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Estimation of Drought by Streamflow Drought Index (SDI) and Artificial Neural Networks (ANNs) in Ankara-Nallihan Region

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ARTICLE INFO	ABSTRACT
	In this study, it is aimed to predict drought in Nallihan region by using streamflow drought index and artificial neural network method which is a part of artificial intelligence approaches. The measured data of some meteorological stations (Nallihan, Beypazari, Mihaliccik, Catacik, Goynuk, Mudurnu, Seben and Eskisehir) in the Sakarya Basin and the Nallihan streamflow observation station between 1996 and 2015 were used to forecast 2015-2030 streamflow values. The correlation coefficient in the education and test stages of the ANN model was realized with a high consistency of 0.990 and 0.967, respectively. According to the mean absolute error method, the error performance values of ANN model are 0.19 for the training phase and 0.26 for the test phase. Cumulative streamflow series were created for the reference periods (k1, October-December; k2, October-March; k3, October-June; k4, October-September) and the streamflow drought index values were obtained using measured and predicted values. According to these values, mild droughts were more frequent between 1997-2015 and 2016-2030, but the number of moderate and severe droughts increased gradually. It is predicted that in the future, it may be seen in extreme arid periods in the region. Drought in the 6-month period between October and March is similar to the average of all periods for 1997-2015 and 2016-2030. The use of 6-month drought data for the streamflow drought index is expected to be useful in predicting future drought.

Ankara Nallıhan Bölgesinde Akarsu Kuraklık İndeksi Ve Yapay Sinir Ağları Kullanılarak Kuraklığın Tahmini

MAKALE BİLGİSİ	ÖZ
	Bu çalışmada, yapay zekâ yaklaşımlarının bir parçası olan yapay sinir ağları ve akarsu kuraklık indeksi yöntemi kullanılarak, Nallıhan bölgesinde yaşanabilecek olası kuraklığın tahmin edilmesi amaçlanmıştır. Çalışmada, Sakarya Havzası'nda yer alan Nallıhan, Beypazarı, Mihalıççık, Çatacık, Göynük, Mudurnu, Seben ve Eskişehir meteoroloji istasyonları ve Nallıhan akım gözlem istasyonuna ait 1996-2015 yılları arasındaki veriler kullanılarak 2015-2030 yılları arasında oluşabilecek akımlar tahmin edilmiştir. ANN modelinin eğitim ve test aşamalarındaki korelasyon katsayısı sıra ile 0.990 ve 0.967 düzeyinde yüksek bir tutarlılıkla gerçekleşmiştir. ANN modelinin ortalama mutlak hata yöntemine göre hata performans değerleri, eğitim aşaması için 0.19 ve test aşası için 0.26'dır. Geçmiş ve YSA modeli kullanılarak elde edilen gelebilecek akım verileri kullanılarak su yılını oluşturan referans periyotlar (k1, Ekim-Aralık; k2, Ekim-Mart; k3, Ekim-Haziran; k4, Ekim-Eylül) için birikimli akım serileri oluşturulmuş ve akarsu kuraklık indeksi değerleri elde edilmiştir. Bu değerlere göre, 1997-2015 ve 2016-2030 arasında hafif kuraklık daha fazla görülmüş, ancak, orta şiddetli ve şiddetli kuraklıkların sayısı giderek artmıştır. Gelecekte bölgede, aşırı kurak dönemlerinde görülebileceği tahmin edilmektedir. Ekim-Mart arasındaki 6 aylık periyotta yaşanan kuraklıklar, 1997-2015 ve 2016-2030 yılları için benzer şekilde tüm periyotların ortalamasına yakın seyretmektedir. 6 aylık kuraklık verilerinin akarsu kuraklık indeksi için gelecekteki kuraklık tahmininde kullanılmasının faydalı olacağı düşünülmektedir.

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Introduction

Drought differs from other natural disasters due to the difficulty of determining the beginning and ending and the absence of an emergency. It gradually increases its strength and can continue its effect even years after the end of the activity. The effects of drought are generally seen in agriculture and gradually spread to other water-dependent sectors.

Drought is generally classified in three stages as meteorological, agricultural and hydrological drought. Meteorological drought is defined as the rainy periods observed below the average in a given period of time (Agnew, 1990). Agricultural drought is described by Agnew and Warren (1996) as a period of significant reduction in agricultural production as a result of the lack of moisture in the soil. Hydrological drought is defined as the level drop in surface and groundwater (Palmer, 1965).

