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# Drought forecasting using artificial neural networks and time series of drought indices

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## Abstract:

Drought forecasting is a critical component of drought risk management. The paper describes an approach to drought forecasting, which makes use of Artificial Neural Network (ANN) and predicts quantitative values of drought indices – continuous functions of rainfall which measure the degree of dryness of any time period. The indices used are the Effective Drought Index (EDI) and the Standard Precipitation Index (SPI). The forecasts are attempted using different combinations of past rainfall, the above two drought indices in preceding months and climate indices like Southern Oscillation Index (SOI) and North Atlantic Oscillation (NAO) index. A number of different ANN models for both EDI and SPI with the lead times of 1 to 12 months have been tested at several rainfall stations in the Tehran Province of Iran. The best models in both cases have been found to include, among the others, a corresponding drought index value from the same month of the previous year. Both best models have the $R^2$ values of 0.66-0.79 for a lead time of 6 months, but it is also shown that the EDI forecasts are superior to those of the SPI for all lead times and at all rainfall stations. The better performance of the EDI model is illustrated by its more accurate prediction of the overall pattern of 'dry' and 'wet' conditions. The structure of the model inputs (previous rain and drought indices) does not vary with the lead time, which makes the models very convenient for the operational purposes. The final forecasting models can be utilized by drought early warning systems, which are emerging in Iran at present. Copyright © 2007 Royal Meteorological Society

KEY WORDS drought forecasting; drought indices; artificial neural networks; Iran

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## INTRODUCTION

Drought is a temporary and recurring meteorological event, which originates from the lack of precipitation over extended period of time. It is a normal part of any climate and, perhaps, the most complex natural hazard, because it develops slowly, is difficult to detect and has many facets in any single region. The success of drought preparedness and mitigation depends, to a large extent, upon timely information on drought onset, development in time and spatial extent. This information may be obtained through continuous drought monitoring, which is normally performed using drought *indices*. Drought indices are continuous functions of rainfall and/or other water-related variable(s) or temperature (e.g. http://www.drought.unl.edu/whatis/indices.htm). They reflect emerging drought severity and can be used to trigger drought contingency plans, if those are designed and supported with appropriate institutional structure and responsibilities. Indices like Palmer Drought Severity Index (PDSI), Deciles or Standard Precipitation Index (SPI) are well known and frequently used in drought monitoring, as shown, e.g. in (Boken *et al.*, 2005). However, monitoring, although useful for identifying early signs of droughts, detects only events that are already happening. The major challenge is to predict the future drought periods and their extremity – i.e. to enhance the early warning capability of drought monitoring systems through drought forecasting.

Various tools and methods for drought forecasting have been suggested and tested in different regions over the last decades. The two predictants most commonly used in medium-range climate forecasting are El Niño Southern Oscillation (ENSO) and North Atlantic Oscillation (NAO) indices (Hurrell, 1995; Nicholson and Selato, 2000; Trenberth and Caron, 2000). The ENSO is an anomalous large-scale ocean-atmosphere system associated with strong fluctuations in ocean currents and surface temperatures. NAO is the dominant mode of winter climate variability in the North Atlantic region ranging from central North America to Europe and much into Northern Asia. ENSO and NAO have different impacts on climate throughout the globe. For example, ENSO is a good indicator to droughts in Australia (Chiew and McMahon, 2002), but not necessarily in central and northern parts of Asia (http://www.fao.org/sd/eidirect/eian008.htm). Both

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phenomena can point to the possibility of a dry or wet period, but they do not indicate the anticipated severity of dryness or wetness, which is the most critical type of information for water resources management.

Application of statistical models has a long history in drought forecasting. It goes back to Gabriel and Neumann (1962) and Torranin (1976) who were the first to apply Markov and regressions models for drought forecasting respectively. The recent decade has seen a wide application of new statistical technique known as *Artificial Neural Network* (ANN) – ASCE, 2000; Govindaraju and Rao, 2000. The superior performance of the ANN for short-term streamflow forecasting in the Winnipeg River system (Canada) within a stochastic-deterministic watershed model was described by Zealand *et al*. (1999). Jain *et al*. (1999) compared ARIMA time series model and ANN for streamflow forecasting in India and again concluded in favor of the ANN approach. Thirumalaiah and Deo (1998) demonstrated the ability of ANN to accurately predict hourly flood runoff and daily water stage in real-time. Birikundavyi *et al*. (2002) established that ANN outperformed a conventional conceptual model in forecasting of daily streamflow in the Mistassibi River in Quebec, Canada. Wang *et al*. (2006) used ANN to forecast daily streamflow from streamflow records alone, without employing exogenous variables of runoff generating process such as rainfall. Hall (1999) applied ANN for rainfall forecasting in Texas, Kuligowski and Barros (1998) – to predict 6-h rainfalls in two drainage basins in Pennsylvania, Luk *et al*. (2000) – for short-term rainfall forecasting within a flood warning system and Ramirez *et al*. (2005) – for daily rainfall forecasting. As a rule, forecasts of precipitation and streamflow by means of ANN are based on past observed data of these variables. Overall, medium or long-term streamflow and rainfall forecasts using the ANN received less attention to date.

