Sürdürülebilir Mühendislik Uygulamaları ve
Teknolojik Gelişmeler Dergisi
2021, 4(2): 121-135

Yeşilırmak Havzası için Hidrolojik ve Meteorolojik Kuraklık Tahmini, Türkiye

Hydrological and Meteorological Drought Forecasting for the Yesilirmak River Basin, Turkey

[1]Alyar Boustani Hezarani, [2]Utku Zeybekoglu, [1]Asli Ulke Keskin
[1]Ondokuz Mayis University, Engineering Faculty, Civil Engineering Department, Samsun, Turkey
[2]Sinop University, Boyabat Vocational School of Higher Education, Construction Department, Sinop Turkey

Doi: 10.51764/smutgd.993792

Geliş Tarihi : 10.09.2021
Kabul Tarihi : 07.12.2021

ÖZET

Kuraklık en tehlikeli doğal afettir. Diğer afetlerden farkı, sinsi bir şekilde gerçekleşmesi, etkilerinin yavaş yavaş ortaya çıkması ve uzun süre devam etmesidir. Kuraklığın hem toplum hem de doğal ekosistemler üzerinde çok büyük, olumsuz etkileri vardır. Bu çalışmada, Yapay Sinir Ağları (YSA) kullanılarak kuraklık tahmin modelleri oluşturmak için Standardize Yağış İndeksi (SPI) değerleri kullanılmıştır. Ek olarak, YSA ile Akarsu Kuraklık İndeksi (SDI) değerlerini tahmin etmek için SPI değerleri kullanılarak hidrolojik kuraklık olasılığı belirlenmiştir. Ayrıca YSA modellerinde İleri Beslemeli Sinir Ağları (FFNN) ile birlikte sırasıyla meteorolojik ve hidrolojik kuraklık indeksleri olarak SPI ve SDI kullanılmıştır. Bu amaçla, Türkiye Yeşilırmak Havzasında bulunan üç yağış ve üç akış ölçme istasyonu çalışma birimi olarak seçilmiştir. YSA tahmin modellerini oluşturmak için istasyonlara ait SPI ve SDI değerleri hesaplanmıştır. SPI ve SDI için farklı YSA tahmin modelleri eğitilmiş ve test edilmiştir. Ayrıca, SDI tahmin modelini geliştirmek için Thiessen Metodu kullanılarak yağışların mekansal dağılımının akışlar üzerindeki etkileri belirlenmiştir. YSA tahmin modellerinin ürettiği sonuçlar ve elde edilen değerler karşılaştırılarak modellerin performansları analiz edilmiştir. ANN ve SPI kombinasyonu meteorolojik kuraklığı yüksek doğrulukla öngördü, ancak ANN ve SDI kombinasyonu hidrolojik kuraklığı tahmin etmede o kadar iyi değildir.

Anahtar Kelimeler: YSA, Kuraklık Endeksleri, Hidrolojik Kuraklık, Meteorolojik Kuraklık, Yeşilırmak Havzası, Türkiye.

ABSTRACT

Drought is the most dangerous natural disaster. It differs from the other disasters in that it occurs insidiously, its effects are revealed gradually, and it persists for a long period. Drought has huge, negative effects on both society and natural ecosystems. In this study, values from the Standardized Precipitation Index (SPI) were used to generate drought estimation models by using Artificial Neural Networks (ANN). In addition, the probability of hydrological drought was determined by using SPI values to predict Streamflow Drought Index (SDI) values with ANN. Also, the SPI and SDI were used as the meteorological and hydrological drought indices, respectively, in conjunction with Feed Forward Neural Networks (FFNN), in ANN models. For this purpose, three rainfall and three flow gauging stations located in the Yesilirmak River Basin of Turkey were selected as the study units. The SPI and SDI values for the stations were calculated in order to create ANN estimation models. Different ANN forecasting models for SPI and SDI were trained and tested. In addition, the effects of the spatial distribution of precipitation on flows were determined by using the Thiessen Method to develop the SDI prediction model. The results generated by the ANN prediction models and resulting values were compared and the performances of the models were analyzed. The combination of ANN and SPI predicted meteorological drought with high accuracy but the combination of ANN and SDI was not as good in predicting hydrological drought.

Keywords: ANN, Drought Indices, Hydrological Drought, Meteorological Drought, Yesilirmak Basin, Turkey.

Alyar Boustani Hezarani, Orcid: 0000-0001-8763-6607, alyar_boostani@yahoo.com
Utku ZEYBEKOĞLU, Orcid: 0000-0001-5307-8563, utkuz@sinop.edu.tr
Aslı ÜLKE KESKİN, Orcid: 0000-0002-9676-8377, asli.ulke@omu.edu.tr

INTRODUCTION

Drought, an environmental disaster, can have worldwide impacts, and occur in almost all climatic zones and is associated with water shortage (Mishra & Singh, 2010), and causes the deaths of many thousands of people. As drought is linked to many factors like climate and regional properties, defining it is hard and is still the subject of debate. Setting the debate aside, the effects of drought are being increasingly felt worldwide. Drought has major effects, especially on the availability of water resources, agriculture, forestry, hydro-electricity generation, health and socio-economic activities. The effects of drought on water resources are seen in low soil moisture and river flows, reduction in reservoir levels and less groundwater storage (Tallaksen & Van Lanen, 2004). Generally, humans become aware of drought when faced with water shortage (Hejazizadeh & Javizadeh, 2011). Drought is evident when the water requirements of plants and water supplies to city dwellers are not being adequately provided because the amount of water entering dams is insufficient to meet the demand (Salinger, 1995). It is not easy to detect the beginning of a drought which can arise suddenly, spread quickly and end in different ways (Wilhite, 2000).

Describing and monitoring drought is also difficult. The criteria that different researchers take into account in drought analysis sometimes differ (Guttman, 1998). Some of the criteria are rainfall-temperature ratio, precipitation-evaporation rate, precipitation regime and vegetation. Inconsistencies in approaches to make drought analysis generate differences in the calculation of the water balance sheet. To minimize inconsistencies and understand their origins, several methods should be used in drought analysis. To that end, researchers have employed more than one drought index. The best known of these are the De Martonne Index, the Palmer Drought Severity Index (PDSI) (Palmer, 1960) and the Standardized Precipitation Index (SPI) (McKee, Doesken, & Kleist, 1993). Guttman (1998) compared the performance of the use of PDSI and SPI across the United States. The results of this study indicated that indices based on precipitation were simpler and more successful in predicting drought. SPI-1 deals with soil moisture, while SPI-3 examines the flow conditions of small rivers (White & Walcott, 2009). On the other hand, the use of SPI-6, SPI-9, SPI-12 and SPI-24 are generally based on the flows in larger rivers, reservoir levels and even groundwater (Merkoci, Mustaqi, Mucaj, & Dvorani, 2013).

Mishra and Singh (2011) examined the definition of drought and compared the strengths and weaknesses of different indices. They defined the degree, intensity, sharpness and return time of drought with different indices and reported that the best results for the SPI method were obtained with the use of gamma distribution because rainfall fits it better than other distributions. Mishra and Singh (2011) thoroughly reviewed various aspects of methods and models used for the prediction of drought. They examined different drought indices for different drought types, namely agricultural, hydrological meteorological and socioeconomic. Based on these investigations, they proposed the use of the PDSI for agricultural drought and the SPI for meteorological drought. Soleimani, Ahmadi, and Zehtabian (2013) examined drought in a semi-arid region of Iran with three methods, namely the SPI, Modified China Z-Score and Rainfall Deciles. They reported that the best results were generated with SPI. In a study from the southern hemisphere, Deo and Sahin (2015) examined the usefulness of Extreme Learning Machine (ELM) and ANN models to predict the Effective Drought Index (EDI) in eastern Australia with the data of 1957 to 2008 and the monthly EDI of the period 2009 to 2011. The authors reported that ELM showed excellent performance in comparison to the ANN model.

