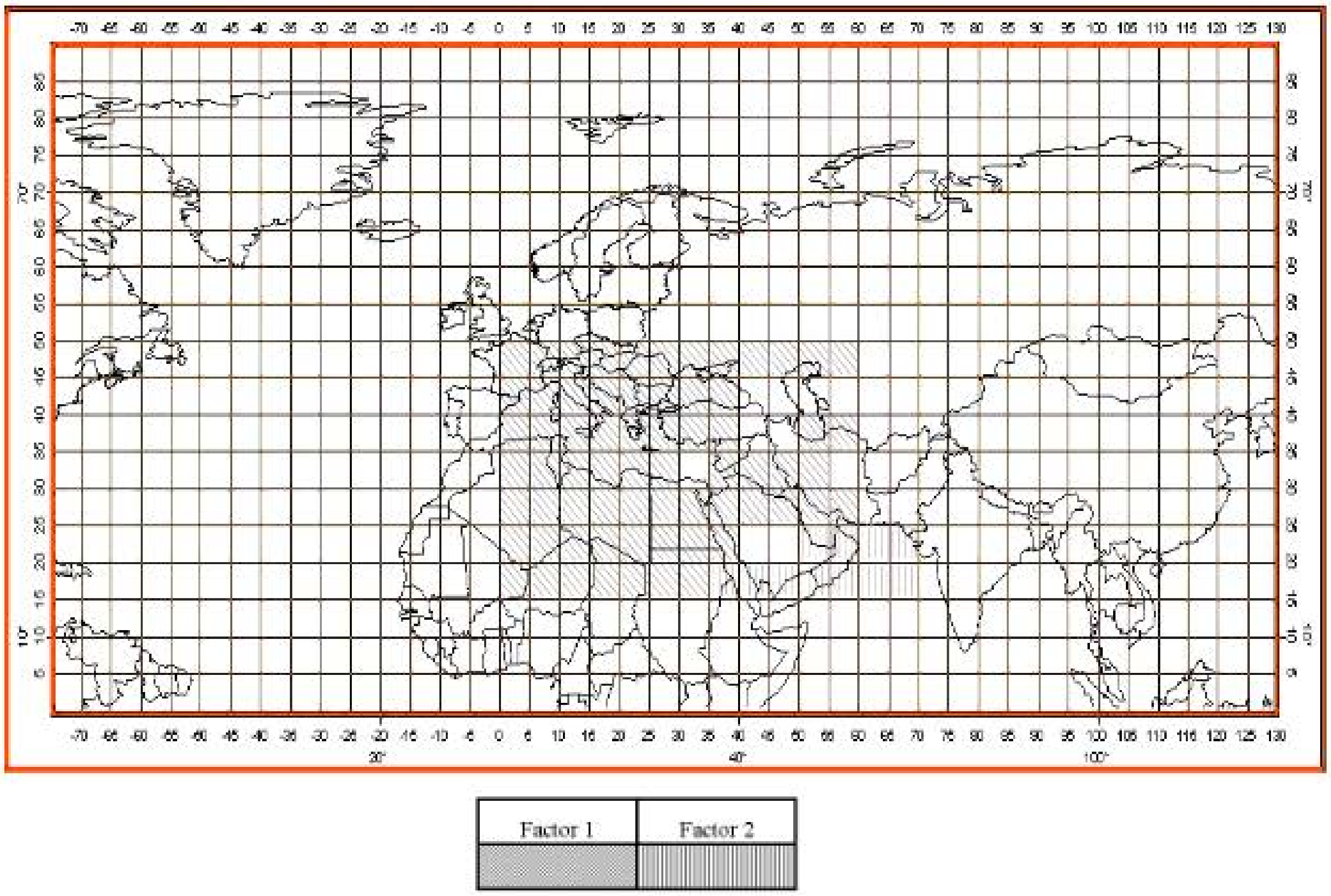

Fig. 3: The detected areas of relative humidity at 300 mb level in networks of 5×5 degree