This paper examines the utility of ANN approach for medium and long-term forecasting of both the likelihood of drought events and their severity. The study is carried out in the Tehran province located in the northern part of Iran (Figure 1). The province has the total area of 17 250 km$^2$, the population of 14 million people and the mean annual precipitation varying from 700 mm in the north to 120 mm in the south. Similarly, to many other parts of Iran, the province experiences frequent droughts and research is under way to develop appropriate drought monitoring procedures. Morid *et al*. (2006) compared the performance of seven indices for drought monitoring in this province, including Deciles Index (DI), Percent of Normal (PN), Standard Precipitation Index (SPI), China-Z Index (CZI), Modified CZI (MCZI), Z-Score and Effective Drought Index (EDI). The comparison of indices was based on drought events that they detected in the Province over the 32 years, using the observed time series of monthly rainfall. The results reported by Morid *et al*. (2006) illustrated the superiority of the SPI and EDI in detecting the onset of droughts and their spatial and temporal variation – compared with other indices. These two 'best' indices are therefore also used in this study – both as predictants (inputs to the ANN) and predictors. Other inputs to the ANN include large-scale climate signals describing ENSO and NAO phenomena. The avid focus on drought indices *per se*, as opposed to rainfall amounts is one novel aspect of the study. Another novelty is the lead time of the forecast, which ranges from 1 to 12 months, which is the crucial lead times for drought risk management in particular and for water resources management – overall.

## DATA AND METHODS

### *Rainfall data and drought indices*

Observed monthly and daily rainfall data from six meteorological stations (Dehsomeh, Siera, Mehrabad, Abali, Ammameh and Firozkoh) located in different parts of the Tehran province, have been selected for this study (Figure 1). The length of available records at these stations is from January 1970 to December 2000. The accuracy of all data sets was evaluated using nonparametric tests described in Pilon *et al*. (1985), including Mann-Whithney (for homogeneity), Spearman (for independence and trend) and Runs (for randomness). The SPI and EDI drought indices for this study have been calculated on the basis of these rainfall data and using Drought Index Package (DIP) software (Morid *et al*., 2005). The brief description of the two indices is given below.

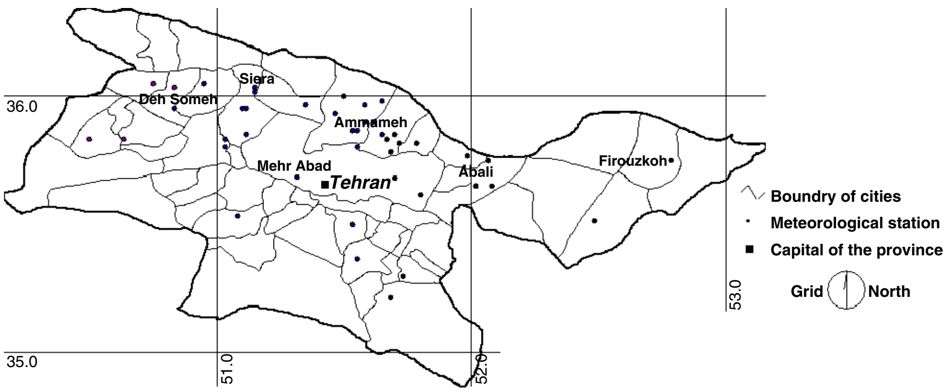


Figure 1. A schematic map of the Tehran Province. This figure is available in colour online at www.interscience.wiley.com/ijoc

The *SPI* is calculated from precipitation records, which is first fitted to gamma distribution and then transformed into a normal distribution so that the mean SPI is zero (McKee *et al.*, 1993). The SPI may be computed with different time steps (e.g. 1 month, 3 months., 24 months). Positive and negative SPI values indicate wet and dry conditions respectively. The 'drought' part of the SPI range is split into 'near normal' ($0.99 > \mathrm{SPI} > -0.99$), 'moderately dry' ($-1.0 > \mathrm{SPI} > -1.49$), 'severely dry' ($-1.5 > \mathrm{SPI} > -1.99$) and 'extremely dry' ($\mathrm{SPI} < -2.0$) conditions. A drought event starts when SPI value reaches $-1.0$ and ends when SPI becomes positive again.

