Prediction of short and long-term droughts using artificial neural networks and hydro-meteorological variables

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Abstract: Drought is a natural creeping threat with numerous damaging effects in various aspects of human life. Accurate drought prediction is a promising step in helping policy makers to set drought risk management strategies. To fulfill this purpose, choosing appropriate models plays an important role in predicting approach. In this study, different models of Artificial Neural Network (ANN) are employed to predict short and long-term of droughts by using Standardized Precipitation Index (SPI) at different time scales, including 3, 6, 12, 24 and 48 months in Tabriz city, Iran. To this end, different combination of calculated SPI and time series of various hydro-meteorological variables, such as precipitation, wind velocity, relative humidity and sunshine hours for years 1992 to 2010 are used to train the ANN models. In order to compare the models performances, some well-known measures, namely RMSE, Mean Absolute Error (MAE) and Correlation Coefficient (CC) are utilized in the present study. The results illustrate that the application of all hydro-meteorological variables significantly improves the prediction of SPI at different time scales.

Keywords: Drought prediction, Standardized precipitation index, Hydro-meteorological variables, Artificial neural networks, Machine Learning

1. Introduction and Background

Different studies have been done on the impact of the water science and management issues on the future of the human and aquatic life-cycle (Jozaghi and Shamsai 2017; Jozaghi et al. 2018; Baharvand and Lashkar-Ara 2019; Mahmoudian et al. 2019; Martinez et al. 2019; Singh et al. 2019; Darabnoush Tehrani et al. 2019). However, with the changes in climate variables and their impact on water resources, the entire water cycle process should be studied as the requirement of the water budget investigation.
Drought “A sustained, extended deficiency in precipitation” (WMO 1986) is an expected meteorological event, impossible to avoid, causing spread spectrum of complex socio-economic and environmental impacts (Mishra and Desai 2006; Farokhnia et al. 2010; Farahmand and Aghakouchak 2015). Statistics reveal that droughts have affected large amounts of people around the globe: almost 35% of people who have suffered from natural disasters and 50% of mortalities. In terms of financial damages, droughts have cost up to 7% of global economy (Chen et al. 2013). In the last few decades, severe droughts have affected numerous regions in almost every continent on the world. For more information on global drought events and impacts in recent decades, see: Around the world (Mishra and Singh 2010), Africa (Batterbury and Warren 2001; OCHA 2011; Funk 2011; USAID/FEWSN 2011), Australia (Murphy and Timbal 2007; Bond et al. 2008; Aghakouchak et al. 2014), Asia (Agrawala et al. 2001; Guha-Sapir et al. 2004; OFDA/CRED 2008), Europe (European Communities 2007; Feyen and Dankers 2009), and United States (Riebsame et al. 1990; FEMA 1995; Wilhite and Hayes 1998; Ross and Lott 2003; Aghakouchak et al. 2014).

Like many other countries, droughts are normal feature of climate in Iran. Being located mainly in semi-arid and arid regions of the world (with long-term average precipitation 224-275 mm/year, less than one third of the world average), Iran has been exposed to severe droughts during last decades, causing complex environmental, social and economic damages (Keshavarz et al. 2013). According to the various studies, the recurring droughts could worsen the water resources of the most parts of Iran (Golian et al. 2015). In this way, there are many outstanding achievements in drought modeling of Iran (e.g., Abbaspour and Sabetraftar 2005; Morid et al. 2006, 2007; Karamouz et al. 2009; Shiau and Modarres 2009; Raziei et al. 2009, 2011; Dezfuli et al. 2010; Farokhnia et al. 2011; Tabari et al. 2012; Abdi et al. 2017a, b, c).

Traditionally, various models such as linear and multi linear regression models (Kumar and Panu 1997; Liu and Negron-Juarez 2001), stochastic models (Rao and Padmanabhan 1984; Chung and Salas 2000; Mishra and Desai 2005a; Han et al. 2010), Markov Chain and loglinear models (Lohani and Loganathan 1997; Lohani et al.1998; Paulo et al. 2005; Paulo and Pereira 2007; Moreira et al. 2006; Sen 1990; Steinemann 2003) have been used for drought prediction. Limitation of all these linear models in capturing nonlinearities and nonstationarities in hydrologic time series, in addition, complexity and uncertainty in input variables (in drought analysis: e.g., climate or/and drought indices) have made scientists to use better solutions.