Nalbantis (2008) reported a new index named the Streamflow Drought Index (SDI), which is a simpler and more effective index than other hydrological drought indices. This new method, which was first applied to the Evinos and Boeoticos Kephisos basins in Greece, allows the identification of drought conditions with non-stationary models, such as in the Markov chain. In a study from Iran in western Asia, Tabari, Abghari and Talaee (2012) calculated the SDI-3, SDI-6, SDI-9 and SDI-12. In their study, which was based on the analysis of the hydro-meteorological data from 14 different stations in the north-west of the country generated between 1975 and 2009, it was concluded that there was a high level of drought at almost every station, and in the last 12 years of that period, the drought reached maximum intensity. In a Chinese study, Hong, Guo, Zhou, and Xiong (2015) conducted a drought analysis of the Yangtze River Basin for the years 1882 to 2009 by using the SDI-12 and stated that the model was very successful in predicting drought.

Tanoglu (1943) conducted one of the first studies on drought in Turkey. A drought map was prepared by using temperature and precipitation values based on the De Martonne method. Following that study, Erinç (1949) investigated drought in Turkey with the Thornwaite method, which uses monthly precipitation, temperature and evaporation values.

The same author applied the index developed from the rainfall and evaporation rates at 80 meteorological stations in Turkey to develop a climate classification system. Fifty-three years later, Sırdas (2002) used SPI to analyze the spatial and temporal records of 60 weather stations in Turkey for the period 1930 to 1990. The study revealed that the southern, western, and eastern regions are drier than the north-eastern and north-western regions. Sonmez, Komuscu, Erkan, and Turgu (2005) also investigated drought spatially and temporally in Turkey with SPI and reported severe droughts over short time periods (quarterly) in south-eastern and eastern Anatolia. Later, Keskin, Terzi and Taylan (2009) modeled SPI-3, SPI-6, SPI-9 and SPI-12 values with the Adaptive Neuro Fuzzy Inference System (ANFIS) models and fuzzy logic models. They used the index values for the precipitations of the current month and the previous month as the input variables and modeled the current month's SPI value as the output variable. The authors reported that SPI-12 and ANFIS models showed better agreement than fuzzy logic models. Bacanli, Firat, and Dikbas (2009) also investigated the application of the ANFIS method to the prediction of drought. Different ANFIS models were created by using SPI values generated from the mean monthly rainfalls at 10 stations in Central Anatolia. They compared the best results of the ANFIS and FFNN models and determined that ANFIS can be successfully applied to the prediction of drought. Oguztürk (2010) used SPI to investigate the occurrence of drought by analyzing the data generated by 14 meteorological stations in the Kizilirmak River Basin between 1950 and 2007. By using the SPI values for all the months back to 1950 for ANN modeling, the SPI values for 2007 were estimated. The authors stated that the ANN model estimates for the first three months of the year were close to the actual data, but they deviated from the actual results for the following months. Durdu (2010) investigated meteorological drought in the Buyuk Menderes River Basin between 1975 and 2006 by using SPI. The ARIMA and Seasonal-ARIMA models were applied to drought detection, with ARIMA modeling successfully predicting drought two months in advance. Separately, Oguzturk and Yildiz (2016) determined the Theissen coefficients for the Kirsehir, Nevsehir, Kayseri, Gemerek, Sivas and Zara meteorological stations, which are in the catchment of the Hirfanli Dam, and then calculated their SPI values for the period 1950 to 2013. They stated that the reason for using the SPI is that only the precipitation data are needed and that by using them, drought could be successfully predicted for different time periods. Based on their research results, Oguzturk and Yildiz (2016) further reported that the Hirfanli Dam Basin is vulnerable to drought. Selcuk (2017) studied drought by using hydrological and meteorological drought indices and reported that these two indices yielded partially compatible results. In addition, models were created with WEKA to estimate the SDI and flows by using meteorological parameters independent of SDI. However, modeling did not produce satisfactory results. Altin, Saris, and Altin (2019) studied hydrological drought with the SDI at eight river-gauging stations in the Eastern Mediterranean in Turkey, namely, between 1972 and 2014 (4 stations), between 1973 and 2015 (2 stations), and between 1969 and 2011 (2 stations). SDI analyses showed that the number of drought years was highest in the 3-month period between October and December. Many researches aiming at the determination and prediction of hydrological and meteorological drought are available for various geographies of the world (Masinde, 2014; Buckland, Bailey, & Thomas, 2019; Poornima & Pushpalatha, 2019; Azimi & Moghaddam, 2020; Erogluer & Apaydin, 2020; Shin, Huang, Dirmeyer, Halder & Kumar, 2020; Taylan, Terzi & Baykal, 2021).

Against that background of the use of different approaches to the global problem of drought and its prediction, the basic aim of this study was to bring a different perspective to drought prediction by investigating the applicability of ANN to SPI and SDI modeling. The estimation of the SDI, in combination with ANN, is the novel element in this study. Moreover, the use of the SDI was applied for the first time to the Yesilirmak River Basin in Turkey.

MATERIAL

The Yesilirmak River, which is 519 km in length, is a major water resource in the north-east of Turkey. Its drainage basin covers an area of 36,114 km2 or approximately 5% of the nation's surface area. It originates in the Kose Mountains in the south-west of Susehri District of Sivas Province. The average annual rainfall across the basin is 646 mm. The average monthly rainfall is around 50 mm, which increases to 60 to 65 mm in winter. The lowest average rainfall is received in the summer months, namely 26.5 and 24.6 mm in July and August, respectively. The average annual temperature in the basin is around 12°C. Temperatures in the seaside areas are relatively high compared to the interior areas. The average basin water yield is 5.1 L/sec/km² and the average annual flow is 5.80 km³. The data from nine meteorological stations, and three flow gauging stations (Cirdak, Gemerek and Seyhoglu), in the Yesilirmak River basin, were used for this study. The most important factor in the selection of these flow observation stations is the absence of any dam effect on their upstream.

The monthly rainfall records available from the meteorological stations covered the period between 1970 and 2015. The SPI values were calculated on the basis of these data. In addition, the monthly flow data from the gauging stations for the period 1970 to 2011 were used to calculate the SDI.

Figure 1. The geographical location of the Yesilirmak River Basin (TUBITAK, 2010)

Table 1. Statistical details of stations used in this study

	Station	Latitude (°N)	Longitude (°E)	Elevation (m.)	Min.	Max.	Mean	SD	Variance	Skewness	Kurtosis
Weather Stations (mm)	Corum	40.5461	34.9362	776	0.00	220.10	37.23	28.70	823.53	1.39	4.45
	Gumushane	40.4598	39.4653	1216	0.00	141.90	38.51	27.14	736.51	0.82	0.52
	Samsun	41.3435	36.2553	4	0.00	269.80	58.35	38.86	1510.18	1.36	3.23
	Sivas	39.7437	37.0020	1294	0.00	139.20	36.99	28.48	811.19	0.83	0.42
	Susehri	40.1623	38.0752	1164	0.00	162.20	34.68	26.83	720.04	0.99	1.16
	Tokat	40.3312	36.5577	611	0.00	141.10	36.69	28.06	787.38	0.90	0.57
	Yozgat	39.8243	34.8159	1301	0.00	192.30	49.19	37.84	1432.13	0.83	0.44
	Zile	40.2960	35.8905	719	0.00	158.10	37.49	29.69	881.68	1.12	1.47
	Zara	39.8928	377.7473	1338	0.00	171.40	43.22	33.74	1138.06	0.93	0.60
Flow Gauging Stations (m^3/sec)	Cirdak	40.0029	36.0847	1040	0.00	29.10	3.90	4.76	22.64	2.23	5.60
	Gomeleonu	40.1822	37.0724	865	1.01	103.00	18.15	20.31	412.38	1.70	2.28
	Seyhoglu	40.2706	35.2503	530	0.00	41.90	6.24	7.29	53.21	2.10	4.85