In many regions of Turkey, even if the precipitation is above average, it is quite difficult to meet the water needed by the plant in the period when the plant production is done. Plant grading period and rainfall should be evaluated together in grading and determining the duration of drought. The assessment of drought severity requires the determination of effective precipitation by considering soil moisture and plant conditions, rather than simply lack of total precipitation (Wilhite and Glantz, 1985).

Agricultural production decreases significantly during dry times and even short-term periods without rainfall can cause serious problems for farmers. In this regard, it is very important to know the dry period in the plant growing period besides the irrigation time (Unlukara et al., 2010). Precise and accurate estimation of drought plays an important role in the solution of the socio-economic problems caused by drought and taking measures.

In our daily lives, technological products such as telephones, computers, etc. have an important place. Computers have been developed to perform detailed, long and time-consuming calculations. With developments in software, they evolved into intelligent systems that can learn the connections between events, make comments and make decisions. (Ogucu, 2006).

Problems with complex structure and uncertainties can be solved by some developed methods or algorithms. Inspired by the learning and decision-making mechanisms of the human brain, these methods are included in the studies called artificial intelligence. These studies led to the emergence of different approaches and hence different methods. Artificial intelligence technologies can be examined under two headings. These are traditional (expert systems and case-based reasoning) and computational based artificial intelligence (artificial neural networks-ANNs, fuzzy logic and evolutionary calculation) approaches (Ogucu, 2006).

When the studies are examined, it is understood that using ANN within the scope of artificial intelligence applications can be used to reach more effective results in the control of physical systems, engineering problems, water resources management and operation, hydrology, material to examine the behaviour, to model the experimental design for statistical evaluation, to correlate the data obtained in experimental studies with the results, to group the results of the clustering analysis, to analyse

the data, the development of diagnosis and treatment methods in basic areas such as civil engineering, chemistry, biochemistry, physics, biotechnology, biomedical and medicine (Akpolat, 2014).

To date, many studies have been done using ANN in the fields of hydrology. McKee et al. (1993), taking into account the drought in Colorado, proposed the Standardized Precipitation Index (SPI) for drought monitoring. Wilhite (1996) proposed a planning process consisting of ten stages that countries can follow to prepare for drought. Keyantash and Dracup (2002) examined the strengths and weaknesses of 14 different drought indexes. Chantasut et al. (2004) have made the precipitation forecast in Thailand using the ANN technique and data obtained from the rainfall monitoring stations. Morid et al. (2007) calculated the Effective Drought Index (EDI) and SPI values using the rainfall data obtained from the 6 precipitation stations in Tehran- Iran and the ANN method. Bacanli et al. (2008) developed models using SPI and monthly mean rainfall to make drought predictions and investigated the feasibility of adaptive neuro-fuzzy inference system (ANFIS) for drought prediction. Illeperuma and Sonnadara (2009) used artificial neural networks in the prediction of drought for Sri Lanka. Yurekli et al. (2010) aimed to determine the drought according to SPI, RDI and EDI index in Karaman province. Abarghouei et al. (2011) used ANN to estimate drought in the extremely dry Ardakan region of Iran. Yu et al. (2013) calculated 3 and 12 months SPEI using the observed monthly precipitation and air temperature values from 609 locations in China. Anli (2014) conducted a meteorological drought analysis using temporal change of the ETo and RDI parameters in the Southeastern Anatolia Region. Maca and Pech (2016) compared drought indices estimates based on 2 different ANN models. Monthly rainfall, potential plant water consumption, Southern Oscillation Index and Nifio 4 index were used as input and estimated monthly standard precipitation index by applying artificial neural networks by Dayal et al. (2016) in Australia. Agana and Homaifar (2017) examined the use of deep learning algorithms in drought predictions. Katip (2018) determined the meteorological drought in Bursa province by SPI index and ANN method. Sonmez et al. (2018) used ANFIS model to predict Cadmium (Cd) concentrations in the Filyos River.

Nallihan region is located in Sakarya basin. County is composed of 18% is agriculture, 51% is forest, 3% is meadow and pasture, 28% is non-agricultural area. Ceylan et al. (2009) examined the changes in areas prone to desertification. According to results of their study, Nallihan is among the semi-arid-very arid regions. Within the boundaries of Ankara, among the Ankara, Kizilcahamam, Nallihan, Beypazari and Polatli stations, Nallihan has the lowest average rainfall (Karakoc and Tagil, 2014).

ANN is an approach that changes the weights of input data by the ratio of the forces that affect the output, and then transfers it to the output by using the activation function, then it is a frequently used method in basin modelling in recent years (Maier and Dandy, 2000). In this study, future streamflow estimation will be made by using

streamflow, meteorological parameters and artificial neural networks in Nallihan region and the past and possible future drought status will be examined by SDI method according to the results obtained.