Soft computing methods including Multi-Criteria Decision Making (MCDM) methods (Jozaghi et al. 2018), Artificial Neural Network (ANN) (Büyükşahin & Ertekin 2019, Kardan Moghaddam et al. 2019), fuzzy rule based systems (Jiang et al. 2019, Bose & Mali 2019, Vijayalaksmi & Babu 2015), kernel methods such as Support Vector Machine (SVM) (Shabani et al. 2017), and hybrid models have been increasingly used in hydrology and consequently drought prediction during last two decades. Kim and Valdes (2003) were first scientists to use hybrid wavelet-ANN model for drought prediction in Conchos
River Basin, Mexico using PDSI as input variable. Mishra and Desai (2006) compared SPI forecast results of ANN models and linear stochastic models (ARIMA) in India. Mishra et al. (2007) combining ARIMA and ANN introduced a new hybrid model to forecast SPI time series in the same region. Morid et al. (2007) applied ANN models to forecast time series of SPI and EDI indices in Iran. For this purpose, they used different combination of mentioned drought indices and climate indices including Southern Oscillation Index (SOI) and North Atlantic Oscillation (NAO). In a similar study, Bacanli et al. (2008) employed Adaptive Neuro-Fuzzy Interface System (ANFIS) to predict quantitative amounts of SPI in Central Anatolia, Turkey. Different combination of preceding monthly rainfall and SPI values were used as input variables. Cutore et al. (2009) used ANN to predict Palmer Hydrological Drought Index (PHDI) with 4 months lead-time in Italy. In a study performed by Farokhnia et al. (2010) Sea Level Pressure (SLP) and effective Sea Surface Temperature (SST) grids derived by data mining methods were used as predictors in ANFIS models to predict drought in Tehran plain, Iran. Ozger et al. (2012) with conjunction of wavelet transform and fuzzy logic modeled the values of Palmer Modified Drought Index (PMDI). Belayneh et al. (2014) compared the performance of five models including ARIMA, ANN, Support Vector Regression (SVR), WANN and WA-SVR to predict SPI in Ethiopia. The above-mentioned studies indicate the superiority of the soft computing methods compared to the traditional methods.

In the present study, time series of SPI at multiple time scales and hydro-meteorological variables including monthly precipitation, wind velocity, relative humidity, and sunshine hours for a period of 18 years from 1992 to 2009 were used as input data for ANN method, we predicted short and long-term droughts in Tabriz city, Iran. For this purpose, different models of the ANN were analyzed and the best model was selected according to three well-known models performances namely RMSE, MAE, and CC. The rest of this paper is organized as follows. Section 2 describes study area and methods used. Section 3 presents the results. Section 4 provides the conclusions and future research recommendations.

2. Methodology

2.1. Case Study

In this study, monthly hydro-meteorological data of Tabriz synoptic station (38.05 °E and 46.17 °N) including precipitation (P), relative humidity (H), wind velocity (V) and sunshine hours (S) from years 1992 to 2009 are utilized to predict drought. The data mentioned above were obtained from the East-Azerbaijan Meteorological Organization. Tabriz city, the capital of East Azerbaijan province, Iran (Fig. 1) with the population of approximately 1.5 million is one of major industrial cities in Iran. This city is located in a semi-arid area where the mean annual precipitation and temperature amounts are 290 mm and 12.5 °C, respectively (Zarghami et al. 2011). The time series of hydro-meteorological data are presented in Fig. 2.
2.2 Standardized Precipitation Index (SPI)

During last decades, several indices have been developed to describe different aspects of droughts. Indices facilitate the evaluation of various characteristics of drought (Wilhite et al. 2000). Standardized precipitation index introduced by Mckee et al. (1993), has a simple structure and does not depend on location or any other meteorological data except for precipitation. It can be calculated for short and long-term at different time scales (e.g., 3, 6, 12, 24 and 48 months). SPI provides unique opportunity to assess different drought types (i.e., meteorological, hydrological, agricultural) and has a standard nature to compare drought conditions in different regions and climates (Farahmand and Aghakouchak 2015; Damberg and Aghakouchak 2013; Raziei et al. 2009; Abdi et al. 2017e). Table 1 provides SPI based drought classification and probabilities introduced by Lloyd-Hughes and Saunders (2002).