Unlike most other drought indices, the *EDI* in its original form (Byun and Wilhite, 1996) is calculated with a daily time step. However, its principles can be used similarly with monthly time step data as has been described in Smakhtin and Hughes (2007). The EDI is a function of precipitation needed for a return to normal conditions (PRN), i.e. for the recovery from the accumulated deficit since the beginning of a drought. PRN, in turn, is related to monthly effective precipitation (EP) – a function of the current month's rainfall and weighted rainfall over a defined preceding period. If Pm is the rainfall m-1 months before the current month and $N$ is the duration of preceding period then the EP for the current month is

$$EP = \sum_{m=1}^{N} \left[ (\sum_{i=1}^{m} Pm)/m \right] \tag{1}$$

For example, if $N = 3$ then $\mathrm{EP} = \mathrm{P1} + (\mathrm{P1} + \mathrm{P2})/2 + (\mathrm{P1} + \mathrm{P2} + \mathrm{P3})/3$, where P1, P2 and P3 are precipitation values during the current month, previous month and two months before respectively. The mean and standard deviations of the EP values for each month are then calculated and the time series of EP values is converted to deviations from the mean (DEP). PRN values are then calculated as:

$$PRN = DEP/\sum(1/N) \tag{2}$$

The summation term is the sum of the reciprocals of all the months in the duration $N$ (i.e. for $N = 3$ months, this term will be equal to: $1/1 + 1/2 + 1/3$). Finally the EDI is calculated as

$$EDI = PRN/Std(PRN) \tag{3}$$

where Std (PRN) is the standard deviation of the relevant month's PRN values. In these calculations, no normalization of the index or rainfall data is performed and therefore the skewness of the original time series is preserved. This means that positively skewed rainfall data can result in a larger range of positive EDI values than the range of negative EDI values. This is not, however, seen as a critical issue as the negative values are the important ones in that they represent the 'rainfall' that is required for a return to normal from a drought. The EDI varies in the range from $-2.5$ to 2.5. Similarly to the SPI, it has thresholds indicating the range of dryness/wetness. The 'drought range' of the EDI indicates extremely dry conditions at $\mathrm{EDI} < -2.5$, severe drought at $-1.5 > \mathrm{EDI} > 2.49$ and moderate drought at $-0.7 > \mathrm{EDI} > -1.49$. Near normal conditions are indicated by $-0.69 < \mathrm{EDI} < 0.69$.

### *Large-scale climatic indices*

The Southern Oscillation Index (SOI) is an index which is used to quantify the strength of an ENSO event. It is calculated as the difference between the sea level pressure at Tahiti and Darwin, Australia (Philander, 1990). The NAO phenomenon is quantitatively described by the NAO index, which is a normalized pressure difference between measurements at the Azores and Iceland. The index varies from year to year, but also exhibits a tendency to remain in one phase for intervals lasting for several years (Hurrell, 1995). Modarres Pour (1995) showed the correlation between the SOI and rainfall in the Tehran province of Iran and Koureh Pazan (2003) reported the correlation of this index with the occurrence of dry years in parts of Iran. The monthly values of the SOI and NAO from 1969 to 2000 have been obtained from the Internet at www.cru.uea.ac.uk/cru/data.

### *Artificial neural network (ANN)*

The ANN is an information processing approach that resembles the structure and operation of the brain. The approach was developed in the 1940s by McCulloch and Pitts (1943) and gradually progressed after that with advances in calibration methodologies (Rumelhart *et al.*, 1986). Given sufficient data and complexity, ANN can be designed to model any relationship between a series of independent and dependent variables – inputs and outputs to the network respectively (Hornik *et al.*, 1990; Luk *et al.*, 2000). One of the advantages of the ANN technique is that there is no need for the modeler to fully define the intermediate relationships (physical processes) between inputs and outputs (Morid *et al.*, 2002; Anctila *et al.*, 2004; Dawson *et al.*, 2006). This feature makes ANNs particularly suitable for the analysis of complex processes, like drought forecasting, where relationships of a large number of input variables with the output need to be explored. Although there is now a significant number of network types and training algorithms, this paper employs the Multi-Layer Perceptron (MLP) – the most widespread (in hydrological research) topological tool at present (Coulibaly *et al.*, 2000; Maier and Dandy, 2000).

In the network structure, the neurons are arranged in interconnected groups called layers. Every ANN include: (1) input layer(s) – where data are introduced to the network, (2) hidden layer(s) – where data are processed, and (3) output layer(s) – where the results for the given inputs are produced. A neuron computes its output response based on the weighted sum of all its inputs according to an activation function.



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## RESULTS AND DISCUSSION

### *Drought forecasting models*

To predict the future values of the SPI and the EDI, the inputs to the networks are represented by various combinations of their present and previous values with different time lags supplemented by present and past values of actual precipitation, SOI and NOA. All input and output values are standardized to range between *FMIN* and *FMAX* ($FMIN = 0.1$ and $FMAX < 1$) rather than between zero and one, so that

$$X_n = FMIN + \frac{(X_u - fact\_\min)}{(fact\_\max - fact\_\min)} \times (FMAX - FMIN) \quad (4)$$

Where *Xu* and *Xn* represent the original variable and the standardized value respectively, while '*fact_max*' and '*fact_min*' are the maximum and the minimum values present in the original *X* vector. Caution should be exercised while selecting the values of *FMIN* and *FMAX* as, on the one hand, reduction of the range to a very small value will have a negative influence on training while, in contrast, the amount of allowed extrapolation should not exceed a certain limit (Sajikumar and Thandaveswara, 1999). For the current case, the values of $FMIN = 0.1$ and $FMAX = 0.9$ were associated with better results.