Materials and Methods

Materials

In this study, which is made by using artificial neural networks, meteorological data obtained from Nallihan, Beypazari, Mihaliccik, Catacik, Goynuk, Mudurnu, Seben and Eskisehir stations of Turkish State Meteorological Service (TSMS) (Figure 1) and streamflow data of Nallihan streamflow gauging station belonging to The General Directorate of Hydraulic Works (DSİ) were used.

Nallihan district is located in the west of Ankara and is surrounded by Beypazari in the east, Goynuk in the northwest, Mudurnu-Seben in the north, Saricakaya in the west, Eskisehir and Mihaliccik in the south. The distance to Ankara is 160 km. It was founded on the edge of Nallihan Stream. Its surface area is 1978 km² and its altitude is 625 meters above sea level. At the junction of the Sariyar Dam in Nallihan with the Aladag Stream, there is the Nallihan Bird Sanctuary, an artificial wetland. Nallihan region and the location of the streamflow gauging station is shown in Figure 1, and the duration curve of streamflow of 1997-2015 is shown in Figure 2.

Nallihan has a semi-arid climate. The average temperature in Nallihan is 12.1°C. Nallihan's climate shows the characteristics of Central Anatolia and the Western Black Sea climate. Although spring, autumn and winter are rainy, there is not much rainfall in summer. Winters are not too cold and rainy. Most precipitation falls in December.
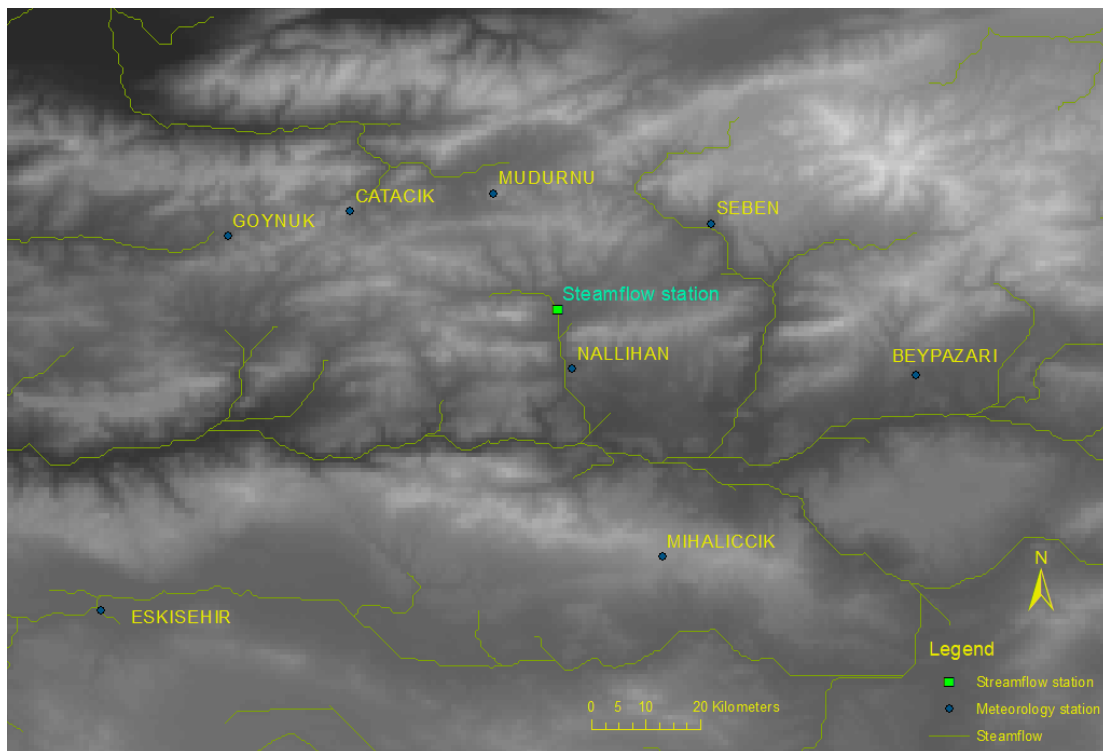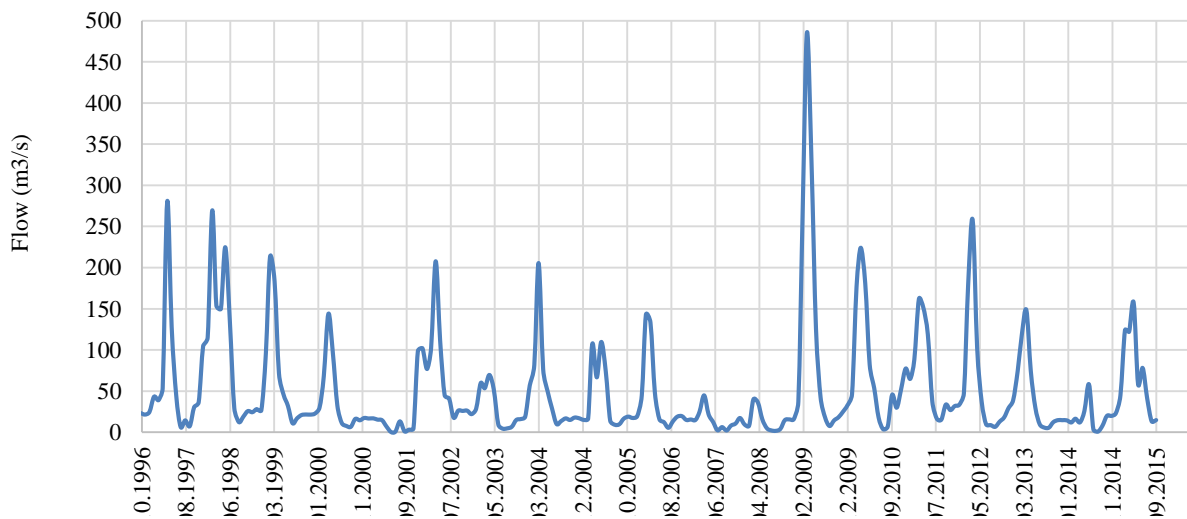