METHODOLOGY

Standard Precipitation Index (SPI)

SPI developed by McKee et al. (1993, 1995). SPI is used for the modelling of rainfall data, and is obtained by dividing the difference between the precipitation and mean of precipitation in a specific period by the standard deviation (Eq. (1)) and the SPI classes are shown in Table 2 (McKee et al., 1993).

$$SPI = \frac{x_j - \mu}{\sigma} \qquad (1)$$

Table 2. Drought classification with SPI values (McKee et al., 1993)

SPI	Drought category
2≤SPI	Extremely wet
1.50≤ SPI <2.0	Very wet
1.0≤SPI <1.50	Moderately wet
-1.0≤ SPI <1.0	Near normal
-1.50< SPI ≤-1.0	Moderately dry
-2.0<SPI ≤-1.50	Severely dry
-2 ≥ SPI	Extremely dry

Thom (1958) proposed Gamma distribution for historical precipitation time series (Yacoub & Tayfur, 2020). Probability density function of Gamma distribution is defined as (Eq. (2)) (Yacoub & Tayfur, 2020):

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{\frac{-x}{\beta}}; x, \alpha, \beta > 0 \quad (2)$$

where x is the amount of rainfall, Γ(α) is the gamma function and α is shape, β is scale parameter. Shape and scale parameters can be estimated as (Eqs. (3-5)) (Bacanli, 2017; Yacoub & Tayfur, 2020):

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

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

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

Here, n refers to the number of rainfall observations, with cumulative probability distribution function given below (Eq. (6)) (Bacanli, 2017):

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

Then cumulative probability function is calculated for a given period (1, 2, 6, 9, 12, 24 months). If the precipitation data series have zero values, then cumulative probability becomes as follows (Eq. (7)):

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

The cumulative probability value H(x) is converted into a Z variable with the standard normal random value showing the SPI with a mean value of zero and variance that equals to 1 (Abramowitz & Stegun, 1965; Yacoub & Tayfur, 2017). H(x) is the value of the SPI. Normalization of the SPI values enables the prediction of temporal and spatial variations in the precipitation series for that station (McKee et al., 1993; Guttman, 1999).

Streamflow Drought Index (SDI)

The SDI method was developed by Nalbantis (2008). It is hypothesized that a series of monthly streamflow volumes, (Q_(i,j)) is available, with i refering to the hydrological year and j denoting the month in that year, that is, October - September (Gumus & Algin, 2017). Based on this, cumulative volumes are shown in Eq. (8):

$$V_{i,k} = \sum_{j=1}^{3k} Q_{i,j} \, i = 1,2,\ldots j = 1,2,\ldots,12 k = 1,2,3,4 \quad (8)$$

Here, V_(i,k) refers to the cumulative streamflow volume of ith hydrological year, and kth reference period (Nalbantis, 2008; Nalbantis & Tsakiris, 2009).

Based on the cumulative streamflow volumes, V_(i,k), the SDI is defined for the ith hydrological year, as follows (Eq. (9)):

$$SDI_{i,k} = \frac{V_{i,k} - \overline{V}_k}{s_k} i = 1,2,\ldots,kk = 1,2,3,4 \qquad (9)$$

From the mean (¯(V_k)), and standard deviation, S_k, of the cumulative stream flow volume, the SDI for kth reference period within ith hydrological year can be calculated via Equation 9, with the truncation level set at V_k, although other values can be used.

The SDI has five categories ranging between extreme wet and extreme drought, as given in Table 3 (Nalbantis, 2008).

Table 3. Drought classification with SDI values (Nalbantis, 2008)

State	SDI	Drought category
0	0≤SDI	Non-drought
1	-1.0≤ SDI <0.0	Mild drought
2	-1.5≤ SDI <-1.0	Moderate drought
3	-2.0≤ SDI <-1.5	Severe drought
4	SDI <-2.0	Extreme drought

DROUGHT FORECASTING WITH ANN

Input variables

In the present study, the values of SPI for the previous months were used to generate a drought estimation model with the Feed Forward Neural Networks (FFNN) in ANN method, with the SPI outputs for 1, 3, 6, 12 and 24 months included. To do this, various models were used for each SPI output of 1, 3, 6, 12 and 24 months. Also, one model was produced for predicting the SDI outputs for the 3-, 6-, 9- and 12-month periods. The datasets for all stations were divided into three subsets, namely training, validating, and testing. The training dataset included data records between 1970 and 2001 for SPI, and 1970 to 1999 for SDI. The validation dataset was 2002 to 2008 for SPI, and 2000 to 2005 for SDI. The testing dataset consisted of data records 2009 to 2015 for SPI, and 2006 to 2011 for SDI. The models were tested via the evaluation of a dataset not employed in the training process to have a more reliable evaluation and comparison.

Detailed explanations and functioning of FFNN's are available in the literature (Lowe & Tipping, 1996; Zhang, Patuwo, & Hu, 1998; Dawson & Wilby, 2001; Firat & Gungor, 2004; Şen, 2004; Dogan, Isik, & Sandalci, 2007; Cigizoglu, 2008; Feng and Hong, 2008; Oyebode & Stretch, 2019; Demir & Ulke Keskin, 2020).

Model Structures

One of the most important decisions in the development of a satisfactory forecasting model is the selection of the appropriate input variables. In the present study, different combinations of the antecedent SPI values of stations were used to develop the appropriate input structures, as shown in Table 4.

Table 4. The structures of drought forecasting models for the Yesilirmak River Basin

Model	Input structure	Output
M1	SPI(t-1)	SPI(t)
M2	SPI(t-1) SPI(t-2)	SPI(t)
M3	SPI(t-1) SPI(t-2) SPI(t-3)	SPI(t)
M4	SPI(t-1) SPI(t-2) SPI(t-3) SPI(t-4)	SPI(t)
M5	SPI(t-1) SPI(t-2) SPI(t-3) SPI(t-4) SPI(t-5)	SPI(t)
M6	SPI(t)	SDI(t)

where SPI(t)/SDI(t) represents the SPI/SDI values at time (t), and SPI(t-1), …, SPI(t-n) are the antecedent SPI values respectively at times (t−1), …, (t−n).

The performances of the developed FFNN models were evaluated on the basis of statistical criteria (e.g. the Correlation Coefficient (R) (Eq. (10)), and Efficiency, (E) (Eqs. (11-13)), (Nash & Sutcliffe, 1970; Kitanidis & Bras, 1980), and the Root Mean Square Error (RMSE) (Eq. (14)).

$$R = \frac{\sum_{t=1}^{N}\left(Y_{obs(t)}-\overline{Y_{obs}}\right)^2 .\left(Y_{for(t)}-\overline{Y_{for}}\right)^2}{\sqrt{\sum_{t=1}^{N}\left(Y_{obs(t)}-\overline{Y_{obs}}\right)^2 .\left(Y_{for(t)}-\overline{Y_{for}}\right)^2}} \tag{10}$$

$$E = \frac{E_1-E_2}{E_2} \tag{11}$$

$$E_1 = \sum_{t=1}^{N}\left(Y_{obs(t)} - \overline{Y_{obs}}\right)^2 \tag{12}$$

$$E_2 = \sum_{t=1}^{N}\left(Y_{for(t)} - Y_{obs(t)}\right)^2 \tag{13}$$

$$RMSE = \sqrt{\frac{\left(Y_{obs}-Y_{for}\right)^2}{N}} \tag{14}$$

where Yfor is the forecasted SPI/SDI value, Yobs is the observed SPI/SDI value, (Yfor) is the average of the forecasted SPI/SDI values, and (Yobs) is the observed SPI/SDI value.