Establishing the appropriate number of neurons and hidden layers (an ANN 'architecture') are the main two issues in setting up the ANN. There exists no systematic way by which to establish a suitable ANN architecture. Networks that are too small and simple can lead to the under-fitting, while networks that are too complex tend to over-fit the training pattern (Dawson and Wilby, 1998). In the present study, different architectures have been examined in which various combinations of hidden layers and neurons have been tested. Most of the resulting architectures are simple which allows the over-fitting of networks to be avoided (As an example, Table I for Mehrabad Station). For complex architectures, it is recommended to apply some re-sampling method like cross validation, stopped training approach or bootstrapping (Coulibaly *et al*., 2000; Nayaka *et al*., 2004).

Also, through testing various networks and learning methodologies, the feed forward training with standard back propagation algorithm was found to be the most suitable. The years from 1970 to 1993 were set for training and the years from 1994 to 2000 – for validation of the networks. The performance of the networks was evaluated using by $R^2$, RMSE and MAE that are commonly used for such validation. Altogether over 20 different network models have been tested for the forecasting of each index – the EDI and the SPI. The example set of models for the EDI, which have been found to exhibit a better performance are:

$$E_{(t+n)} = f(R, R_{t-1}, R_{t-2}) \ \textit{Input model 1}$$

$$E_{(t+n)} = f(So_t, So_{t-1}, So_{t-2}) \ \textit{Input model 2}$$

Table I. Results of EDI forecasting (six months in advance) at Mehrabad Station.

| | | Training | | | Validation | | |
|---|---|---|---|---|---|---|---|
| Input model | Architecture[a] | $R^2$ | RMSE | MAE | $R^2$ | RMSE | MAE |
| **1** | 5-2-1 | 0.49 | 0.46 | 0.34 | 0.36 | 0.75 | 0.63 |
| **2** | 6-3-1 | 0.34 | 0.86 | 0.67 | 0.17 | 1.33 | 0.88 |
| **3** | 5-2-1 | 0.44 | 0.73 | 0.55 | 0.23 | 1.51 | 1.10 |
| **4** | 4-3-1 | 0.61 | 0.54 | 0.36 | 0.45 | 0.68 | 0.55 |
| **5** | 6-2-1 | 0.57 | 0.42 | 0.60 | 0.47 | 0.62 | 0.45 |
| **6** | 6-4-1 | 0.41 | 0.79 | 0.90 | 0.19 | 1.11 | 0.70 |
| **7** | 4-3-1 | 0.31 | 0.88 | 0.50 | 0.11 | 1.21 | 0.75 |
| **8** | 5-4-1 | 0.45 | 0.92 | 0.75 | 0.18 | 1.01 | 0.88 |
| **9** | 5-6-1 | 0.84 | 0.36 | 0.24 | 0.79 | 0.55 | 0.33 |

[a] The three digits refer to numbers of neutrons in input, hidden and output layers respectively. For example, an architecture 5-2-1 refers to five neurons in the input layer, two neurons in the hidden layer and one neuron in the output layer.

$$E_{(t+n)} = f(N_t, N_{t-1}, N_{t-2}) \ \textit{Input model 3}$$

$$E_{(t+n)} = f(E_t, E_{t-1}, E_{t-2}, E_{t-3}) \ \textit{Input model 4}$$

$$E_{(t+n)} = f((E_t, E_{t-1}, E_{t-2}), (R_t, R_{t-1}, R_{t-2})) \ \textit{Input model 5}$$

$$E_{(t+n)} = f((E_t, E_{t-1}, E_{t-2}), (So_t, So_{t-1}, So_{t-2})) \ \textit{Input model 6}$$

$$E_{(t+n)} = f((E_t, E_{t-1}, E_{t-2}), (N_t, N_{t-1}, N_{t-2})) \ \textit{Input model 7}$$

$$E_{(t+n)} = f((E_t, E_{t-1}, E_{t-2}), (R_t, R_{t-1}, R_{t-2}), (So_t, So_{t-1}, So_{t-2})) \ \textit{Input model 8}$$

$$E_{(t+n)} = f((E_t, E_{t-1}, E_{t-2}, E_{t-12}), (R_t, R_{t-1})) \ \textit{Input model 9}$$

where $E$ is the EDI index, $R$ is precipitation, $So$ is SOI, $N$ is NAO and $n$ is the time lag which is effectively the lead time of the forecast. Similar steps have been followed for the SPI forecasting. The following model was found to be the best.

$$S_{(t+n)} = f((S_t, S_{t-1}, S_{t-2}, S_{t-3}, S_{t-4}, S_{t-12}), (R_t, R_{t-1})) \ \textit{Input model 10}$$

where $S$ is the SPI.