Figure 1. Location of Nallihan region

Figure 2. Streamflow time series of Nallihan River

Methods

Artificial neural networks

ANN can be defined as mathematical modelling of the biological process taking place in the stages of reasoning, learning, recall, evaluation, interpretation and generalization and decision-making. It consists of neural units called neurons. By placing these neurons in different layers, the most appropriate architecture is obtained for the solution of the problem (Haykin, 1999). When this system works; learning, memorizing, establishing a relationship between the data and information, such as forecasting-inference takes place. ANN is especially applicable to various industrial problems due to its success in processing incomplete, ambiguous, complex and fuzzy information. Due to their structure, they can work very quickly, especially in real time events (Bayir, 2008).

In ANN, there are basically three different layers: the input layer, the hidden layers, and the output layer. The neurons in the input layer accept inputs to the problem, while those in the output layer produce the desired result of the problem. For each different input and output type, there is a neuron. The term "hidden" refers to the fact that this part of the neural network is not seen directly from either the input or output of the network. The function of hidden neurons is to intervene between the external input and the network output in some useful manner. By adding one or more hidden layers, the network is enabled to extract higher-order statistics from its input. The hidden units are not part of the output or input of the network hence their designation as "hidden." The first hidden layer is fed from the input layer made up of sensory units (source nodes); the resulting outputs of the first hidden layer are in turn applied to the next hidden layer; and so on for the rest of the network. The activation function in the hidden layer is a sigmoid type function, with widespread use (Haykin, 1999).

Input data in ANN is x_1, x_2, ..., x_N that data used for network learning. The weights are w1, w2, ..., wN and indicate the effect of the corresponding inputs on the output. These correspond to the long-term memory in the ANN and the learning process in the ANN takes place by repeatedly adjusting these weights. The activation function threshold prevents the value of the processing elements and the output of the network from being zero. The activation function converts the received data to the output by means of an algorithm (Demirer et al., 2010). There are various options such as Weighted Total, Product, Maximum, Minimum, Majority and Cumulative total as the merge function. There is no formula found to determine the optimal coupling function for a problem. In general, the joining function is determined by using the trial and error method (Oztemel, 2006).

There is no an optimal value for the hidden layer and the number of neurons in this layer. Although these values differ according to the problem, usually the single hidden layer is sufficient for solving almost all problems (Haykin, 1999).

A large secret layer of education may result in the reduction of the generalization ability of the educational set, in other words, excessive learning. If excessive learning occurs, the number of units in the hidden layer can be reduced or the number of units in the hidden layer can be increased if the training results are not at the desired level (Mehrotra et al., 1997).

In ANN models, the data set is divided into two parts, usually training and testing, at a rate of 0.70 and 0.30, respectively. After the training and data sets have been determined, the architecture of the network can be designed first, starting with a simple architectural structure, and architectures that are more complex can be designed by revising the network structure to reach the optimum results by trial and error.