Values of R and E close to 1.0 indicate good model performance. The RMSE is used often as a measure of the difference of values predicted by a model or an estimator. Such a difference is named “residual”. Theoretically, if this value were to equal zero, the model would represent the perfect fit, which is not possible (Firat, 2008; Firat & Gungor, 2009).

RESULTS AND DISCUSSION

In the first stage of this study, five models with various input variables were trained and tested with the FFNN method. The performances of the models for SPI forecasting were then compared. Ultimately, the best model was identified, based on the criteria selected for performance evaluation. The performances of the best fit FFNN models for each SPI value in Gumushane, Samsun and Sivas stations are shown in Table 5. The purpose of choosing these three stations is that Gümüşhane meteorological station is located at the upstream of Yeşilırmak River basin, Sivas meteorological station is located in the middle of the basin and Samsun meteorological station is located downstream of Yeşilırmak River basin.

Table 5. The performances of the best fit models for SPI-1 for three meteorological stations in the Yesilirmak River Basin, Turkey

	Station	Training R	Validating R	R	Testing Set RMSE	E
SPI-1	Gumushane (M4)	0.46	0.20	0.46	0.7024	0.16
	Samsun (M1)	0.21	0.09	0.20	0.9200	0.02
	Sivas (M5)	0.55	0.48	0.60	0.6356	0.20
SPI-3	Gumushane (M4)	0.84	0.74	0.83	0.3493	0.59
	Samsun (M3)	0.76	0.72	0.73	0.5135	0.49
	Sivas (M4)	0.84	0.82	0.87	0.2715	0.68
SPI-6	Gumushane (M3)	0.88	0.85	0.89	0.2090	0.78
	Samsun (M2)	0.82	0.76	0.85	0.3412	0.68
	Sivas (M2)	0.87	0.90	0.89	0.2627	0.72
SPI-12	Gumushane (M5)	0.91	0.90	0.94	0.2394	0.73
	Samsun (M4)	0.87	0.89	0.92	0.2516	0.75
	Sivas (M4)	0.90	0.89	0.93	0.2195	0.82
SPI-24	Gumushane (M4)	0.96	0.96	0.96	0.0200	0.97
	Samsun (M3)	0.94	0.93	0.93	0.0663	0.92
	Sivas (M4)	0.95	0.94	0.95	0.0975	0.90

As seen in Table 5, the models showed major variations, based on the three performance criteria. The best results were generated with the Gumushane M4, SPI24 model which had the lowest value of RMSE at 0.0200, the highest efficiency at 0.97, and the highest correlation at 0.96. The overall results from this study indicate that the results of ANN modeling are better if long-term SPI values are used. In Figs. 2-4, the time series graphs for the best model results and real SPI values for the Samsun, Gumushane and Sivas meteorological stations are given. The SPI-1 results had the worst performance in all cases.