### *Analysis of models' performance*

The forecast lead times varied from 1 to 12 months. Because it is the medium-range and the long-range forecasts that are critical for drought preparedness, we further discuss only the results of forecasting with a lead time of 3 months and longer. It is also virtually



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impossible to illustrate all results for all stations. We therefore primarily use the results from the Mehrabad station (Figure 1) to illustrate the main points. This station is located in the Mehrabad International airport and has the most reliable data.

The statistics presented in Table I indicate that among the first four models (with single type input), the models 1 and 4 have performed better than 2 and 3. This emphasizes the importance of rainfall and a drought index itself for accurate forecasting. It also illustrates the lack of impact of SOI and NAO on the performance of the networks. Models 5 to 8, with different combinations of inputs, have not resulted in accurate forecasts. However, the forecasts have significantly improved with model 9, where the $R^2$ values for training and validation periods are 0.84 and 0.79 respectively. Model 9 retains a relatively simple architecture and its main difference from others is that it includes the same month of the past year. Table I illustrates the results with a lead time of 6 months only, but model 9 has also appeared to be superior to others if used with other lead times. Figure 2 shows the variation of $R^2$, *RMSE* and *MAE* for forecasting of the EDI with lead times of 1 to 12 months during the validation period for six selected stations in the Province.

As in the case of the EDI forecasting, different models have been tested for the SPI. Similarly, the SOI and NAO have been found to have limited positive impact on the accuracy of the forecasts. Model 10 was found to be the best for the SPI forecasting. Its architecture is similar to that of model 9 for the EDI, but more past information have been used in it. Figure 3 illustrates the variations of $R^2$, *RMSE* and *MAE* for forecasting of the SPI with different lead times during the validation period at six selected stations.

Figure 4 displays the observed time series of the EDI values against the forecasted ones with the lead times of 3, 6, 9 and 12 months. In addition, the corresponding scatter plots are also presented. Similar results of the SPI forecasting are illustrated by Figure 5. In all cases the significance level of $R^2$ is 1%. The results effectively illustrate the high accuracy of medium and long-range forecasts of both drought indices at Mehrabad station. The results at other stations are broadly similar.

### *Comparison of the EDI and SPI forecasts*

Figure 6 presents the results of forecasting two indices at Mehrabad Station with lead times of 1, 3, 6, 9 and 12 months. It is clear that all validation statistics – $R^2$, *RMSE* and *MAE* – are better for the EDI. This can be related to the different response of the EDI and the SPI to rainfall as illustrated by Figures 4 and 5 respectively. The EDI time series are more sluggish with no immediate fluctuations. This pattern can be related to the *EP* parameter of the EDI – which represents the

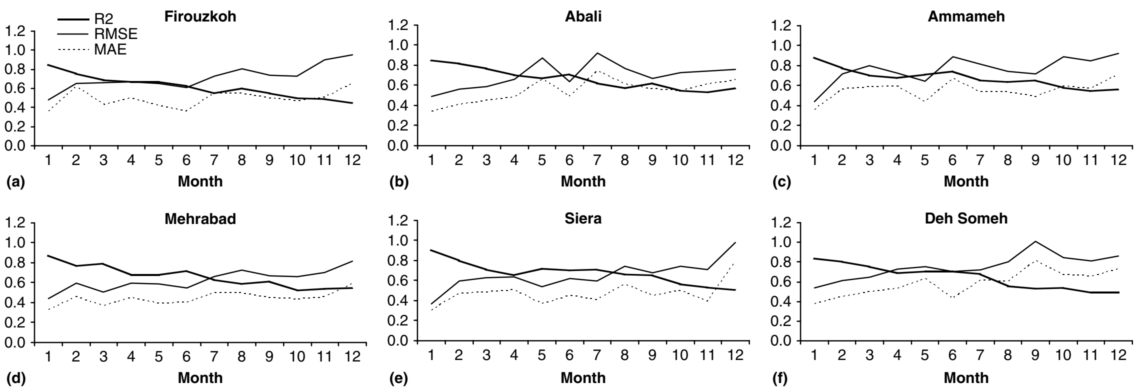


Figure 2. Evaluation of the EDI forecasts using $R^2$, RMSE and MAE criteria for different future months during validation period at selected stations.