During the training phase of the ANN, these weights are changed by revising them to obtain the desired outputs against the input values of the problem. At this stage, some of the data containing both input and output are used from the data of the problem. During the training process, ANN sees all data. However, during the test phase, the ANN generates outputs of data that it has never seen before. If successful at this stage, ANN is said to be appropriate for the given problem.

At the end of the training and testing, the outputs produced by the ANN method are compared with the measured values of the problem. A low error in the training period does not mean that the network is always healthy. Even the total error near zero is an undesirable situation because it is an over-learning indicator. Because in such cases, ANN becomes more dependent on the educational set (Cura, 2008).

Python language was used to model the study with artificial neural networks. The model consists of 2 hidden layers with 200 and 150 neurons respectively. Relu was used as activation function and Adam algorithm was used for optimization. The streamflow data used as input data were delayed up to 7 days.

Walk forward forecast and validation

In practice, the ANN model will be retrained as new data becomes available. This would give the model the best opportunity to make good forecasts at each time step. There are two ways to make a decision. The first one is minimum number of observations. Minimum number of observations required to train the model must be determined. This may be thought of as the window width if a sliding window is used. The second one is size of sliding or expanding window. Whether the model will be trained on all data it has available or only on the most recent observations. This determines whether a sliding or expanding window will be used. After a sensible configuration is chosen for test-setup, models can be trained and evaluated.

Starting at the beginning of the time series, the minimum number of samples in the window is used to train a model. The model makes a prediction for the next time step. The prediction is stored or evaluated against the known value. The window is expanded to include the known value and the process is repeated. Because this methodology involves moving along the time series one-time step at a time, it is often called Walk Forward Forecast (or Validation). Additionally, because a sliding or expanding window is used to train a model, this method is also referred to as Rolling Window Analysis or a Rolling Forecast.

The performance of the model was determined by correlation coefficient, Nash-Sutcliffe coefficient (NS), mean absolute error (MAE) and root mean square error (RMSE) values.

Stream drought index (SDI) method

In the study, the stream drought index (SDI) was used to determine the hydrological drought in Nallihan region. The streamflow data observed in streamflow gauging station shown in Figure 1 were used in the study.

If the streamflow of any hydrological year (i), any month (j) is defined as Qij, the time series of cumulative streamflows ($V_{i\ k}$) can be obtained by equation 1:

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

$V_{i,k}$ gives the cumulative flow amount for the *k*-reference period of the hydrological year *i*. N indicates the number of hydrological years.

K-reference period;
k = 1 means the October-December period,
k = 2 is the period of October-March,
k = 3 for October-June period,
k = 4 means the period of October-September.

The cumulative flows from October to September represent annual flows.

SDI is obtained from equation 2 for cumulative stream flows ($V_{i,k}$) for each hydrological year, depending on each k-reference period:

$$SDI_{i,k} = \frac{V_{i,k} - \overline{V_k}}{S_k} \qquad (2)$$

$i = 1, 2, \ldots N$
$k = 1, 2, 3, 4$

Results and Discussion

In this study, daily meteorological data (rainfall, humidity, wind and temperature data) from Nallihan, Beypazari, Mihaliccik, Catacik, Goynuk, Mudurnu, Seben and Eskisehir stations of the Turkish State Meteorological Service (TSMS) and data observed from Nallihan streamflow gauging station of The General Directorate of State Hydraulic Works (DSİ) were used. Spatial mean of meteorological parameters of Nallihan area was calculated by using meteorological data measured at eight meteorological stations and spatial interpolation method proposed by Apaydin et al. (2004) was applied. 7-day backward flow data in daily steps was used as input data for the artificial neural network modelled using Python language. As a result, forward flow data were estimated. With the observed daily flow data for October 1996-September 2015 period, the training and testing phase of ANN was completed (Figures 3a and 3b). Then, the daily flows that may occur for October 2015-September 2030 period are estimated in 1-day steps and by adding the estimated 1-day data to the historical data, n + 1 day data is obtained and the next day's flow data is estimated (Figure 4). The correlation coefficients of the model in the train and test stages were realized at a high consistency of 0.990 and 0.967, respectively. According to Chiew et al. (1993), the simulation is Nash-Sutcliffe coefficient (NS)> 0.90, whereas the simulation is very acceptable; if 0.60 <NS <0.90, acceptable and NS <0.60 the simulation is classified