Table 2: Time series of rainfall and selected predictors

Years	Regional rainfall (mm)	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
1970	139	-1.96	-2.42	-1.36	-1.15	-2.72	-0.23	0.03	0.34	2.04	-0.24	0.20	1.16
1971	172	-0.55	-0.99	0.14	-0.22	-1.65	-0.09	0.00	-0.25	0.94	1.47	-0.10	0.46
1972	297	1.19	0.39	0.29	0.54	0.49	0.52	0.16	-0.02	-0.51	-1.79	0.59	1.80
1973	201	-1.09	-1.72	-1.20	-0.84	-1.96	-0.46	-0.27	0.28	1.72	0.57	-0.42	0.79
1974	274	0.92	-0.45	-0.78	1.15	1.75	-0.10	1.15	-1.21	-1.25	-1.52	0.02	0.89
1975	171	-1.95	-1.96	-0.77	-0.77	-1.92	-0.20	0.72	-0.21	1.20	-0.24	-0.02	0.53
1976	273	-0.08	-0.91	0.53	0.95	0.03	0.75	0.29	-0.12	-2.02	-1.64	-0.08	0.94
1977	186	-0.53	-0.86	0.60	0.81	-0.92	0.13	-0.02	0.17	-0.97	0.41	0.54	0.28
1978	229	0.44	-0.46	0.96	1.15	-2.90	0.27	0.57	-0.48	1.37	0.52	0.55	-0.10
1979	251	1.61	1.44	0.64	1.79	1.12	0.84	0.69	-0.40	-1.81	-0.49	0.66	1.44
1980	197	0.77	-0.01	0.34	0.94	0.71	0.06	-0.07	0.04	-0.78	0.88	0.59	0.37
1981	259	0.27	0.66	0.17	0.77	-0.53	0.33	1.04	-1.13	1.36	-1.61	1.01	0.66
1982	238	0.37	1.76	1.69	0.77	1.37	0.44	1.25	-1.25	-0.75	-0.52	-0.21	0.99
1983	221	-0.18	0.84	1.27	0.71	-0.81	-0.73	1.03	-0.93	0.13	0.73	-0.29	0.95
1984	151	0.59	0.50	0.41	0.73	-0.11	0.12	0.01	-0.32	-0.87	-0.87	-0.68	0.72
1985	183	0.52	0.22	0.43	0.62	-0.94	0.57	-0.35	0.00	0.14	0.11	0.13	0.05
1986	231	1.21	1.48	1.27	1.22	-0.66	0.54	-0.03	0.40	0.21	1.00	0.28	-0.93
1987	192	0.35	1.36	0.87	0.58	1.51	0.97	0.58	-0.69	-0.89	-1.69	-0.06	0.14
1988	233	-0.84	-0.72	-0.72	-0.47	-0.95	0.36	0.01	0.12	0.66	1.22	-0.03	-0.47
1989	169	-0.14	0.33	0.36	-0.59	0.00	0.80	-0.86	0.82	0.80	-0.34	-0.95	-0.12
1990	165	0.31	-0.36	0.40	0.32	0.24	-0.28	-0.90	0.70	-0.67	0.75	-0.56	-0.12
1991	273	0.17	0.21	0.66	0.44	0.40	-0.33	-1.00	0.98	-0.33	0.69	-0.08	-1.51
1992	311	1.36	1.26	0.86	0.87	1.98	0.61	0.44	-0.36	-0.84	-0.61	-0.24	0.40
1993	228	0.66	0.98	0.13	-0.05	1.30	0.20	0.41	-0.51	-0.85	-0.36	-0.16	0.09
1994	158	0.38	-0.19	-0.65	0.08	-0.51	0.21	-0.15	0.23	-0.03	0.83	-0.79	0.22
1995	181	-0.28	-0.51	-1.04	-1.06	-0.43	0.30	0.00	0.10	0.49	1.32	-0.27	-0.14
1996	210	-0.52	-0.03	-1.30	-1.12	0.67	0.59	-0.35	0.68	0.69	-0.80	0.54	-0.81
1997	182	0.90	0.74	-0.13	0.11	2.09	-1.13	-1.10	1.00	-2.50	0.34	0.24	-0.16
1998	284	-1.49	0.73	-1.17	-1.67	0.99	-1.15	-0.50	0.77	1.38	-0.02	0.50	-1.69
1999	190	-1.19	-1.29	-1.29	-1.38	-0.74	-1.86	-1.23	1.28	0.41	0.15	-0.29	-1.44
2000	106	-1.96	-0.48	-2.40	-2.83	-0.19	-0.97	-0.68	0.65	2.04	-0.17	-0.12	-2.17
2001	115	-1.04	-0.49	-1.23	-1.59	-0.49	-0.90	-0.60	0.70	1.74	2.21	0.13	-2.04
2002	197	0.87	0.37	-0.96	-0.38	2.43	-0.65	-1.05	0.76	-1.35	0.69	-0.67	-1.16