2.2.1 SPI time series calculation based on precipitation data

Following Mishra and Desai (2006), Gamma distribution is used to fit to the frequency distribution of precipitation summed over individual month (for various time scales). The gamma probability density function is defined as:

\[ g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \quad \text{for } x > 0 \]  

where \( \alpha \) and \( \beta > 0 \) are shape and scale parameters, respectively, and \( x > 0 \) is the precipitation amount. The following improper integral defines the gamma function:
In order to fit the gamma distribution to the precipitation data series, it is necessary to calculate both parameters. Thom (1958) approximation equations (eq. (3) to (6)) for parameter estimation are employed following Edwards and Mckee (1997).

Fig. 2 Time series of precipitation (upper left), wind velocity (upper right), relative humidity (lower left) and sunshine hours (lower right) data of Tabriz synoptic station (1992-2010)

Table 1 Drought classification by SPI value and corresponding event probabilities (Lloyd-Hughes and Saunders, 2002)

| SPI value  | Category        | Probability (%) |
|------------|-----------------|-----------------|
| 2.00 or more | Extremely wet   | 2.3             |
| 1.50 to 1.99 | Severely wet    | 4.4             |
| 1.00 to 1.49 | Moderately wet  | 9.2             |
| 0 to 0.99   | Mildly wet      | 34.1            |
| 0 to −0.99  | Mild drought    | 34.1            |
| −1.00 to −1.49 | Moderate drought | 9.2           |
| −1.50 to −1.99 | Severe drought  | 4.4             |
| −2 or less  | Extreme drought | 2.3             |
\[ \hat{\alpha} = \frac{1}{4A} \left( 1 + \sqrt{1 + \frac{4A}{3}} \right) \]  
\[ \hat{\beta} = \frac{x}{\hat{\alpha}} \]  
\[ A = \ln(\bar{x}) - \frac{\ln(x)}{n} \]

where \( \bar{x} \) is the mean of precipitation distribution and \( n \) is the number of precipitation records. Gamma cumulative probability \( G(x) \) of a desired precipitation value, now can be calculated as following equation (Mishra and Desai 2006; Lloyd-Hughes and Saunders 2002).

\[ G(x) = \frac{1}{\beta^\alpha x^\alpha} e^{-\beta x} \]

Since the observed precipitation time series may contain zeros, according to Mishra and Desai (2006) the cumulative probability, \( H(x) \), can be expressed by:

\[ H(x) = q + (1 - q)G(x) \]

\[ q = \frac{m}{n} \]

In the above equation, \( m \) and \( n \) are the number of zero precipitation and sample size, respectively. The cumulative probability is then transformed to standard normal variable (\( Z \)) with mean zero and variance one (Lloyd-Hughes and Saunders 2002). For this purpose, graphical and analytical methods (Lloyd-Hughes and Saunders 2002) have been suggested. In this study the analytical approximation of Abramowitz and Stegun (1965), which is routinely used to derive \( Z \) values, has been employed. Related equations can be found in Mishra and Desai (2006) and Lloyd-Hughes and Saunders (2002).

2.3 Artificial Neural Networks (ANN)

Artificial neural networks helps to understand the brain, human cognition, and perception and have been proven to be successful for solving different problems in pattern classification, decision making, and predicting (Fine 1999). Among various ANN models and training algorithms, multi-layer perceptron neural network model (MLP) trained with feed-forward backpropagation algorithm have been extensively used for simulating and predicting purposes in hydrology and water resources (ASCE 2000a, b; Maier and Dandy 2000). MLPs consist of an input layer (data are presented to the network via input layer), hidden layer(s) (where the actual processing is done via a system of weighted connections) and an output layer (where the answer is produced). Individual neurons in a layer are connected with different weights to every neuron in the following layer (Belayneh et al. 2016). Weighted inputs are mapped to the output of individual neurons by a linear or nonlinear activation function (Fig. 2).