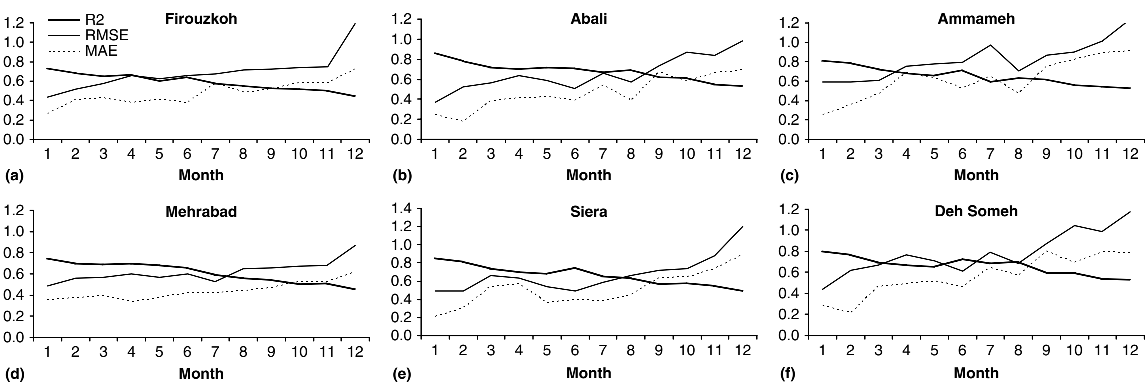


Figure 3. Evaluation of the SPI forecasts using $R^2$, RMSE and MAE criteria for different future months during validation period at selected stations.



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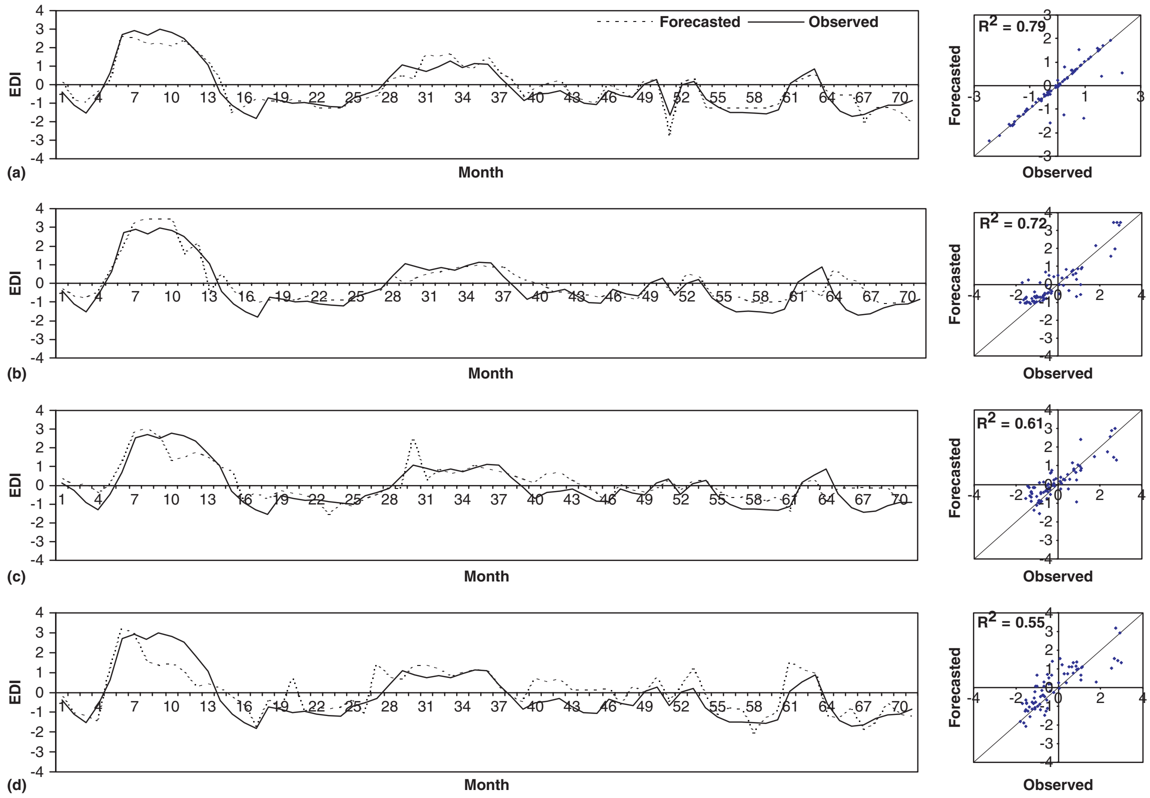


Figure 4. Comparison of observed and forecasted EDI at the Mehrabad station with lead times of 3 months(a), 6 months (b), 9 months (c) and 12 months (d), starting January 1995. This figure is available in colour online at www.interscience.wiley.com/ijoc