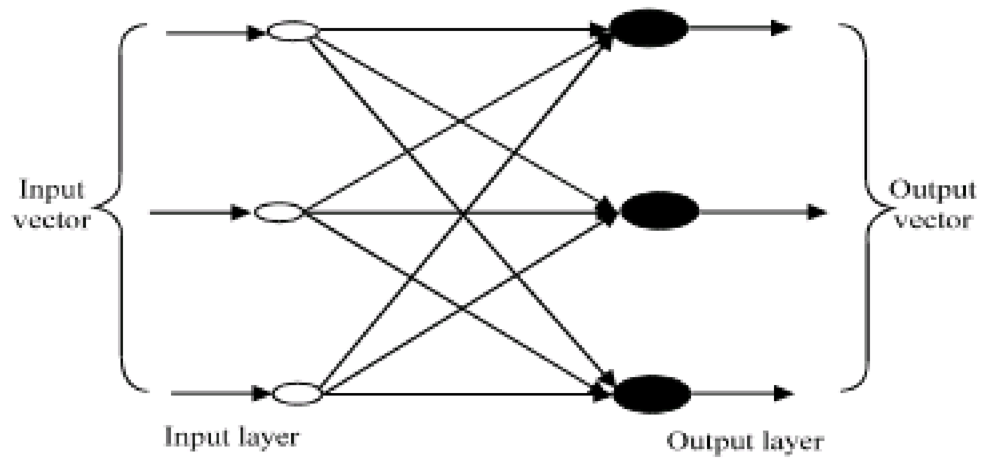

Fig. 4: The overall structure of feed forward monolayer neural networks

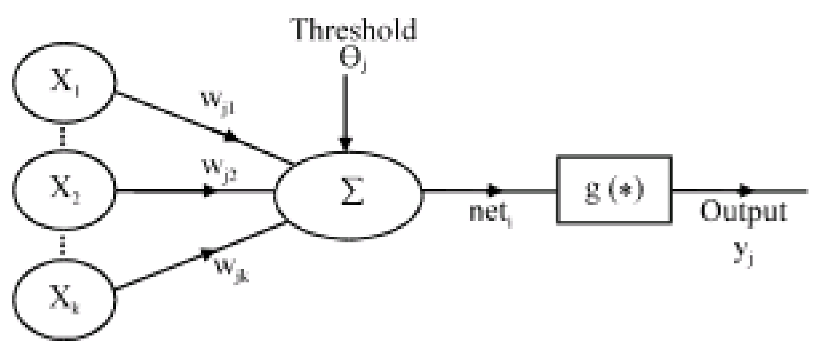

Fig. 5: A model of a multi-input neuron

a negative effect on the neuron j. Special attention should be paid to the written form and the subtitle of the weight of the synapse w_{jk}. The first subtitle belongs to the target neuron and the second to the source neuron of the intended synapse.

B) A capacitor for collecting the incoming signals which are weighted by the synapses of the neuron. The accumulating effect of all neurons which are connected to the intended neuron (Neuron j) is calculated by adding up all the effects of individual neurons on the neuron j.

C) A function of activity is used to limit the output range of the neuron. Activity function is considered as a constraining function in which the eligible changes of the range of output signals is restricted to some finite values. The net input and the output y are calculated by Eq. 1 and 2.

$$\text{net } j = \sum_{K=0}^{K} w_{jk}\ x_k + b \tag{1}$$

$$y_j = g(\text{net}_j) \tag{2}$$

In the Equation $x_1, x_2, \ldots, x_k$ represent the incoming signals, $w_{j1}, w_{j2}, \ldots, w_{jk}$ stand for synaptic weights accumulating in a neuron, net is the accumulated effect of all the neurons connected to the neuron j and the internal threshold of the neuron j. g is activity function and y_j is the output signal of the neuron.