$\overline{V_k}$ and $\overline{S_k}$ give the mean and standard deviation amounts of the cumulative streamflows for the k-reference period. Equation 2 is used when the time series of cumulative streamflows obtained for the k-reference period shows normal distribution. Therefore, the normality test should be performed to determine whether the cumulative streamflows have a normal distribution. Okman (1994) stated that the hydrological variables generally show a displacement shifted to the right. If the cumulative time series does not show a normal distribution, the 2-parameter gamma distribution is applied to the data and converted to the standard normal distribution. Nalbantis and Tsakiris (2009) also made logarithmic transformations of the cumulative streamflows obtained to ensure that the data conform to the normal distribution. In this study, data sets performed with Lognormal Distribution (LN), The 3-Parameter Lognormal Distribution (LN3), The 2-Parameter Gamma Distribution (G2), The 3-Parameter Gamma Distribution (G3-PE3), Log Logistic Distribution (LLO) and The 3-Parameter Log Logistic Distribution (3-LLO) (Table 3 and 4). Drought categories of stream drought index are given in Table 1.

Table 1. Stream drought index categories

Drought Category	SDI
Non drought	SDI ≥ 0.0
Mild drought	-1.0 ≤ SDI < 0.0
Moderate drought	-1.5 ≤ SDI < -1.0
Severe drought	-2.0 ≤ SDI < -1.5
Extreme drought	SDI < -2.0

as unacceptable. NS values in the study were above 0.90 in both train and test stages (Table 2). Input data were standardized by using different standardization methods from -1 to 1 and used in the model. Accordingly, among the original data series and standardized data series, the most optimum data set based on regression and error performance was selected and used in the SDI calculations (Table 2).

Using the observed data from the stations and forecasted data from ANN, cumulative flow data for the reference periods of October-December, October-March, October-June and October-September were obtained (Figures 5 and 6).

The distribution type and function of this distribution, which is the most compatible with the cumulative flow data series, were determined. The best fit distributions to the data sequences were shown in bold in Tables 3 and 4, and optimum value was selected considering the probability value of P and the Anderson Darling (AD) test.

The cumulative flow series were consistent with the lognormal distribution in all reference periods for the years 1997-2015. For the years 2016-2030, all series except the October-December reference period were found to be compatible with normal distribution and weibull distribution. Observed data were consistent with LN, G2 and LLO distribution in all periods. SDI can also be calculated according to these distributions.

Table 2. Performance values of ANN Model

Data	LR*	DE*	Epoch	CC		NS		RMSE		MAE	
				Train	Test	Train	Test	Train	Test	Train	Test
OF	0.01	0.0001	300	0.9826	0.9556	0.9602	0.9072	0.5318	0.6518	0.3320	0.3936
OF	0.01	0.0001	500	0.9902	0.9672	0.9800	0.9354	0.3766	0.5438	0.1932	0.2664
OF	0.1	0.01	500	0.9757	0.9685	0.9510	0.9377	0.5903	0.5341	0.2144	0.2545
SF	0.01	0.01	500	0.9661	0.9248	0.8238	0.7497	0.4437	0.4242	0.3813	0.3547
SF	0.01	0.0001	500	0.9902	0.9670	0.9801	0.9350	0.1487	0.2161	0.0729	0.1034
SF	0.01	0.0001	300	0.1865	0.1539	-1.13E+16	-1.98E+16	1.79E+16	1.90E+16	1.65E+15	1.79E+16

*LR: Learning rate, DE: Decay; OF: Original flow; SF: Standardized flow

Table 3. Distribution Parameters for Observed Data

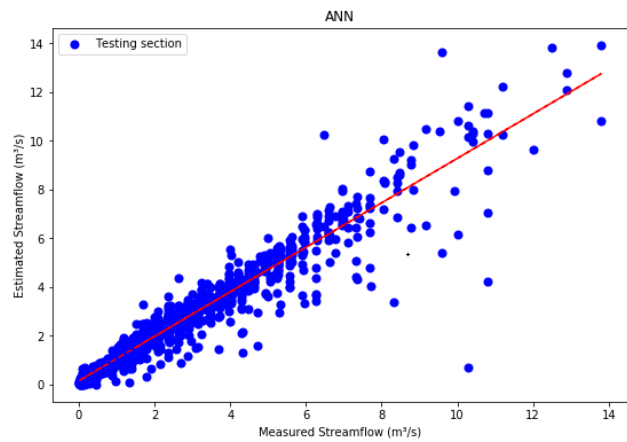|	Measured (1997-2015)							
Period	October-December		October -March		October -June		October -September	
Distribution	P	AD	P	AD	P	AD	P	AD
Normal	<0.008	1.128	0.066	0.674	0.360	0.884	0.408	0.361
LN	0.422	0.355	0.424	0.355	0.062	0.683	0.056	0.703
LN3	*	0.408	*	0.396	*	0.357	*	0.363
G2	0.162	0.568	>0.250	0.302	>0.250	0.444	>0.250	0.465
G3-PE3	*	0.322	*	0.309	*	0.325	*	0.345
Weibull	0.019	0.897	>0.250	0.322	>0.250	0.347	>0.250	0.358
LLO	>0.250	0.275	>0.250	0.362	0.073	0.607	0.063	0.627
3LLO	*	0.105	*	0.409	*	0.323	*	0.331