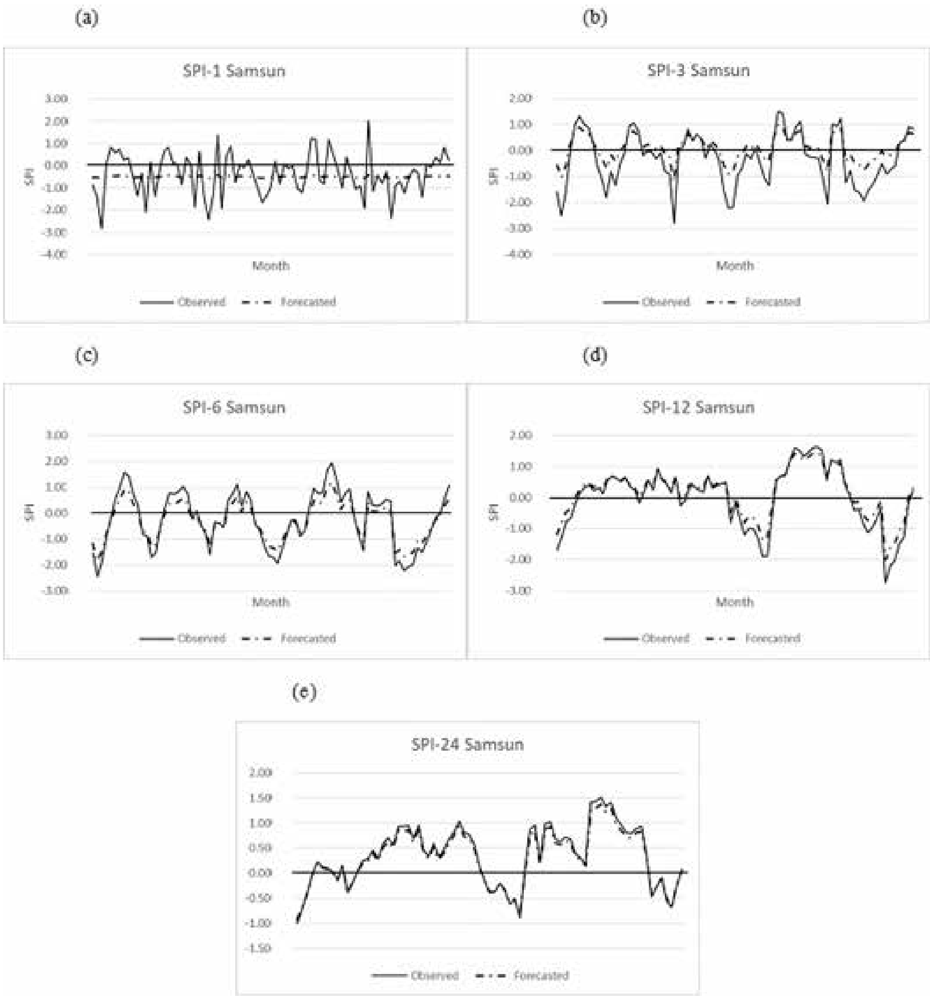

Figure 2. The testing data results of best fit models for the Samsun SPI

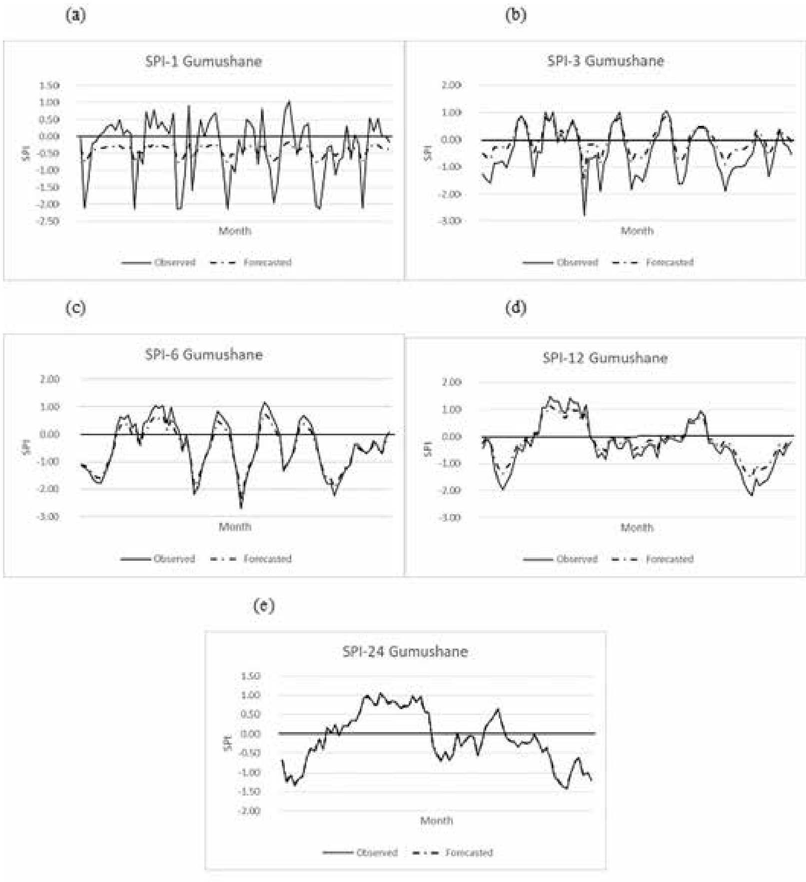

Figure 3. The testing data results of best fit models for the Gumushane SPI

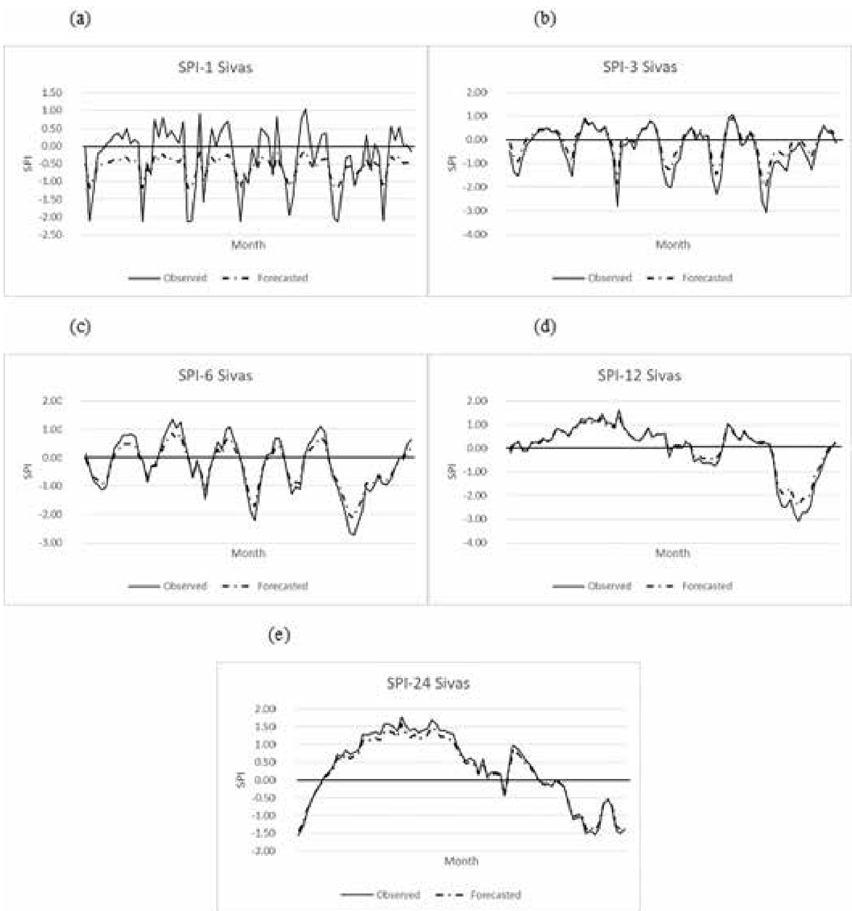

Figure 4. The testing data results of best fit models for the Sivas SPI

In Figs. 2-4, the series almost overlap for the 12 and 24-month SPI time intervals for Samsun (Figs.2a, 2b), Gumushane (Figs.3a, 3b) and Sivas (Figs.4a-4b).

In the second part of this study, the aim was to estimate the SDI values by using SPI (M6). The relationships between the recordings at the meteorological stations and the flows at the three flow observation stations (Gomelonü, Cırdak and Seyhoglu) were calculated with the Theissen method (Eq. (15)):

$$P_{moy} = \frac{\sum_i (W_i \sum_T P_i(t))}{\sum_i W_i} \qquad (15)$$

where P_moy is the mean areal rainfall, W_i is the weighting factor of i and is the rainfall depth measured at time t at gauge i. The weighting factor (W_i) of gauge i is calculated by using the Thiessen polygons (Eq. (16)) (Boyogueno, Mbessa & Tatietse, 2012):

$$W_j = \frac{a_{i,j}}{A_i} \qquad (16)$$

where a_(i,j) is the surface intersection of the “polygon j” and “sub- basin i”; and A_i is the total area of sub-basin i (Boyogueno et al., 2012).

The Theissen coefficients are given in Table 6 and the Theissen areas of the stations in the basin are presented in Fig. 5. After the contributions of flows at the individual meteorological stations to total flow were determined, the SPI values were calculated for intervals of 3, 6, 9 and 12 months. These new index values were used as inputs to the FFNN model, with the results given in Table 6.

Table 6. Thiessen coefficients for the meteorological stations

		Meteorological Stations						
		Thiessen Coefficient						
		Corum	Yozgat	Zara	Tokat	Susehri	Zile	Sivas
Flow Gauging Stations	Gomeleonu	-	-	67.5%	28.3%	4.2%	-	-
	Cirdak	-	-	-	93%	-	6.3%	0.7%
	Seyhoglu	89.2%	10.8%	-	-	-	-	-

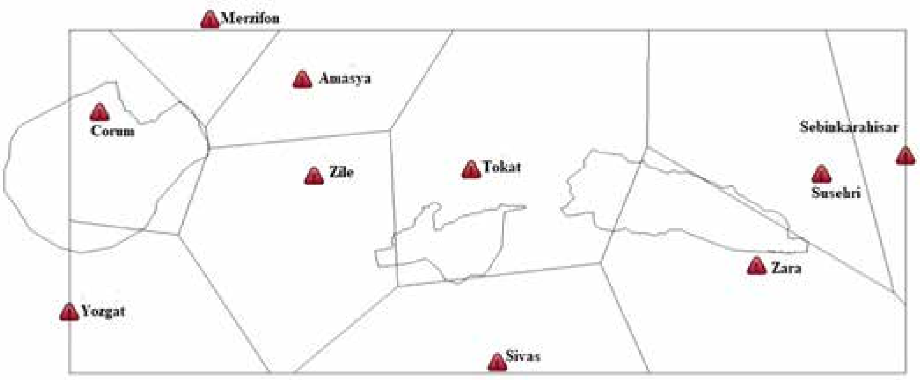

Figure 5. Rainfall gauging stations and Theissen areas

Table 7. The performances of modelling for SPI to SDI for three flow gauging station in Yesilirmak River basin, Turkey

	Station	Training R	Validating R	R	Testing Set RMSE	E
SPI-3	Gomeleonu	0.85	0.56	0.62	0.6196	0.47
	Cirdak	0.60	0.40	0.50	0.7134	0.31
	Seyoglu	0.72	0.76	0.61	0.5374	0.48
SPI-6	Gomeleonu	0.92	0.83	0.81	0.2304	0.77
	Cirdak	0.74	0.76	0.72	0.4697	0.50
	Seyoglu	0.66	0.71	0.60	0.5637	0.43
SPI-9	Gomeleonu	0.82	0.72	0.79	0.3659	0.63
	Cirdak	0.77	0.75	0.71	0.3686	0.63
	Seyoglu	0.78	0.50	0.69	0.4963	0.50
SPI-12	Gomeleonu	0.74	0.78	0.75	0.3376	0.53
	Cirdak	0.73	0.72	0.68	0.5072	0.47
	Seyoglu	0.58	0.74	0.74	0.6916	0.30

In Table 7, the model SDI-6(M6) for the Gomeleonu station had the best performance. This model had the best efficiency, correlation rates and the lowest RMSE values. As can be seen in Fig. 6, the time-series graph of the model with the best performance is more compatible than the other conversion of SPI to SDI models.