To assess the accuracy of the model, the index of Root Mean Square Error (RMSE) has used which is calculated by the following formula:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(o_i - e_i)^2}{n}} \tag{3}$$

In the above Equation, RMSE is Root Mean Square Error, o_i and e_i are the observed and predicted value of the variable, respectively in the point i and n number of observations.

Research methodology: The methodology described is used as a diagnostic tool to derive anomalous atmospheric patterns characteristic of rainfall events and to derive seasonal rainfall at the area and local scales. The methodology consists of three main steps: (1) classification of the atmospheric controls into different climate signals (i.e., weather types), (2) derivation of large-scale climate anomalies associated with rainfall events and (3) derivation of empirical transfer functions between the atmospheric controls and seasonal rainfall at the area and local scales.

The statistical methods are used to discover patterns; in this case, the correlation between rainfall and climate signals is supposed to find significant features that characterize the seasonal atmospheric circulation and the atmospheric control fields (e.g., humidity) during June to November over the study area.

The purpose of this study is to improve our understanding of the physical and remote linkages associated with rainfall events over the Iran region. This is accomplished by exploring the climate anomalies characteristic of seasonal rainfall events. As explained earlier, the factor analysis classes are used to composite upper troposphere moisture, temperature and mid troposphere geopotential height patterns. These mean fields and their anomalies are chosen to explore the physical characteristics of the atmosphere during seasonal rainfall events in Khorasan Province in Iran during the 1970-2002 period.

Experimentation setup for training and performance evaluation: The data was obtained for the period from 1970 to 2002. The rainfall data was standardized and divided from 1970-1992 as training set and the data from 1993-2002 as test set. The operation was started with a network having 12 input nodes. Further experimentation showed that it was not necessary to include information corresponding to the whole year, but 6 month information centered over the predicted month of the 33 years in the time series would give good generalization properties because in the area under study, 80% total of the rainfall fall from Dec. to May and predictors of the pre-season (from June to Nov.) is suitable to predict amount of the rainfall from Dec. to May.

Thus, based on the information from the earlier years, the network would predict the amount of rain to be expected in each 6 month of the each year. The training was terminated after 1000 epochs. Experiments were carried out on a machine and the model was executed using Neuro Solution software. In this research, tangent hyperbolic axon transfer function was used in the hidden layer and linear tangent hyperbolic axon transfer function in the output layer. Test data was presented to the network and the output from the network was compared with the actual data in the time series. Following are the details of network training.

ANN training: For neural networks using momentum algorithm, 1 input layer, 1 hidden layers and an output layer were used. Input layer consists of 12 neurons corresponding to the input variables and the hidden layer consists of 10 neurons and the output layer consists of 1 neuron (rainfall) [12-10- 1].

RESULTS AND DISCUSSION

After conducting various tests to test the network and the number of neurons of the hidden layer and different functions of activity in the hidden and output layers, as mentioned above, the final model with one input layer, one hidden layer and one output layer (rainfall from Dec. to May), had the least error, so in this research, used it as the main model.

Table 3 shows the training results for ANN model. As an evident from Table 3, Mean Square Error (MSE), Normalized Mean Square Error (NMSE), Mean Absolute Error (MAE), Minimum Absolute Error (Min. Abs Error), Maximum Absolute Error (Max. Abs. Error) was obtained 1755.43, 0.9642, 36.21, 6.51, 73.009 and 0.3, respectively. Table 4 shows the comparative performance of between the actual rainfall and the predicted rainfall by using ANN. Figure 6 also shows actual data versus predicted data. Table 5 shows the characteristic of ANN structure. Root mean square error for the model was obtained 41 mm.

