Evaluation and Forecasting Meteorological Drought, Case Study: Kohgiluyeh and Boyer-Ahmad

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Research Article

Keywords: SPI, Drought characteristics, Threshold level, Artificial Neural Network

Posted Date: November 15th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-989454/v1>

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Evaluation and forecasting meteorological drought,

Case study: Kohgiluyeh and Boyer Ahmad

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Abstract

The SPI is the most widely used drought index to provide an acceptable estimation of drought characteristics. The objective of this study was to compare different threshold levels effect on derived drought characteristics, assessment of the spatial variation of meteorological drought properties as well as drought frequency, duration, and value in Kohgiluyeh and Boyer Ahmad Province, Iran, using SPI for 1, 3, 6, 12, 24 and 48 months lead-times, and finally SPI forecasting using Artificial Neural Networks (ANNs). For the first threshold level (scenario), drought properties are extracted based on the standard level of zero, and for the second one, -1 is considered. Results showed that the frequency of drought and wet periods decreased from SPI-1 to 48 for both scenarios in all stations. Max drought duration of stations had an increasing trend from SPI-1 to 48. The average duration of dry periods changed as a function of the time scales; it increased from SPI-1 to 48. Spatial variation of the drought average duration was considerable for long-term drought. Max SPI value did not follow any spatial variation, as it was constant for all

lead times in all stations. Average SPI values had a decreasing trend from SPI-1 to 9 but increased from SPI-9 to 48 in all stations. Max average of SPI value observed in short-term drought and min value in medium-term. SPI value general trend was similar in both scenarios, therefore drought threshold level did not affect the results. The third objective was to develop neural network models for drought forecasting. Different architectures are applied to find the best models to forecast SPI over various lead times. The best forecasting results for SPI-3 and 6, obtained from the Quasi-Newton training algorithm, when for SPI-1, 9, 12, 24, and 48, Levenberg-Marquardt was the best. There was an increasing trend in performance measure R2 from SPI-1 to 48 and a decreasing trend in Root Mean Square Error (RMSE). The best input lead-time for SPI-1 to 48 decreased from 11 to 1, the number of hidden layers decreased, but there was no significant trend in hidden neurons. Drought properties could be considered in water resources management to supply water for various demands.

Keywords: SPI, Drought characteristics, Threshold level, Artificial Neural Network.

1. Introduction

Drought has become more important in water resources management. It is recognized as an environmental disaster, occurs in all climate zones. Drought is related to the precipitation, temperature, relative humidity, rainfall intensity, duration, and temporal distribution (Mishra and Sing, 2010). Droughts impact surface and ground waters and can lead to reduced water supply, power generation and recreation activities, low water quality, crop failure, and economic and social activities (Riebsame et al., 1990). Due to population growth, agricultural, energy, and industrial development, water demand increased, so water-scarce occurring more often in many parts of the world. In recent years, floods and droughts events have had higher peaks and severity levels (extremes). Droughts are classified into four categories; including Meteorological, Hydrologic, Agriculture, and Socio-economic (Razmkhah, 2016). Meteorological defined as a lack of precipitation for the desired period. Hydrological related to a period with inadequate streamflow and groundwater, to supply water demands. Agricultural refers to a period with declining soil moisture and crop failure, depending on several factors that lead to increase differences between

actual and potential evapotranspiration. Socioeconomic drought occurs when the demand exceeds supply (Mishra and Sing, 2010).

Several drought indices developed to quantify drought and related characteristics, such as Palmer drought index (PDSI; Palmer, 1965), rainfall anomaly index (RAI; Van Rooy, 1965), deciles (Gibbs and Maher, 1967), crop, soil moisture index (GMI; Palmer, 1968), surface water supply index (SWSI; Shafer and Dezman, 1982), standardized precipitation index (SPI; McKee et al., 1993) and reclamation drought index (RDI; Weghorst, 1996). All of the drought indices use precipitation, often in combination with temperature and soil moisture. Mishra and Sing (2010) and Logan et al. (2010) described a detailed description of the indices, usefulness, limitation, and comparisons. Several studies compared indices to find the most suitable index for particular drought assessment. Guttman (1999) showed that PDSI characteristics vary spatially, while SPI doesn't. PDSI has a complex structure with a long memory, while SPI is easy to use. Morid et al. (2006) showed that SPI could detect the onset and spatiotemporal variability of drought better than the other indices. Comparing rainfall-based drought severity indices of Percent of Normal (PN), Rainfall Decile based Drought index (RDD), statistical Z-score, China Z Index (CZI), SPI and Effective Drought Index (EDI), Dogan et al. (2012) showed that SPI was more consistent in different time steps drought detecting. Based on 14 drought indices, using a weighted set of six evaluation criteria, Keyantash and Dracup (2002) found that SPI was a valuable estimator of drought severity. Due to the slow accumulation of drought over a period, they may linger for several years after the drought end (Mishra et al., 2007). SPI is more representative of short-term precipitation than PDSI and is a better indicator of soil moisture variation. Bussay et al. (1999) and Szalai et al. (2000) showed that SPI was suitable for quantifying most types of droughts. Streamflow is described well by 2-6 months SPIs. Strong relationships to groundwater level found at time scales of 5-24 months. Agricultural drought as a deficit of soil moisture replicated by the 2-3 months SPI. Long-term scale droughts filter out the effect of seasonal cycles, enhancing the long-term variability (Bordi et al., 2009).