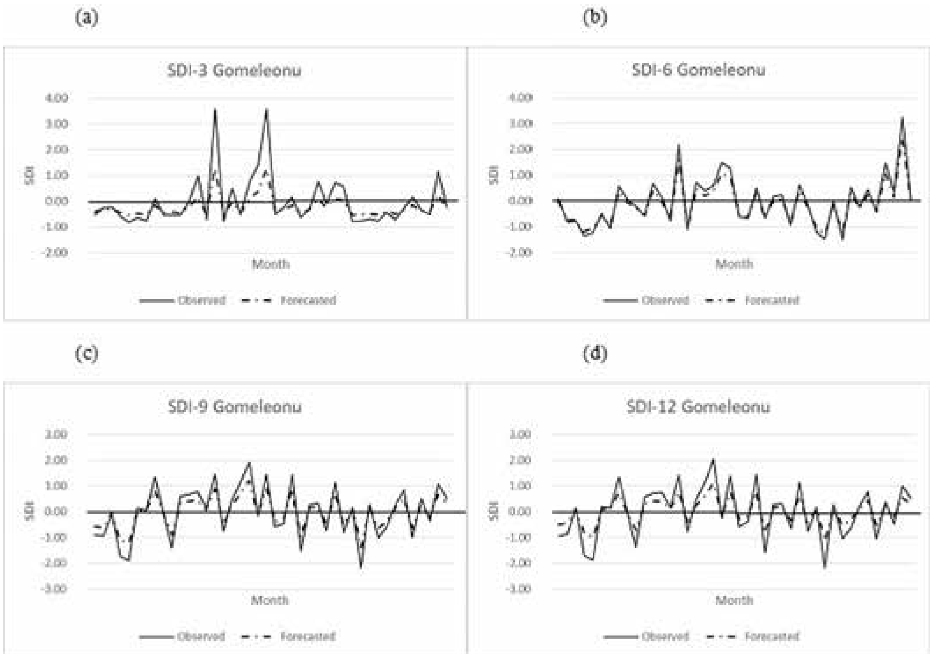

Figure 6. The results of testing data for Gomeleonu SDI

The best efficiency and RMSE results for Cirdak are for the 9-month period (SDI-9, M6) but the highest correlation rate is seen for SDI-6(M6) (Table 10). In addition, the time series adaptation of SDI-9(M6) is quite high compared to other Cirdak SPI to SDI conversion results (Fig. 6).

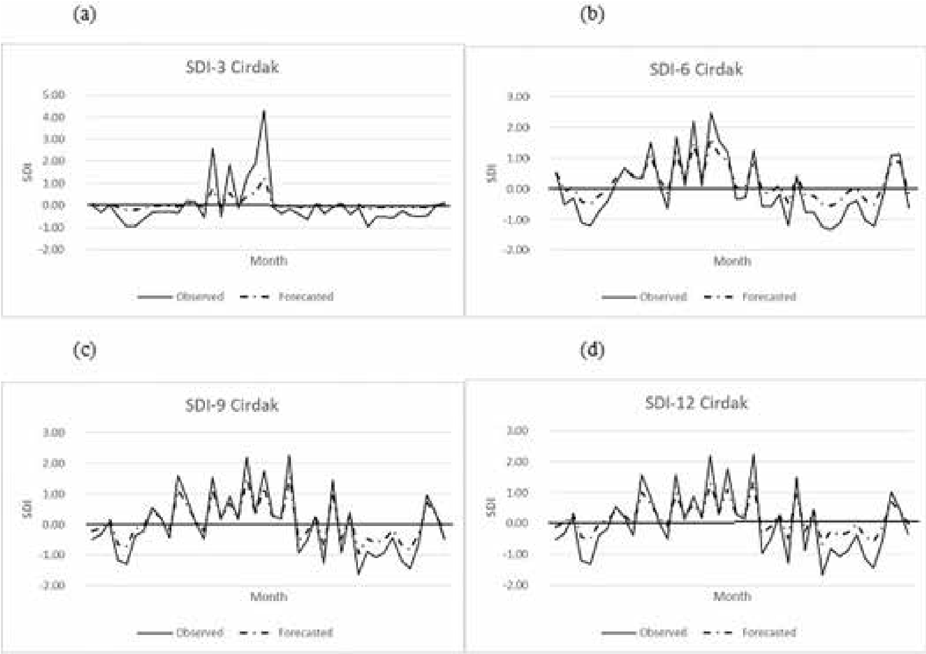

Figure 7. The results of testing data for Cirdak SDI

In Table 7, the best results for Seyhoğlu are for the modeling of the 9-month period (SDI-9, M6). This model had better correlation, efficiency and RMSE than the other Seyhoglu SDI-6 models. Moreover, the time-series graph showed less consistency than all the other SPI to SDI modeling results (Fig. 8d).

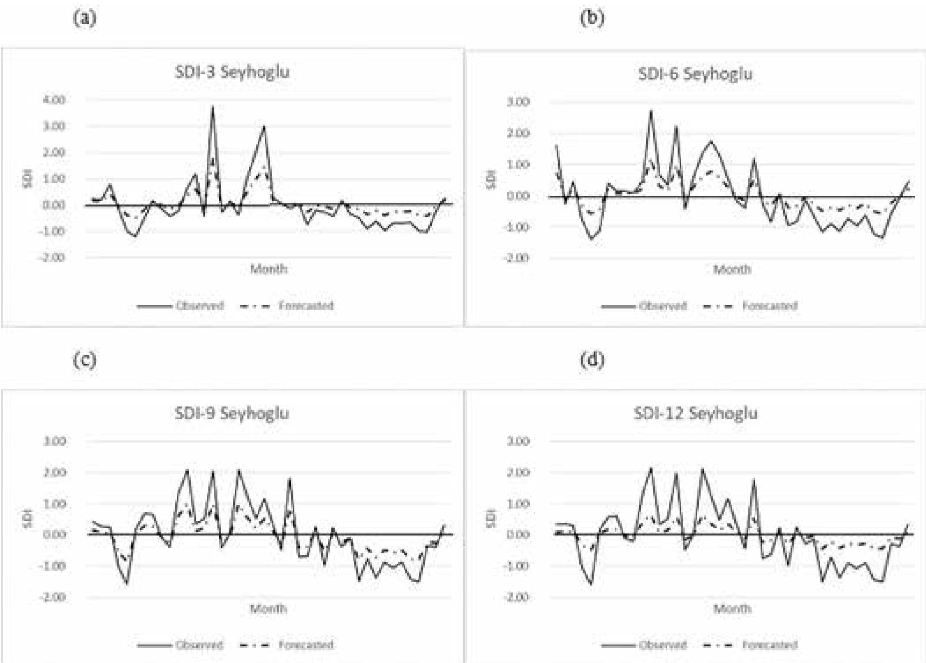

Figure 8. The results of testing data for Seyoglu SDI

As can be seen in Figs. 6-8, the developed models were not successful in capturing peak SDI values. This situation is more evident in low efficiency models, suggesting that low efficiency models cannot effectively capture peak SDI values.