LN: Lognormal Distribution; LN3: The 3-Parameter Lognormal Distribution; G2: The 2-Parameter Gamma Distribution; G3-PE3: The 3-Parameter Gamma Distribution; LLO: Log Logistic Distribution; 3 LLO: The 3-Parameter Log Logistic Distribution; P: Probability Value; AD: Anderson Darling Test Value

Table 4. Distribution Parameters for Estimated Data

	Forecast (2016-2030)							
Period	October-December		October -March		October -June		October -September	
Distribution	P	AD	P	AD	P	AD	P	AD
Normal	0.025	0.828	0.175	0.501	0.111	0.578	0.084	0.624
LN	0.181	0.496	<0.005	1.219	<0.005	1.308	<0.005	1.318
LN3	*	0.497	*	0.516	*	0.587	*	0.631
G2	0.192	0.533	0.017	0.965	0.009	1.054	0.008	1.079
G3-PE3	*	0.639	*	2.628	*	5.354	*	5.846
Weibull	0.017	0.919	0.101	0.605	0.123	0.582	0.136	0.569
LLO	>0.250	0.383	0.008	0.941	0.009	0.921	0.009	0.913
3LLO	*	0.390	*	0.430	*	0.438	*	0.453
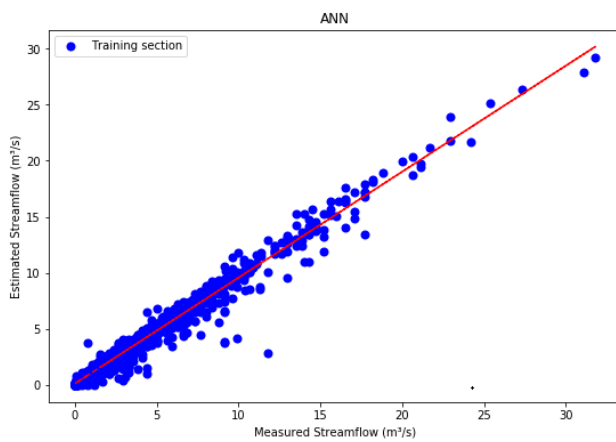
(a)   (b)