According to Kim and Valdes (2003) the output value of the above network is given by:
\[
\hat{y}_k = f_o \left[ \sum_{j=1}^{m} W_{kj} \cdot f_h \left( \sum_{i=1}^{n} W_{ji} \cdot x_i + W_{jo} \right) + W_{ko} \right]
\]

where \(n\) and \(m\) are the number of samples and neurons in hidden layer, respectively. In addition, \(x_i\) is the \(i\)-th input data, \(w_{ji}\) is the weight connecting the \(i\)-th neuron in the input layer and the \(j\)-th neuron in the hidden layer, \(w_{jo}\) is bias for the \(j\)-th neuron in the hidden layer, \(f_h\) is the activation function used in the hidden layer, \(f_o\) is activation function for the output layer. \(w_{kj}\) is the weight connecting the \(j\)-th neuron in the hidden layer and \(k\)-th neuron in the output layer, \(w_{ko}\) is bias for the \(k\)-th neuron in the output layer, and \(f_o\) is activation function for the output layer. \(X_1, X_i, X_n\) represents input layer, \(H_1, H_j, H_m\) represents hidden layer, \(Y_1, Y_k, Y_\hat{k}\) represents output layer.

As shown in Fig. 3, the error value is calculated based on the output and real values and then back propagates to the network to adjust connection weights using training algorithms. The objective of using training algorithms is to optimize the parameters of output function (weights in Eq. 9) so that the \(E(x,w)\) value i.e. network’s global errors, becomes minimal.

\[
E(x,w) = \sum_{p=1}^{P} E_p
\]

\[
E(p) = \frac{1}{2} \sum_{k=1}^{K} (y_k - \hat{y}_k)^2
\]

where \(P\) is the total number of training patterns, \(K\) is the total number of output neurons (in this study equals 1), \(y_k\) is desired output at \(k\)-th neuron and \(\hat{y}_k\) is actual output at the \(k\)-th neuron. For this purpose, second order Levenberg-Marquardt (LM) back propagation algorithm is used for neural networks training. By combination of gradient descent method (also known as back propagation method) and the Gauss-Newton method, the LM algorithm solves the problems existing in both methods for neural networks training. The stability, fast convergence and less easily falling into the local minima trap has made
the LM algorithm one of the most efficient training algorithms (Hagan and Menhaj 1994; Sun et al 2016).

In this research, feed-forward ANN models comprised of one input layer, one hidden layer and one output layer are used to predict SPI values. All models are trained using LM backpropagation algorithm. The activation functions for both hidden and output layers are tangent sigmoid (tansig) function. The numbers of hidden layer’s neurons are selected using a trial-and-error approach. ANN models are developed using MATLAB (R2014a) ANN toolbox. For all models, first 75% of input data time series are used for training and the next 25% for validation. To this end, all input data are normalized using following equations:

\[
Y_i = \begin{cases} 
\frac{X_{oi}}{X_{o\text{ max}}} , & X_{oi} \geq 0 \\
\frac{X_{oi}}{X_{o\text{ min}}} , & X_{oi} < 0 
\end{cases}
\]

(12)

Where \(X_{oi}\) is the observed value, \(X_{o\text{ min}}\) and \(X_{o\text{ max}}\) are respectively the minimum and maximum data in input time series (Zarghami et al., 2011).