The investigation of the model results showed that the difference between actual rainfall (mm) and predicted rainfall (mm) is acceptable and the model can predict the amount of the rainfall in the most years. The root mean square error for the model was obtained 41.5 mm. As a result, the entered variables in the model can successfully explain the rainfall distribution and dispersal pattern of the seasonal rainfall in the study area. This object has the important role in the planning and agricultural water management.

The results comparative of this research and other researches such as Karamouz *et al.* (2004) and Maria *et al.* (2005) showed that ANN techniques are efficiencies in the rainfall prediction and they can successfully predict amount of the rainfall. Then, the results of this research support the other researches in the study area and with considering of these predictions; we can planning future politicals for the maximum operation.

Table 3: Training results for ANN

Variables	Value
MSE	1755.433042000
NMSE	0.964235151
MAE	36.209511700
Min. Abs error	6.513554910
Max. Abs error	73.009179240
R	0.300884145

Table 4: Seasonal rainfall prediction (6 months) using ANN

Years	Observed rainfall (mm)	Predicted rainfall (mm)
1993	227.5	191.2
1994	158.1	148.6
1995	181.0	174.5
1996	210.0	183.3
1997	182.0	221.1
1998	274.5	183.0
1999	189.6	166.1
2000	106.4	179.4
2001	115.0	169.6
2002	197.2	224.6

Table 5: Properties of ANN network

Variables name	Value
Number of input	13.0
Number of output	1.0
Number of hidden layer	1.0
Epoch	100.0
Hidden rows	10.0
Hidden momentum	0.7
Hidden step size	0.1
Output momentum	0.7
Output step size	0.1

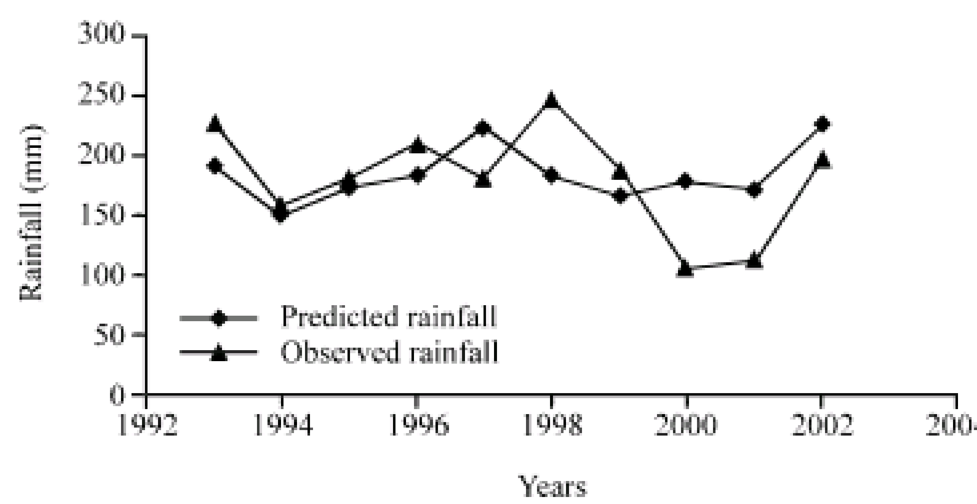

Fig. 6: Comparative of observed rainfall and predicted rainfall using ANN model

CONCLUSIONS

In this study, it has been attempted to evaluate amount of the rainfall (six month ahead) based on Artificial Neural Network (ANN). As the RMSE values on test data are comparatively less, the prediction model was reliable. There have been few deviations of the predicted rainfall value from the actual. As climate and rainfall predication involves tremendous amount of imprecision and uncertainty. The proposed prediction model based on soft computing on the other hand is easy to implement and produces desirable mapping function by training on the given data set. A network requires information only on the input variables for generating forecasts. In these experiments, only 23 years training data were used to evaluate the learning capability. Network performance could have been further improved by providing more training data. Moreover, the considered connectionist models are very robust, capable of handling the noisy and approximate data that are typical in weather data and therefore should be more reliable in worst situations. Choosing suitable parameters for the soft computing models is more or less a trial and error approach. Optimal results will depend on the selection of parameters. Selection of optimal parameters may be formulated as an evolutionary search (Fogel, 1999) to make ANN models fully adaptable and optimal according to the requirement.

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