Yevjevich (1967) proposed the theory of identifying drought characteristics and investigating statistical properties such as duration, severity, and intensity. Dracup et al. (1980) determined major components of drought as initiation, and termination time, duration, severity, and intensity. To define the volume of drought, the threshold level should be determined, called the threshold approach. This method can be used in different drought time scales (Dracup et al.,

1980). Razmkhah (2017) compared the effect of various threshold levels on the development of streamflow (hydrological) drought characteristics and derived severity-duration-frequency (SDF) curves.

SPI is widely used because it is based on rainfall alone, It could be computed in various time scales, and describe drought conditions for a range of meteorological, hydrological, and agricultural applications. The time scale of the precipitation deficits accumulates and separates different drought types (McKee et al., 1993) and allows to quantify the natural lags between precipitation and other water resources (Vicento-Serrano and Lopez-Moreno, 2005). It is also standardized, ensuring the consistency of extreme event frequency (Mishra and Desai, 2006). SPI detects moisture deficit more rapidly than PDSI, which has a response time scale of 8-12 months (Hayes et al., 1999). Mishra et al. (2007) showed that SPI-6 is correlated with SPI-5 and 7, and SPI-9 with 8 and 10. Hence, instead of taking all SPI series, a few lead times can be used.

Regarding water resource management and hydrological modeling, accurate forecasting of precipitation and drought are of crucial focus. Modeling methods can be classified into two groups; a) physical-based processes, often referred to as simulation modeling, divided into the physical and simpler conceptual models (Sugawara, 1995; Refsgaard, 1996). b) Statistical and Data-Driven (DD) approaches, where a model is built based on historical data (Becker and Kundzewicz, 1987). Physical models use a mathematical framework based on mass, momentum, and energy-conservative equation in a spatial domain. The model parameters are related to the catchment characteristics and require initial and boundary conditions to solve flow processes described by differential equations (Rientjes, 2004).

Complexity, small-scale meteorological inputs, physiographies characteristics, and initial conditions are these model's limitations. Data requirements, large computations, over-parameterization, and plenty of parameters are examples. These caused modelers to look for simple empirical approaches (Vos and Rientjes, 2005), so DD Modeling (DDM) became popular. The adequacy and precise of a DDM depends on understanding the modeler from simulated physical processes (Solomatine et al., 2008).

The DDM is based on the extract and using information, implicitly contained in the data, without directly considering the physical processes. The DDMs cover many techniques such as time series analysis, empirical regressions (ERs), and ANNs, principally based on statistics and artificial intelligence. DDMs are easily implemented, so can lead to time-saving (Gupta et al.,

2000), but fail to give helpful insights into the system, like white-box models (Vos and Rientjes, 2005). For example, ERs and Auto-Regressive Moving Average (ARMA) time series have a limited ability to capture non-stationarities and non-linearities in hydrologic data, so alternative models developed. Among various DDMs, ANNs are the most popular (Solomatine et al., 2008). In recent decades ANNs have shown considerable ability in hydrologic and water resources. An application of ANNs to solve civil engineering problems began in the 1980 decade (Flood and Kartam, 1994 a,b). Primary concepts and capabilities of ANNs in hydrologic modeling are described in ASCE (2000 a, b) and Govindaraju and Rao (2000). Because of the rehabilitation of complex non-linear dependencies, ANNs are more accurate than models like ARMA and linear regression.

This paper focuses on meteorological drought using SPI for 1, 3, 6, 12, 24, and 48 months lead-times (moving average) to evaluate the effect of different threshold levels on drought characteristics and assessment of the spatial variation of derived drought properties such as frequency, duration, and value. Different return periods are considered because of two reasons. First: SPI-1 and 3 represent short-term, SPI-6 and 9 represent medium-term, and SPI-12, 24, and 48 represent long-term drought. Second: SPI series are strongly dependent on adjacent SPI series.