2.4 Model performance measures

In this study, to evaluate the performances of all ANN models, following goodness of fit measures namely Correlation Coefficient (CC), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used (Wang et al. 2009; Hassanzadeh et al. 2011; Abdi et al. 2017d; Jozaghi et al. 2019).

\[
CC = \frac{\sum_{i=1}^{n} [(X_{ai} - \bar{X}_a)(X_{ci} - \bar{X}_c)]}{\sqrt{\sum_{i=1}^{n} (X_{ai} - \bar{X}_a)^2 \sum_{i=1}^{n} (X_{ci} - \bar{X}_c)^2}}
\]

(13)

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (X_{ai} - X_{ci})^2}
\]

(14)

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |X_{oi} - X_{ci}|
\]

(15)

Where \(X_{oi}\) and \(X_{ci}\) are observed and predicted SPI values, \(n\) is the number of samples, \(\bar{X}_0\) and \(\bar{X}_c\) are the mean values taken over \(n\).

3. Results and discussion

In this research various ANN models with different combination of SPI and hydro-meteorological variables and different architectures (different number of neurons in
hidden layer) are considered for predicting short and long-term drought. For this purpose, at first, the values of SPI at different time scales (i.e., 3, 6, 12, 24 and 48 months) are calculated based on observed precipitation data of Tabriz synoptic station. Calculated SPI values are shown in Fig. 3. In addition, the probability of drought occurrences related to drought category are computed by using the SPI values at different time scales (Table 2).

In this study, by using more than two preceding months of hydro-meteorological parameters, the models lead to more complexity due to increasing the input neurons and cause overfitting in training phase. So all models are based on two preceding month values of predictors. To highlight the study results, among all models, models with better performances (qualified models) are selected to be compared with each other. The aim of this process was two fold: first, to investigate the significance of individual predictors in SPI predicting. Second, to examine the models performance to predict the SPI with different time scales.

Fig. 4 Model performance measures for SPI prediction at different time scales
### Table 2 Probability of drought occurrences related to drought category

| Drought category | Probability of drought occurrences (%) |
|------------------|----------------------------------------|
|                  | SPI3 | SPI6 | SPI12 | SPI24 | SPI48 |
| Mild             | 43.5 | 39.8 | 48.6  | 48.1  | 39.4  |
| Moderate         | 9.7  | 15.3 | 15.7  | 29.2  | 27.3  |
| Severe           | 2.8  | 4.6  | 3.7   | 5.6   | 17.6  |
| Extreme          | 2.3  | 1.4  | 2.3   | 0.9   | 0.0   |

3.1 Model selection results

Among various tested models with only one type of predictors (i.e. SPI, V, H, P, S), model 1 comprised of SPI values of two preceding months showed the best performance in predicting SPI in different time scales both in training and validation phases. This test illustrates the significance of SPI itself in precise predicting. In addition, different models with different combination of two types of predictors were examined. An analogy between all model performance criteria indicated that the presence of SPI index in models significantly improves the forecast results. Models numbered 2 to 5 with better performances in this category are illustrated in Table 3. Finally model 6 with combination of all 5 predictors is presented to be compared with other models. Qualified models are illustrated in Table 3 where P is monthly average precipitation amount (mm), H is relative humidity (%), V is the monthly average wind velocity (m/sec), S is the monthly average sunshine hours (hours).

The values of the model performance measures for SPI prediction at different time scales are presented in Fig. 4. Among six presented models in Table 3, model 6 provided the most accurate predictions of all time scales in terms of model performance measures. Models 2, 4, 3, 5, respectively showed better performances and model 1 which was based on the drought index alone had the lowest performance of all. Model ranking results based on their performances emphasize the significance of using hydro-meteorological variables in SPI prediction. The forecast results indicate that, models 2 and 4 which employ precipitation and relative humidity in addition to SPI itself, performed better than model 3 and 5 which employ average wind velocity and sunshine hours. This analogy clarifies the importance of precipitation and humidity in SPI predicting than two other predictors. A holistic review also indicates that the precipitation and sunshine hours, respectively have the most and least impact on forecast results improvement. In terms of performance measures, as shown in Fig. 4 all predicting models performed better in SPI predicting with larger time scales. Results illustrate that the increase in time scales of predicted SPI will increase the correlation coefficient (CC) values of all models and decrease RMSE and MAE values in both training and validating. According to Fig. 4, a significant convergence in individual performance measures values of all models are detected in larger time scales. In other words, by increasing the time scale of SPI index,
the monthly fluctuations of the time series are decreased. So, the performance criteria of the considered models are increased for larger SPI scale.