CONCLUSION

SPI is among the common methods used to predict drought. This study investigated the applicability and capability of FFNN methods, in combination with SPI, for drought forecasting by employing a series of independent variables.

To determine the applicability of the ANN method to drought forecasting, nine rainfall gauging stations located in the Yesilirmak River Basin in Turkey were identified as the study units. Different FFNN forecasting models for SPI-1, SPI-3, SPI-6, SPI-12 and SPI-24 were trained and tested. The results and observations from the developed models were compared and evaluated on the basis of their performance in training and testing sets. The models SPI-12 and SPI-24 were more successful than the models for shorter periods, namely SPI-1, SPI-3 and SPI-6, in predicting long-term drought. In essence, this study has demonstrated that the FFNN method can successfully estimate SPI and hence can be applied effectively to drought prediction.
In the second section, the SDI values were estimated with the FNN model from the SPI values. For this purpose, 10 rainfall and three flow gauging stations in the Yesilirmak River basin were used. In the SDI estimation produced using FFNN, the contributions of the catchment areas of rainfall stations to the flow gauging stations were calculated with the Theissen method. The SPI method was applied to the stations' rainfall data. These new values were used as input for SDI estimation. The results of FFNN did not yield very successful predictions, except for the Gomeleonu station. The main reason appears to be that the ten rainfall stations did not adequately record both the amount of precipitation in the catchment areas of the flow gauging stations and the uncertainties in the rainfall-runoff relationship. The Theissen coefficients were also calculated from the limited amount of information generated by these stations. To the authors' knowledge, no other study has applied SDI estimation based on SPI to the Yesilirmak River Basin.

More broadly, the further development and use of this model are potentially useful in drought prediction in different environments. Global climate change means that more extreme climate events, including drought, are occurring with more regularity and more intensity. The current study demonstrated that FFNN can be used in combination with SPI to effectively predict meteorological drought in the Yesilirmak River Basin in northern Turkey. This novel method can assist water resource managers and representatives of bulk water users, including cities and regions, to more effectively plan for the availability of less water and hence mitigate some of the negative effects of drought.

Authors Contribution

ABH implemented calculations. UZ and AUK wrote manuscript.

REFERENCES

Abramowitz, M., & Stegun, I. (1965). Handbook of mathematical functions. National bureau of standards, applied mathematics series–55. Washington, D.C.

Altın, T. B., Sarış, F., & Altın, B. N. (2019). Determination of drought intensity in Seyhan and Ceyhan River Basins, Turkey, by hydrological drought analysis. Theoretical and Applied Climatology, 139(1-2), 95-107. https://doi.org/10.1007/s00704-019-02957-y

Azimi, S., & Moghaddam, M. A. (2020). Modeling Short Term Rainfall Forecast Using Neural Networks, and Gaussian Process Classification Based on the SPI Drought Index. Water Resour Manage 34(4), 1369-1405. https://doi.org/10.1007/s11269-020-02507-6

Bacanli, U. G., Firat, M., & Dikbas, F. (2009). Adaptive neuro-fuzzy ınference system for drought forecasting. Stochastic Environmental Research and Risk Assessment, 23, 1143-1154. https://doi.org/10.1007/s00477-008-0288-5

Bacanli, U. G. (2017). Trend analysis of precipitation and drought in the Aegean region, Turkey. Meteorologıcal Applıcatıons, 24(2), 239-249. https://doi.org/10.1002/met.1622

Boyogueno, S. H., Mbessa, M., & Tatietse, T. T. (2012). Prediction of flow-rate of Sanaga Basin in Cameroon USING HEC-HMS hydrological system: application to the Djerem sub-basin at Mbakaou. Energy Environ Res, 2(1), 205-216. https://doi.org/10.5539/eer.v2n1p205

Buckland, C. E., Bailey, R. M., & Thomas, D. S. G. (2019). Using artificial neural networks to predict future dryland responses to human and climate disturbances. Sci Rep, 9, 1-13. https://doi.org/10.1038/s41598-019-40429-5

Cigizoglu H.K. (2008). Artificial Neural Networks In Water Resources. In: Coskun H.G., Cigizoglu H.K., Maktav M.D. (eds) Integration of Information for Environmental Security. NATO Science for Peace and Security Series C: Environmental Security. Springer, Dordrecht. https://doi.org/10.1007/978-1-4020-6575-0_8

Dawson, C. W. & Wily, R. L. (2001). Hydrological modelling using artificial neural networks. Progress in Physical Geography: Earth and Environment, 25(1), 80-108. https://doi.org/10.1177/030913330102500104

Demir, V. & Ülke Keskin, A. (2020). Yapay Sinir Ağları Yardımıyla Yükseklik Modellemesi (Samsun-Mert Irmağı Havzası Örneği). Gazi Mühendislik Bilimleri Dergisi (GMBD), 6 (1), 54-61.

Deo, R. C., & Sahin, M. (2015) Application of the extreme learning machine algorithm for the prediction of monthly Effective Drought Index in eastern Australia. Atmospheric Research, 153, 512-525. https://doi.org/10.1016/j.atmosres.2014.10.016

Dogan, E. , Isik, S. & Sandalcı, M. (2007). Günlük Buharlaşmanın Yapay Sinir Ağları Kullanarak Tahmin Edilmesi. Teknik Dergi, 18(87), 4119-4131.

Durdu, O. F. (2010). Application of linear stochastic models for drought forecasting in the Buyuk Menderes river basin, Western Turkey. Stochastic Environmental Research and Risk Assessment, 24, 1145-1162. https://doi.org/10.1007/s00477-010-0366-3

Erinç, S. (1949). The climates of Turkey according to Thornthwaite's classifications. Annals of the Association of American Geographers, 39, 26-46.

Erogluer, T. A., & Apaydin, H. (2020). Estimation of Drought by Streamflow Drought Index (SDI) and Artificial Neural Networks (ANNs) in Ankara-Nallihan Region. Turkish Journal of Agriculture - Food Science and Technology, 8(2), 348-357. https://doi.org/10.24925/turjaf.v8i2.348-357.3045

Feng, L. & Hong, W. (2008). On hydrologic calculation using artificial neural networks. Applied Mathematics Letters, 21(5), 453-458. https://doi.org/10.1016/j.aml.2007.06.004

Fırat, M. & Güngör, M. (2004). Askı Madde Konsantrasyonu ve Miktarının Yapay Sinir Ağları ile Belirlenmesi. Teknik Dergi, 15(73), 3267-3282.

Firat, M. (2008). Comparison of Artificial Intelligence Techniques for river flow forecasting. Hydrology and Earth System Sciences, 12, 123-139. https://doi.org/10.5194/hess-12-123-2008

Firat, M., & Gungor, M. (2009). Generalized Regression Neural Networks and Feed Forward Neural Networks for prediction of scour depth around bridge piers. Advances in Engineering Software, 40(8), 731-737. https://doi.org/10.1016/j.advengsoft.2008.12.001

Gumus, V., & Algin, H. M. (2017). Meteorological and hydrological drought analysis of the Seyhan−Ceyhan River Basins, Turkey. Meteorological Applications, 24(1), 62-73. https://doi.org/10.1002/met.1605

Guttman, N. B. (1998). Comparing the Palmer drought index and the standardized precipitation index. Journal of the American Water Resources Association, 34(1), 113-121. https://doi.org/10.1111/j.1752-1688.1998.tb05964.x

Guttman, N. B. (1999). Accepting the standardized precipitation index: a calculation algorithm. Journal of the American Water Resources Association, 35(2), 311-322. https://doi.org/10.1111/j.1752-1688.1999.tb03592.x

Hejazizadeh, Z., & Javizadeh, S. (2011). Introduction to drought and its indices. Iran: Samt Publications.