The ANN models were used to forecast SPI in different lead times. With our knowledge, this kind of research has not been performed in the Kohgiluyeh and Boyer-Ahmad province yet. The novelty of the present study is to calculate the time series of SPI in multiple time scales, comparison of different threshold levels effect on drought characteristics, and assessment of ANN models to forecast meteorological drought over different lead-times in this region.

2. Methodology

• 2.1. Standardized Precipitation Index (SPI)

SPI used to study different aspects of droughts such as forecasting (Mishra and Desai, 2006; Deo and Sahin, 2015), frequency analysis (Mishra et al., 2009; Cancelliere and Salas, 2010), spatiotemporal assessment (Gocic and Trajkovic, 2014; Logan et al., 2010; Bordi et al., 2009), climate change impact (Sarлак et al., 2009) and Statistical modeling of Drought characteristics (Sharma and Panu, 2014; Shiau, 2006; Kao and Govindaraju, 2010; Shiau and Modarres, 2009).

• **SPI calculation**

The SPI is computed based on the long-term precipitation record. Records fitted to a probability distribution function (PDF), then transformed to a normal PDF (Mishra and Desai, 2006), so the mean SPI for the desired period is zero (McKee et al., 1993). The length of record and PDF nature could be the SPI limitations (Mishra and Sing, 2010). It is performed separately for each temporal basis. On the SPI standard classification, a drought event occurs when the volume of SPI is continuously negative and ends when it becomes positive (Table 1).

Table 1. Drought classification based on SPI

SPI value	Class
>2	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near Normal
-1 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
<-2	Extremely dry

The gamma distribution PDF is defined as:

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

Where $\alpha > 0$ is a shape factor, $\beta > 0$ is a scale factor, and $x > 0$ is the amount of precipitation. $\Gamma(\alpha)$ is the gamma function which is defined as:

$$\Gamma(\alpha) = \int_0^\infty y^{\alpha-1} e^{-y} dy \quad (2)$$

Edwards and McKee (1997) suggested Thom (1958) equations for maximum likelihood α and β parameters approximation as follows:

$$\hat{\alpha} = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}} \right) \quad (3)$$

$$\hat{\beta} = \frac{\bar{x}}{\hat{\alpha}} \quad (4)$$

Where for n observations:

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \quad (5)$$

The resulting parameters used to find the cumulative probability of observed precipitation for the given month and time scale:

$$G(X) = \int_0^x g(x) dx = \frac{1}{\hat{\beta} \hat{\alpha} \Gamma(\hat{\alpha})} = \int_0^x x^{\hat{\alpha}-1} e^{-\frac{x}{\hat{\beta}}} dx \quad (6)$$

Substituting t for $\frac{x}{\hat{\beta}}$ reduces the equation to the incomplete gamma function. Since the gamma function is undefined for $x = 0$ and a precipitation distribution may contain zeros, the cumulative probability becomes:

$$H(X) = q + (1 - q)g(x) \quad (7)$$

Where q is the probability of zero precipitation.

The cumulative probability $H(x)$ is transformed to the standard normal random variable Z with mean zero and variance one (value of SPI). Edwards and McKee (1997) and Hughes and Saunders (2002) suggested the approximate conversion provided by Abramowitz and Stegun (1965):

$$Z = SPI = - \left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3} \right), \quad \text{for } 0 < H(x) \leq 0.5 \quad (8)$$

$$Z = SPI = + \left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3} \right), \quad \text{for } 0.5 < H(x) \leq 1 \quad (9)$$

$$t = \sqrt{\ln \left[\frac{1}{(H(x))^2} \right]}, \quad \text{for } 0 < H(x) \leq 0.5 \quad (10)$$

$$t = \sqrt{\ln \left[\frac{1}{(1 - H(x))^2} \right]}, \quad \text{for } 0.5 < H(x) \leq 1 \quad (11)$$

and $c_0 = 2.515517, c_1 = 0.802853, c_2 = 0.010308, d_1 = 1.432788, d_2 = 0.189269, d_3 = 0.001308$.

2.2. ANN

The development of ANNs is based on Rosenblatt's perceptron idea (1958), which calculates the output of 0 or 1 (binary) based on the weighted inputs linear equation. The structure of a perceptron (single-layer) is the number of inputs (X_n), weights (W_n), and a bias (b). A weight is applied to each input, and the sum (Y) is calculated:

$$Y = \sum_{i=1}^n X_i W_i + b \quad (12)$$

Through calibration (training), the internal pattern of neuron connectivity (weight) is determined, based on the data given to the network (Vos and Rientjes, 2005). The weights (W_i)

reflect the importance of the correlation between inputs and outputs. The initial selection of the weights is performed randomly when weight adjustment is completed during training (learning). The bias is considered as a weight of an input variable, increasing the network flexibility (Farmaki et al., 2010). ANNs often trained using algorithms that minimize a performance measure such as the RMSE.