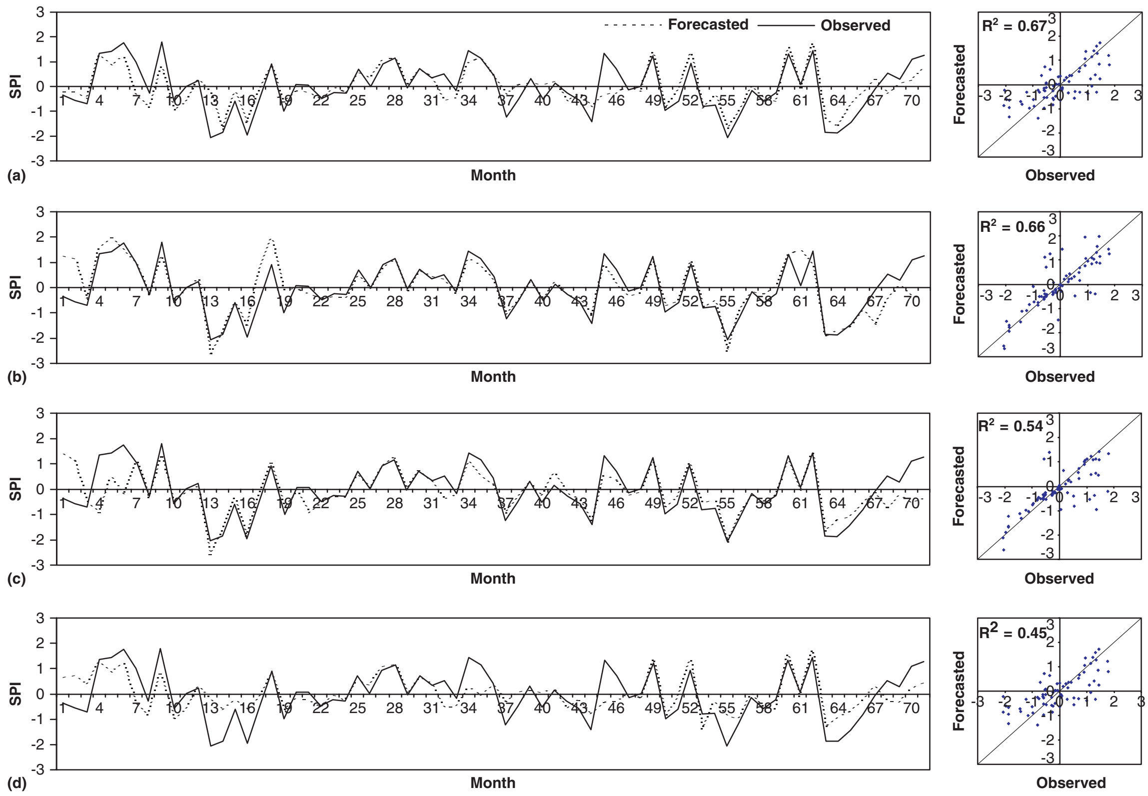


Figure 5. Comparison of observed and forecasted SPI at the Mehrabad station with lead times of 3 months(a), 6 months (b), 9 months (c) and 12 months (d), starting January 1995. This figure is available in colour online at www.interscience.wiley.com/ijoc

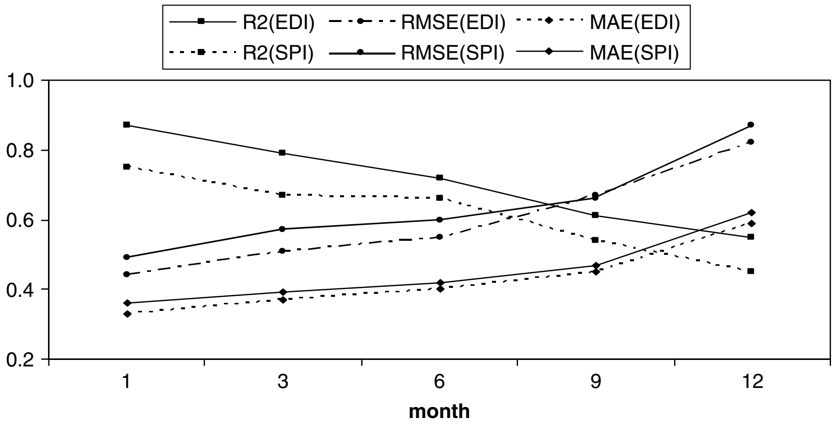


Figure 6. Comparison of the EDI and SPI forecasts at Mehrabad station.

'memory' of the previous rainfall events and ensures more smooth response of the EDI to rainfall fluctuation.

To evaluate the accuracy of forecasts across events of different extremity, the forecast values of indices have been compared by classes of different wetness. Such comparison may be seen as a way to assess the operational accuracy of forecasts and has been used by others for similar purposes (e.g. Zealand *et al.*, 1999). In Tables II and III, number 2 in the DC column (DC stands for Difference in Classes) means that there are two classes of differences between observed and forecasted values (e.g *Normal* is observed and *Sever Drought* is forecasted or vise versa). Table II shows that over the entire period of record the EDI classes are correctly forecasted with a lead time of 6 months for 72 to 89% of all cases (' 0′ DC row). The proportion of correct class forecasts with the same lead time for the SPI ranges from 70 to 85% (Table III). Similarly, for the lead time of 9 months, the correct class forecasts vary between stations from 59 to 80% for the EDI and from 59 to 72% for the SPI. Finally, for the lead time of 12 months, the proportion of correct class forecasts is 55–72% and 54–62% for the EDI and the SPI respectively. It is also evident from Tables II and III that the SPI forecasting errors are more significant. While the EDI has had a maximum mismatch of 2 classes, the SPI forecasting 'makes mistakes's of up to 4 classes difference (e.g. the Siera station in Table III).