Fig. 5 displays the observed versus predicted SPI at different time scales for both training and validation phases in best model (model 6). As it can be seen from this figure, changes of the SPI values over the times have an important effect on the accuracy of the training data. So, the efficiency of the model 6 is improved with increasing the time scales of SPI from 3 to 48 months. In addition, the frequencies of the predicted drought based on the best model are presented in Table 4. Results of this table indicate that the model 6 provides high accuracy in identification of drought probabilities.

**Table 3** Qualified ANN models with the best architecture considered in this study

| Model No. | ANN Model                     | Architecture |
|-----------|-------------------------------|--------------|
| 1         | $SPI_i = f \left( SPI_{i-1}, SPI_{i-2} \right)$ | 2-5-1        |
| 2         | $SPI_i = f \left( SPI_{i-1}, SPI_{i-2}, P_{i-1}, P_{i-2} \right)$ | 4-4-1        |
| 3         | $SPI_i = f \left( SPI_{i-1}, SPI_{i-2}, V_{i-1}, V_{i-2} \right)$ | 4-4-1        |
| 4         | $SPI_i = f \left( SPI_{i-1}, SPI_{i-2}, H_{i-1}, H_{i-2} \right)$ | 4-4-1        |
| 5         | $SPI_i = f \left( SPI_{i-1}, SPI_{i-2}, S_{i-1}, S_{i-2} \right)$ | 4-4-1        |
| 6         | $SPI_i = f \left( SPI_{i-1}, SPI_{i-2}, P_{i-1}, P_{i-2}, V_{i-1}, V_{i-2}, H_{i-1}, H_{i-2}, S_{i-1}, S_{i-2} \right)$ | 10-3-1       |

**Table 4** Predicted drought frequency based on Model 6

| Drought category | Probability of drought occurrences (%) |
|------------------|----------------------------------------|
|                  | SPI3  | SPI6  | SPI12 | SPI24 | SPI48 |
| Mild             | 39.4  | 36.0  | 43.8  | 45.9  | 38.6  |
| Moderate         | 12.6  | 17.8  | 20.1  | 30.8  | 26.2  |
| Severe           | 5.1   | 5.1   | 4.7   | 7.9   | 18.7  |
| Extreme          | 3.2   | 1.4   | 3.1   | 0.5   | 0.0   |
Fig. 5 Observed versus predicted SPI at different time scales in training and validating phases of model 6
4. Conclusion

In this study, artificial neural networks were used to predict short and long-term drought in Tabriz, Iran. To this end, in first step, SPI at different time scales were calculated based on the precipitation time series. In addition to SPI, various hydro-meteorological variables including precipitation, wind velocity, sunshine hours and humidity for a period of 18 years from 1992 to 2010 were utilized in predicting approach. The SPI time series were predicted using two preceding month values of above-mentioned variables. In this study, various models were developed based on different combination of inputs and different architectures. In order to evaluate the performance of each model, three measures namely CC, RMSE and MAE were utilized. Forecast results of all models illustrated the significance of SPI itself in accurate prediction and the role of hydro-meteorological variables in drought prediction improvement. Model performances results indicated that precipitation data and humidity were superior to other used variables in predicting and significantly improved the performance of drought prediction. Prediction Statistics of qualified models revealed that the model using all mentioned input variables simultaneously, leads to the lowest RMSE and MAE and highest CC among all models. Accurate drought prediction can facilitate the mitigation of its devastating impacts by helping governments to better manage water resources systems. Although artificial neural networks have proved to be successful in drought prediction, having access to long term, up to date and reliable meteorological data is inevitable for more accurate predictions.

Recommendations for future research:

- Comparing developed ANN models with time series modeling approaches
- Considering spatiotemporal variables may lead to more accurate results
- Comparing the results of implementing adaptive network-based fuzzy inference system (ANFIS) with ANN

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