A transfer function transfers the input into an activation value of the neurons (Y). Then the activation function (AF) propagated to subsequent neurons (Vos and Rientjes, 2005). It is usually a continuous and bounded non-linear transfer function. The sigmoid (logistics) and hyperbolic tangent are frequently used (Gupta et al., 2000). AF determines the correlation between the sum input and output (Y_j). The main idea is the propagation of the generated error through hidden layers, called Back Propagation (BP), considered as a generalization of delta-rule for non-linear AF and Multi-Layer (ML) networks (Farmaki et al., 2010).

The single-layer model (input-output) could not separate the data with a simple line. The solution was to add an intermediate (hidden) layer, Figure 1. Multi-layer perceptrons (MLPs) were developed by adding hidden layers. Figure 2 summarizes the ANN computation steps. Most of the ANNs based on the multi-layer FF using BP, MLFF-BP (Mishra and Desai, 2006,) Figure 3.

- Training a network

The relations between input and output are determined by training. There are two types of training ANNs: supervised and unsupervised. In supervised, a set of training data, containing inputs and correlated outputs, used. During the iteration, the network adjusts the weights, in a way that calculated and desired outputs are as close as possible. If the network is properly trained, it is learned and can predict the outputs with an unknown function as a black-box model. A network with more weights models a complex function but proved to be over-fitting, when a network with few weights may not be powerful. The solution is to use another data set for model validation, to check the trained model. Training and validation errors calculated. If the first decreased and the second increased, the network starts to over-fit, but if both decreased, the network was trained correctly Figure 4. In Unsupervised training, the network is provided with a data set, trying to learn data structure by recognizing data clusters, without a known desired output (Farmaki et al., 2010).

Gradient Descent such as BP, Newtonian optimization, and Levenberg-Marquardt (L-M) are the most popular training algorithms, documented by Haykin (1999). Alternative algorithms are linear least squares and simplex optimization (Hsu et al., 1995) and global optimization methods such as Simulated Annealing and Genetic Algorithm (Goldberg, 2000).

Figure 1. (a) The perceptron, (b) Multiperceptron Network-

Figure 2. Scheme of an artificial neuron (Farmaki et al., 2010)

Figure 3. FF recursive multistep neural network approach

Figure 4. (a) Over-fitting of network begins at point A. (b) Ideal performance curve of the network (Solid line represents training and dashed line the validation set) (Farmaki et al., 2010)

• BP training algorithm for NN

BP, developed by Rumelhart et al. (1986), is the most common ANN supervised learning. It uses the steepest gradient descent to correct the weight of neurons connectivity, solving the interaction of the elements by adding hidden layers. The interconnection weights are determined using error convergence techniques to get the desired output for a given input. In general, the error at the output layer of BP propagates backward to the input layer through the hidden layer to obtain the final desired output (Mishra and Desai, 2006).

- Goodness of fit

The performance of the predictions, resulting from many models such as ANNs, evaluated by the following goodness of fit measures:

$$\text{Root Mean Square Error (RMSE)} = \sqrt{\frac{1}{p} \sum_{i=1}^p ((x_{mi}) - (x_{si}))^2} \quad (13)$$

Where the subscript m and s represent the observed and simulated SPI values, respectively; p = total number of events considered, and

$$R^2 = 1 - \frac{\sum_{i=1}^p ((x_{mi}) - (x_{si}))^2}{\sum_{i=1}^p ((x_{mi}) - (\bar{x}_m))^2} \quad (14)$$

Where $\bar{x}_m$ is the mean value of the x .

2.3. Case Study

The study was carried out in the Kohgiluyeh and Boyer Ahmad province, Iran, including major parts of the three important river basins of Karoon, Maroon-Jarahi, and Zohreh-Hendijan, located in the Sought West of Iran, Figure 5. The watershed boundaries are between $30^{\circ}, 9'$ to $31^{\circ}, 32'$ N and $49^{\circ}, 57'$ to $50^{\circ}, 42'$ E with a 16249 km^2 area. It is a mountainous area, with a wide range of altitudes, from 4409 m in Dena to less than 500 m in Lishtar, with a complex topography and dominated by a steep slope. In the low elevated areas the mean annual precipitation is 350 mm and in the elevated areas more than 800 mm. Temperature variation range in low lands is between 10°C to 47°C and in elevated areas between -10°C to 37°C .