## CONCLUSIONS

This paper described the procedure for drought forecasting using the ANN and its application in the Tehran Province of Iran. Two rainfall-related drought indices – the EDI and the SPI – have been used as the predictants, while different combinations of the past

Table II. Percent of class differences between observed and forecasted EDI values.

| | Firouzkoh | | | | Abali | | | | Ammameh | | | | Mehrabad | | | | Siera | | | | Deh someh | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DC[a] | 3 | 6 | 9 | 12 | 3 | 6 | 9 | 12 | 3 | 6 | 9 | 12 | 3 | 6 | 9 | 12 | 3 | 6 | 9 | 12 | 3 | 6 | 9 | 12 |
| 0 | 75 | 72 | 70 | 63 | 90 | 87 | 70 | 65 | 81 | 83 | 68 | 62 | 71 | 73 | 66 | 59 | 91 | 89 | 80 | 72 | 78 | 72 | 59 | 55 |
| 1 | 25 | 28 | 30 | 32 | 10 | 13 | 30 | 35 | 19 | 17 | 32 | 37 | 29 | 27 | 30 | 34 | 9 | 11 | 20 | 27 | 22 | 28 | 39 | 42 |
| 2 | 0 | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 4 | 7 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 3 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

[a] DC: Difference between observed and forecasted dry or wet classes.

Table III. Percent of class differences between observed and forecasted SPI values.

| | Firouzkoh | | | | Abali | | | | Ammameh | | | | Mehrabad | | | | Siera | | | | Deh someh | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DC | 3 | 6 | 9 | 12 | **3** | 6 | 9 | 12 | 3 | 6 | 9 | 12 | 3 | 6 | 9 | 12 | 3 | 6 | 9 | 12 | 3 | 6 | 9 | 12 |
| 0 | 73 | 70 | 59 | 56 | 85 | 83 | 70 | 59 | 86 | 83 | 72 | 62 | 76 | 76 | 68 | 61 | 83 | 85 | 62 | 55 | 80 | 82 | 65 | 54 |
| 1 | 25 | 25 | 28 | 24 | 13 | 14 | 20 | 28 | 13 | 15 | 24 | 18 | 23 | 23 | 23 | 25 | 14 | 10 | 24 | 21 | 18 | 15 | 23 | 31 |
| 2 | 2 | 4 | 6 | 10 | 2 | 3 | 7 | 11 | 1 | 1 | 4 | 15 | 1 | 1 | 7 | 10 | 2 | 4 | 8 | 14 | 2 | 3 | 8 | 11 |
| 3 | 0 | 0 | 7 | 10 | 0 | 0 | 3 | 1 | 0 | 0 | 0 | 4 | 0 | 0 | 3 | 4 | 1 | 1 | 6 | 7 | 0 | 0 | 4 | 3 |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 1 |

drought indices, precipitation and large climate signals – SOI and NAO – have been used as predictors. Over more than 25 different network models have been tested for each drought index at six rainfall stations in the Province with lead times from 1 to 12 months. The best models in both cases are found to include a drought index value from the corresponding month of the previous year. It is also established that SOI and NAO do not have a significant forecasting capability in the study area.

The final, best ANN models, for both the EDI and the SPI have a relatively simple architecture. Three layer networks and maximum of six neurons for a hidden layer appear to be sufficient for all stations and all lead times. In drought forecasting, it is particularly important to ensure that accurate medium and long-term forecasts (with lead times of 3 to 12 months) are produced. The best models developed in the paper result in $R^2$ values (e.g. for the lead time of 6 months) of 0.66 and 0.79 for the SPI and the EDI respectively, which is indicative of a high forecasting accuracy, particularly in the case of the EDI.

Comparison of the EDI and the SPI forecasts has shown that the EDI network model has a superior performance over all lead times in terms of statistical criteria used. It is also capable of accurately predicting the pattern of wet and dry classes of the EDI. This is an important outcome considering the need to avoid major errors in and to ensure the consistency of operational forecasts. Both models, however, have the structure of inputs that does not vary with the lead time. This makes both attractive for operational purposes.

It is important to note the superiority of the methodology described in the paper compared to 'traditional's approaches, which normally evaluate the predictive power of the ENSO or NAO phenomena. Such traditional approaches can only indicate whether a future time step (e,g, next 3 months) is likely to be wet or dry, while the proposed method also gives an explicit indication of the severity of a drought. Also, the proposed methodology is effectively not geographically limited, compared to ENSO- or NAO-based forecasts, which have varying accuracy due to limited impacts of these phenomena in many regions. It is imperative to test the approach suggested in this paper at the scale of the entire country and – if proved successful – build it into drought early warning systems, which are currently emerging in Iran.

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