Hong, X., Guo, S., Zhou Y., & Xiong, L. (2015). Uncertainties in assessing hydrological drought using streamflow drought index for the upper Yangtze River basin. Stochastic Environmental Research and Risk Assessment 29, 1235-1247. https://doi.org/10.1007/s00477-014-0949-5

Keskin, M. E., Terzi, O., Taylan, E. D., & Kucukyaman, D. (2009). Meteorological drought analysis using data-driven models for the Lakes District, Turkey. Hydrological Sciences Journal, 54(6), 1114-1124. https://doi.org/10.1623/hysj.54.6.1114

Kitanidis, P. K., & Bras, R. L. (1980). Real time forecasting with a conceptual hydrological model. 2. Applications and results. Water Resour Res, 16(6), 1034-1044. https://doi.org/10.1029/WR016i006p01034

Lowe, D., & Tipping, M. (1996). Feed-forward neural networks and topographic mappings for exploratory data analysis. Neural Comput & Applic, 4(2), 83-95. https://doi.org/10.1007/BF01413744

Masinde, M. (2014). Artificial neural networks models for predicting effective drought index: Factoring effects of rainfall variability. Mitig Adapt Strateg Glob Change, 19(8), 1139-1162. (2014). https://doi.org/10.1007/s11027-013-9464-0

McKee, T. B., Doesken, N. J., & Kleist, J. (1993, January). The relationship of drought frequency and duration to time scales. 8th. Conference on Applied Climatology, Anaheim, California.

McKee, T. B., Doesken, N. J., & Kleist, J. (1995, January). Drought Monitoring with Multiple Time Scales. 9th Conference on Applied Climatology, Dallas. Texas.

Merkoci, A. L., Mustaqi, V., Mucaj, L., & Dvorani, M. (2013). Drought and implementation of Standardised Precipitation Index (Spi) on The Albanian Territory. Journal of the Faculty of Engineering and Architecture of Gazi University, 28(1), 161-166.

Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. Journal of Hydrology, 391(1-2), 202-216. https://doi.org/10.1016/j.jhydrol.2010.07.012

Mishra, A. K., & Singh, V. P. (2011). Drought modeling- a review. Journal of Hydrology, 403(1-2), 157-175. https://doi.org/10.1016/j.jhydrol.2011.03.049

Nalbantis, I. (2008). Evaluation of a hydrological drought index. European Water, 23(24), 67-77.

Nalbantis, I., & Tsakiris, G. (2009). Assessment of Hydrological Drought Revisited. Water Resources Management, 23(5), 881-897. https://doi.org/10.1007/s11269-008-9305-1

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models. I. A discussion of principles. Journal of Hydrology, 10, 282-290. https://doi.org/10.1016/0022-1694(70)90255-6

Oguzturk, G. (2010). A drought analysis of the Kızılırmak basin using the standardized precipitation index (SPI) method and drought estimation using the artificial neural networks method. MSc Thesis, Kırıkkale University, Kirikkale, Turkey.

Oguztürk, G., & Yıldız, O. (2016). Assessing hydrological responses to droughts in the Hirfanli dam basin, Turkey. International Journal of Advances in Mechanical and Civil Engineering, 3(5),116-123.
Palmer, W. C. (1960). Meteorological Drought. Research Paper No.45, US.
Oyebode, O. & Stretch, D. (2019). Neural network modeling of hydrologicalsystems: A review of implementation techniques. Natural Resource Modeling, 32(1), 1-14. https://doi.org/10.1002/nrm.12189
Poornima, S., & Pushpalatha, M. (2019). Drought prediction based on SPI and SPEI with varying timescales using LSTM recurrent neural network. Soft Comput, 23(18), 8399-8412. https://doi.org/10.1007/s00500-019-04120-1
Salinger, J. (1995). Conditions leading to drought in New Zealand. Water Atmosphere, 3(1), 11-12.
Selçuk, D. (2017). Drought analysis and estimation in Kizilirmak basin using hydrometeorological parameters. Master's thesis, Ondokuz Mayıs University, Samsun, Turkey.
Shin, C. S., Huang, B., Dirmeyer, P. A., Halder, S., & Kumar, A. (2020). Sensitivity of U.S. Drought Prediction Skill to Land Initial States. Journal of Hydrometeorology, 21(12), 2793-2811. https://doi.org/10.1175/JHM-D-20-0025.1
Sırdas, S. (2002). Meteorological drought modelling and application to Turkey. Doctoral thesis, Istanbul Technical University, Istanbul, Turkey.
Soleimani H, Ahmadi H, & Zehtabian G. 2013. Comparison of temporal and spatial trend of SPI, DI and CZI as important drought indices to map using IDW Method in Taleghan watershed. Annals of Biological Research, 4(6), 46-55.
Sönmez, F. K., Komuscu, A. U., Erkan, A., & Turgu, E. (2005). An analysis of spatial and temporal dimension of drought vulnerability in Turkey using the standardized precipitation index. Natural Hazards, 35(2), 243-264. https://doi.org/10.1007/s11069-004-5704-7
Şen, Z. (2004). Yapay Sinir Ağları İlkeleri. İstanbul: Su Vakfı Yayınları.
Tabari, H., Abghari, H., & Talaee, H. (2012). Temporal trends and spatial characteristics of drought and rainfall in arid and semiarid regions of Iran. Hydrological Processes, 26, 3351-3361. https://doi.org/10.1002/hyp.8460
Tallaksen, L. M., & Van Lanen, H. A. J. (2004). Hydrological Drought: Processes and estimation methods for streamflow and groundwater. Elsevier, Netherlands.
Tanoglu, A. (1943). Indices D'aridite De La Turquie. Turkish Geographical Review, 1, 36-41.
Taylan, E.D., Terzi, Ö., & Baykal, T. (2021). Hybrid wavelet–artificial intelligence models in meteorological drought estimation. J Earth Syst Sci, 130(1), 1-13. https://doi.org/10.1007/s12040-020-01488-9
Thom, H. C. S. (1958). A note on the gamma distribution. Monthly Weather Review, 86(4), 117-122.
The Scientific and Technological Research Council of Turkey (TUBITAK) (2010) Havza Koruma Eylem Planlarının Hazırlanması-Yesilirmak Havzası, 557 pp (in Turkish).
White, D. H., & Walcott, J. J. (2009). The role of seasonal indices in monitoring and assessing agricultural and other droughts: a review. Crop and Pasture Science, 60, 599–616. https://doi.org/10.1071/CP08378
Wilhite, D. A. (2000). Drought: A global assessment. Routledge Press, London and New York, Volume I.
Yacoub, E., & Tayfur, G. (2017). Evaluation and assessment of meteorological drought by different methods in Trarza region, Mauritania. Water Resour Manage, 31, 825-845. https://doi.org/10.1007/s11269-016-1510-8
Yacoub, E., & Tayfur, G. (2020). Spatial and temporal of variation of meteorological drought and precipitation trend analysis over whole Mauritania. Journal of African Earth Sciences, 163, 1-12. https://doi.org/10.1016/j.jafrearsci.2020.103761
Zhang, G., Patuwo, B.E., & Hu, M. Y. (1998). Forecasting with artificial neural networks: the state of the art. Int J Forecast, 14(1), 35-62. https://doi.org/10.1016/S0169-2070(97)00044-7