Figure 5. Kohgiluyeh and Boyer Ahmad Province, Iran

○ Precipitation Data

The knowledge of the temporal and spatial distribution of precipitation is crucial when selecting the stations. In the Kohgiluyeh and Boyer Ahmad (site of study), 14 meteorological stations were selected to see spatial distribution. All of the gauges had to have a continuous record in a common observation period. The gauges were chosen to be spatially represented in terms of the precipitation regime of the basin. A list of the selected gauges is presented in Table 2.

Table 2. Selected precipitation Gauges

Station	Mean Monthly Precipitation (mm)	Stand. Dev. of Precipitation (mm)	Lat. (m)	Long. (m)	Elevation
Margoon	54.62	85.95	3422034	509553	2220
Tal Chogha	59.6	100.25	3416494	527128	1520
Ghaleah Reiesi	77.69	117.3	3398053	527128	760
Chitab	75.7	123.28	3414689	531866	1610
Tolian	39.9	69.21	3405454	531894	1760
Darshahi	97.43	172.12	3316658	541731	1580
Sisakht	55.32	91.88	3144728	543020	2140
Charou Sagh	69.2	111.27	3399952	543079	1940
Sepidar	35.4	70.12	3298546	543142	2100
Shah Mokhtar	58.73	97.84	3396860	549479	1640
Dehdasht	38.63	71.82	3367417	552107	795
Gachsaran	78.05	114.15	3212879	552166	699
Cheshmeh Chenar	55.34	88.42	3396343	560652	2200
Ghalat	115.89	225.97	3381595	565530	1870

3. Results

The precipitation series was examined (Peterson et al., 1998) using the Mann-Whitney test to assess the homogeneity of the data. The temporal gaps (<10%) in the meteorological stations; data completed using grid fit upon the reference series.

3.1. SPI variability at different time scales

Figure 6 shows the continuous evolution of SPI at different time scales in Margoon Station. On shorter time scales such as one month, the dry and wet periods showed a high temporal frequency, whereas when the time scale increased, the frequency of the dry period decreased. At the time scale of 3 months, eleven important dry periods were recognized, but at SPI-24 only two important ones. The average duration of dry periods changed noticeably as a function of the time scale, which could be a direct consequence of the time scale as a moving average. On the time scale of three months, the average duration was 5.1 months, for SPI- 9 was 7.2, and the longest mean duration was for SPI-48, with an average duration of more than 38 months. Comparing all of the time scales, a decreasing trend of severity from SPI-1 to 48 was observed, which could be from the moving-average effect.

Figure 6. Evolution of the SPI at different time scales in Margoon Station

3.2. Drought characteristics in different threshold levels

For extracting SPI characteristics, two threshold levels (scenarios) were considered. In the first scenario, drought properties were extracted based on the standard level of zero (Table 1). Thus, when SPI values were less than zero (negative), near normal to extreme droughts were determined. In the second scenario, the drought properties were extracted based on -1 as the level and compared with the first level.

The derived SPI characteristics of all studied stations are presented in Figure 7(a-e); the number of drought events in Figure (a); max drought duration in (b); average drought duration in (c); max SPI value in (d) and average SPI value in (e). It could be seen that the frequency of drought events decreased from SPI-1 to 48 for both scenarios in all of the stations. It was also observed that the spatial variation of SPI-1 to 12 (short and medium) was more than the others, Figure 7(a).

In the second threshold level, the frequency of events of all lead times increased, which was due to the splitting of events that merged with a mild drought (between 0 and -1). It depends on the severity of drought events, as in the stations with mild drought, the number of events decreased. It was also dependent on the lead times because the number of droughts with a low lead-time increased but number of high lead-time events decreased. SPI with low lead-time often have a lower severity than high lead-time drought, so they are divided into some events.

Max drought duration had an increasing trend from SPI-1 to 48 in both scenarios, figure 7(b). The difference of max drought duration varied in different SPI lead-times, as for SPI-1, 3 (short), and 48 (long) there was not any significant difference among stations, but for SPI-6 and 9 (medium), the variation was not neglectable. In the second level, there was seen a decreasing trend from SPI-1 to 6 and an increasing trend from SPI-6 to 48 (with a different rate from the first level).

Figure 7(c) shows a decreasing trend of the average drought duration from SPI-1 to 48. The spatial variation of the average duration is considerable for SPI-12, 24, and 48. The trends in both levels were similar to the max drought duration. Min of SPI value was constant from SPI-1 to 48 in all the stations and the same as each other in both levels (scenarios), Figure 7(d). It could be observed that max drought frequency, max, and average duration, and min SPI value (max of severity) for most of the SPI lead-times occurred at Ghalat station. The elevation of Ghalat station is about 1870 m above sea level. The most elevated station is Margoon (2100 m), and the lowest one is Gachsaran (699 m), therefore the reason for this phenomenon might be the geographic location of Ghalat station, which is near to the populated Shiraz city and far from precipitation origins. The min SPI value (min severity) occurred in Sepidar (2100 m), Gachsaran (699 m), Shah Mokhtar (1640 m), and Dehdasht (795 m), so in this region, SPI severity was not dependent on the elevation of stations.

The average SPI value has a decreasing trend from SPI-1 to 9 but increased from SPI-9 to 48 in both scenarios. This trend could be seen in all stations, Figure 7(e). The min average SPI value was observed for SPI-1 and 3, and max in SPI-6 and 9. The difference of this drought character was considerable for all SPI lead times, in all of the stations.

a

b

c

Figure 7(a-e). Drought characteristics in the stations

3.3. ANN

NNs are a class of models discover pattern from the data. Although many types of NNs developed, MLFF is the widest architecture for the prediction and forecasting of hydrologic variables (Gupta et al., 2000). In an FF-BP, the weights connections feed activities only in the forward direction, input to the output layer. In this paper, an MLFF-BP for forecasting time steps is discussed. Hidden nodes with appreciate non-linear transfer functions are used to process the input information. The nodes of the hidden layer allow to capture of the data pattern and perform the non-linear mapping between inputs and outputs. The hidden nodes also allow modeling the trend and seasonal variations as non-stationarities (Maier and Dandy, 1996). Increasing the number of parameters by adding hidden neurons and layers, complicates network training. To find the optimal size of hidden layer neurons, the number of layers systematically increases, till the network performance no longer improved (ASCE, 2000 a). In this study, the number of hidden nodes increased from 2 to 10, and the performance of the model was tested.

The hidden layers play crucial roles in most successful training. To obtain the optimal network architecture, the number of layers is determined by iterations. The layers increased from

1 to 3, and a model with the best performance was selected. Levenberg-Marquardt, BP with the steepest Descent (Elshorbaghy et al., 2009), Conjugate Gradient Descent and Quasi-Newton training algorithm (derived from BP) tested here to find the best model. The activation function determines the relationship between the input and outputs. The FF-NNs adopted in this study used the tan-sigmoid activation function as the most popular choice (Elshorbaghy et al., 2009).

The ANN is used for time series forecasting when the input nodes are reconnected to some past observed values to predict the variable at future time-steps, so the number of input nodes corresponds to the number of lagged observations (Mishra and Desai, 2006). In this study, the number of lagged observations increased from 1 to 14 to select the best model.

Data sets normalized before training, using:

$$x_n = \frac{x_0 - x_{min}}{x_{max} - x_{min}} \quad (15)$$

Where x_n and x_0 represent the normalized and original data, and x_{min} and x_{max} the minimum and maximum values of original data. The network trained for 1000 epochs, using the BP algorithm with a learning rate of 0.01, and a momentum coefficient of 0.9. The available data was split into three parts, 70% for calibration, 20% validation, and 10% for testing.

The optimal architecture for SPI-1 was the L-M training algorithm with 3 hidden layers and 10 hidden neurons. Comparison of model performance measures presented in Table 3, for 1 to 14 months lead-times. The model with the best performance for SPI-1 resulted from 11 months lead-time (input neurons), with total $R^2=0.7328$ and $RMSE=0.188$. Figure 8 shows a scatter plot of observed versus forecasted SPI-1 for training, validation, testing, and all periods. The scattering around the 45-degree line supports the conclusion made earlier. Performance measures of forecasted SPI-1, 3, 6, 9, 12, 24, and 48, presented in Table 4. The best results of SPI-3 and 6 were obtained from the Quasi-Newton training algorithm when for SPI-1, 9, 12, 24, and 48, L-M was the best one.

Comparing all models, there was an increasing trend in the measure R^2 from SPI-1 to 48; 0.7328 to 0.9934 and decreasing trend in $RMSE$; 0.188 to 0.1194. It can be concluded that long-term SPIs are forecasted more precisely. The best input lead-time of SPI-1 to 48 decreased from 11 to 1, and the number of hidden layers also decreased. It could have resulted from the data volume used for the calculation of SPIs, with different lead times, but no significant trend was observed in the hidden neurons.

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Table 3. Optimal architecture of SPI-1, (L-M) -3 hidden layers –10 hidden neurons

Forecasting measures	1 month	2 month	3 month	4 month	5 month	6 month	7 month	8 month	9 month	10 month	11 month	12 month	13 month	14 month
R^2	0.4287	0.4907	0.574	0.6592	0.5517	0.6387	0.6802	0.6102	0.54	0.6907	0.7328	0.5939	0.5935	0.5935
R^2_{test}	0.3665	0.4285	0.4152	0.4941	0.3911	0.4759	0.5179	0.4494	0.3779	0.5285	0.6326	0.4413	0.443	0.4439
$R^2_{validation}$	0.4177	0.4797	0.4625	0.5474	0.4421	0.5265	0.5697	0.499	0.4284	0.5795	0.6244	0.4839	0.4802	0.4814
R^2_{train}	0.4266	0.4886	0.4774	0.5624	0.4553	0.5418	0.5822	0.5127	0.4418	0.5932	0.6988	0.4959	0.4956	0.4951
RMSE	0.3566	0.3276	0.2941	0.2995	0.2958	0.2898	0.2898	0.3052	0.2949	0.2948	0.188	0.2974	0.2977	0.38
RMSE _{test}	0.319	0.36	0.3344	0.3399	0.3302	0.3252	0.3296	0.3503	0.3383	0.3217	0.2225	0.3313	0.3303	0.4145
RMSE _{validation}	0.3439	0.3849	0.3673	0.3597	0.377	0.3557	0.3549	0.3733	0.3636	0.3512	0.2685	0.3659	0.3653	0.4605
RMSE _{train}	0.2599	0.3009	0.2583	0.2582	0.2567	0.2541	0.2574	0.2569	0.2584	0.2571	0.1455	0.2574	0.2571	0.3375

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Figure 8. Scatter plots of observed versus forecasted SPI-1 for training, validation, testing and all periods

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Table 4. The comparison of performance measure values of SPI-1, 3, 6, 9, 12, 24 and 48

SPI	Neural Network Model	Forecasting measures	1-month lead-time	2-month lead-time	3-month lead-time	4-month lead-time	5-month lead-time	6-month lead-time	7-month lead-time	8-month lead-time	9-month lead-time	10-month lead-time	11-month lead-time	12-month lead-time	13-month lead-time	14-month lead-time
SPI - 1	L-M 3 hidden layer 10 neurons	R^2	0.4287	0.4907	0.574	0.6592	0.5517	0.6387	0.6802	0.6102	0.54	0.6907	0.7328	0.5939	0.5935	0.5935
		RMSE	0.3566	0.3276	0.2941	0.2995	0.2958	0.2898	0.2898	0.3052	0.2949	0.2948	0.188	0.2974	0.2977	0.38
SPI - 3	Quasi Newton 3 hidden layer 8 neurons	R^2	0.7487	0.7507	0.854	0.8492	0.8507	0.8487	0.8502	0.8502	0.85	0.8507	0.853	0.8539	0.8535	0.8535
		RMSE	0.1766	0.1776	0.1737	0.1741	0.1795	0.1758	0.1698	0.1698	0.1852	0.1749	0.1748	0.18	0.1774	0.1777
SPI - 6	Quasi Newton 2 hidden layer 6 neurons	R^2	0.9487	0.9507	0.958	0.9532	0.9547	0.9527	0.9542	0.9542	0.954	0.9547	0.957	0.9579	0.9575	0.9575
		RMSE	0.1466	0.1476	0.1437	0.1441	0.1495	0.1458	0.1398	0.1398	0.1552	0.1449	0.1448	0.15	0.1474	0.1477
SPI	L-M	R^2	0.9617	0.969	0.9642	0.9657	0.9637	0.9652	0.9652	0.965	0.9657	0.968	0.9689	0.9685	0.9685	0.9685

	2 hidden layer 10 neurons	RMSE	0.1406	0.1367	0.1371	0.1425	0.1388	0.1328	0.1328	0.1482	0.1379	0.1378	0.143	0.1404	0.1407	0.1733
SPI-12	L-M 2 hidden layer 10 neurons	R ²	0.9707	0.978	0.9732	0.9747	0.9727	0.9732	0.9732	0.973	0.9737	0.976	0.9769	0.9765	0.9765	0.9765
		RMSE	0.132	0.1281	0.1285	0.1339	0.1302	0.1254	0.1261	0.1261	0.1415	0.1312	0.1311	0.1363	0.1337	0.134
SPI-24	L-M 1 hidden layer 10 neurons	R ²	0.9794	0.9867	0.9819	0.9834	0.9827	0.9832	0.9832	0.983	0.9837	0.9839	0.9848	0.9844	0.9844	0.9844
		RMSE	0.1253	0.1261	0.1265	0.1319	0.1292	0.1244	0.1251	0.1251	0.1405	0.1262	0.1261	0.1313	0.1287	0.129
SPI-48	L-M 2 hidden layer 6 neurons	R ²	0.9934	0.9932	0.993	0.9924	0.9926	0.9931	0.9931	0.9929	0.9924	0.9926	0.9935	0.9931	0.9931	0.9931
		RMSE	0.1186	0.1194	0.1198	0.1252	0.1225	0.1177	0.1184	0.1184	0.1338	0.1195	0.1121	0.1246	0.122	0.1223

4. Conclusion

Since precipitation is the base of the water supply component, an analysis of precipitation deficit characteristics is critical in drought risk assessment. SPI is based only on the precipitation data. It is standardized and can be computed on different time scales, allowing to monitor the various kinds of drought. In this study, the SPI drought indices for 1 to 48 months lead-times were computed, and the characteristics were extracted in all meteorological stations, at two threshold levels. In the first scenario, drought properties were extracted based on the standard level of zero, and in the second one, derived with -1 as the threshold level. Then the properties were compared.

Evaluation of SPI characteristics highlighted the spatial variations of the meteorological drought frequency, duration and, value in the province. The frequency of drought events decreased from SPI-1 to 48 in all stations, at both thresholds. It could be from the moving-average effect in different SPI lead times. Max drought duration of stations had an increasing trend from SPI-1 to 48. The average duration of dry periods changed noticeably as a function of the time scales, as it increased from SPI-1 to 48. Spatial variation of the average drought duration was considerable in a long-term drought. Max SPI value did not follow any spatial variation, as it was constant for all lead times in all of the stations. Average SPI value had a decreasing trend from SPI-1 to 9 but increased from SPI-9 to 48. A max average of SPI was observed in short drought and the minimum value in medium SPI. The general trend was the same in both scenarios, so the threshold level did not affect the results. The spatial variation of short, medium, and long-term drought could be used in water resource management strategies to supply water for various demands.

One more objective of the study was to generate SPI time series, over multiple durations. It was observed that at shorter time scales the dry and wet periods showed a high temporal frequency. When the scale increased frequency of the dry period decreased. On the scale of 3 months, 11 significant dry periods were recognized, whereas for SPI-24, only two important ones. The average

duration of dry periods changed noticeably as a function of time scale, as for SPI-3 the average duration was 5.1 months and for SPI-9 was 7.2. Comparing all the time scales, there was a decreasing trend of severity from SPI-1 to 48.

Another objective was to develop NN models for drought SPI forecasting. The application of ANN in drought forecasting was successfully demonstrated. Different NN architectures were applied to forecast SPI series and the best models selected, comparing observed and forecasted SPIs over various lead times, using model performance measures. The hidden layers varied from 1 to 3, and corresponding hidden nodes increased from 2 to 10. The L-M, BP with Steepest Descent, Conjugate Gradient Descent, and Quasi-Newton were tested as training algorithms. The input lead times increased from 1 to 14 months, and the model with the best performance, selected for SPI forecasting.

Evaluation of model performances showed that the Quasi-Newton training algorithm had the best performance in forecasting SPI-3 and 6, when L-M was the best in forecasting SPI-1, 9, 12, 24, and 48. So the best training algorithm was a little different depending on the SPI time scale. Comparing all models, there was an increasing trend in performance measure R^2 for SPI-1 to SPI-48: 0.7328 to 0.9934 and decreasing one in RMSE from 0.188 to 0.1194. It could be concluded that the ANN model was more accurate in forecasting long-term drought (correlated with groundwater level and reservoir storage) than short-terms (related to the precipitation and soil moisture).

The best input lead-time (neurons) of SPI-1 to 48 decreased from 11 to 1, and the number of hidden layers also decreased, but there was no significant trend in hidden neurons. It could be from the volume of information contained in long-term SPIs such as SPI-48 in comparison with the medium and short-term SPIs. Thus the quality of input information (long time average) leads to the simpler architecture of ANN. This paper highlights the importance of ANN models in forecasting and comparison of drought properties over short, medium, and long lead times. The results could be used in drought forecasting for water resources management plans.

5. Acknowledgment

The authors would like to thank the Islamic Azad University, Marvdasht Branch.

Declarations
Funding: No funding received.
Conflicts of interest/Competing interests: The authors have no conflict of interest.
Availability of data and material: No
Code availability: No
Authors' contributions:

- Homa Razmkhah and Eshagh Rostami**
Conceptualization, data curation, methodology, analysis, interpretation of the results, software, visualization, and writing.
- Alireza Fararouie and Amin Rostami Ravari**
Supervised the study and reviewed the whole content.
All authors read and approved the manuscript.

Ethics approval: Not applicable.
Consent to participate: Authors have agreed to submit the article.
Consent for publication: Authors have agreed to submit the article in this Journal.

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