Figure 3a. Measured and Estimated Flow Data at Training Phase
Figure 3b. Measured and Estimated Flow Data at Test Phase
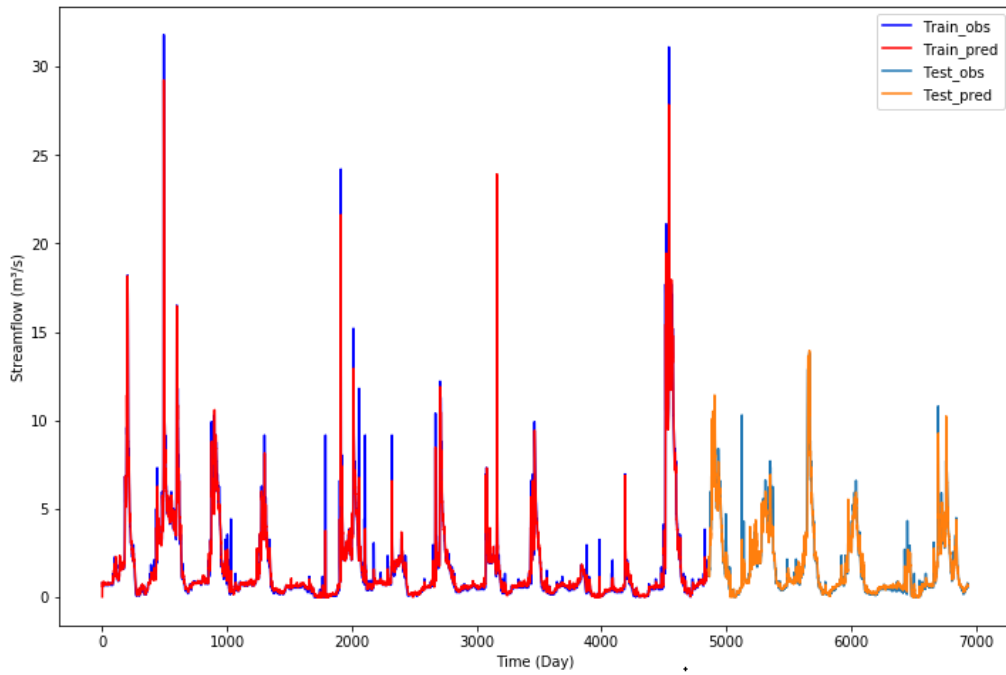
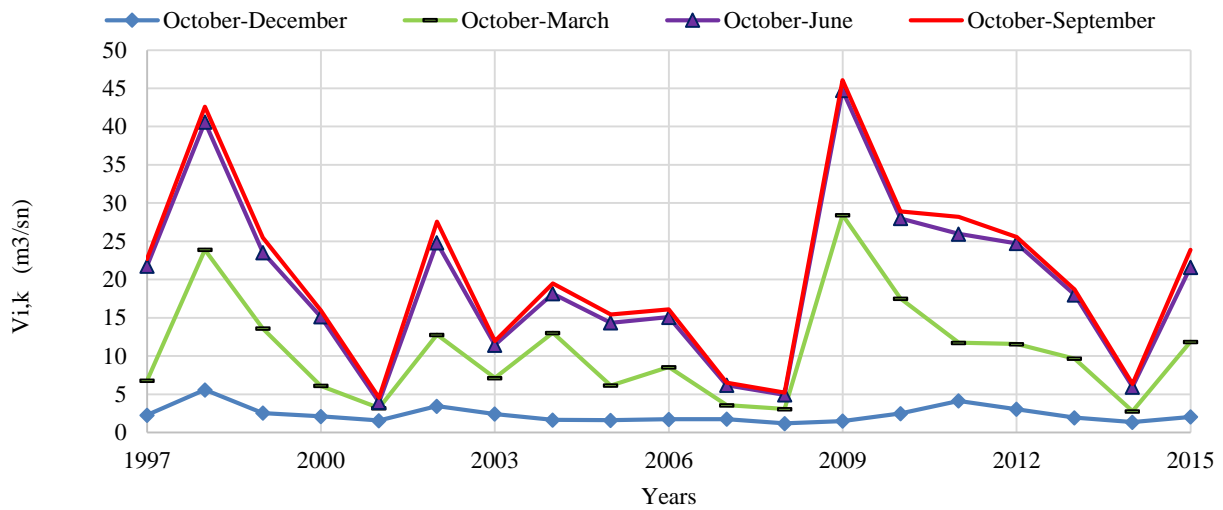Figure 4. Train and test phase of ANN

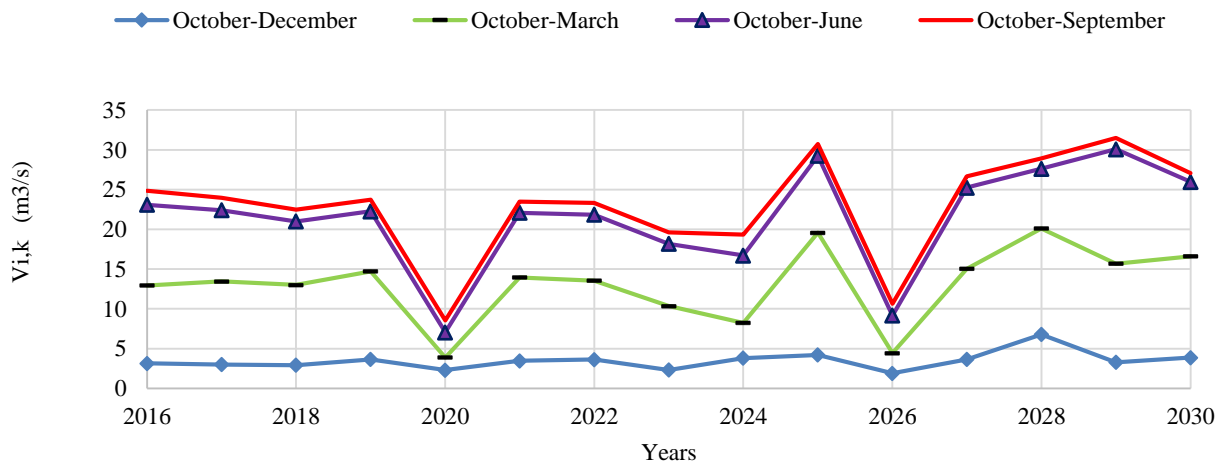Figure 5. Cumulative Observed Flow Data for the 1997-2015 Period

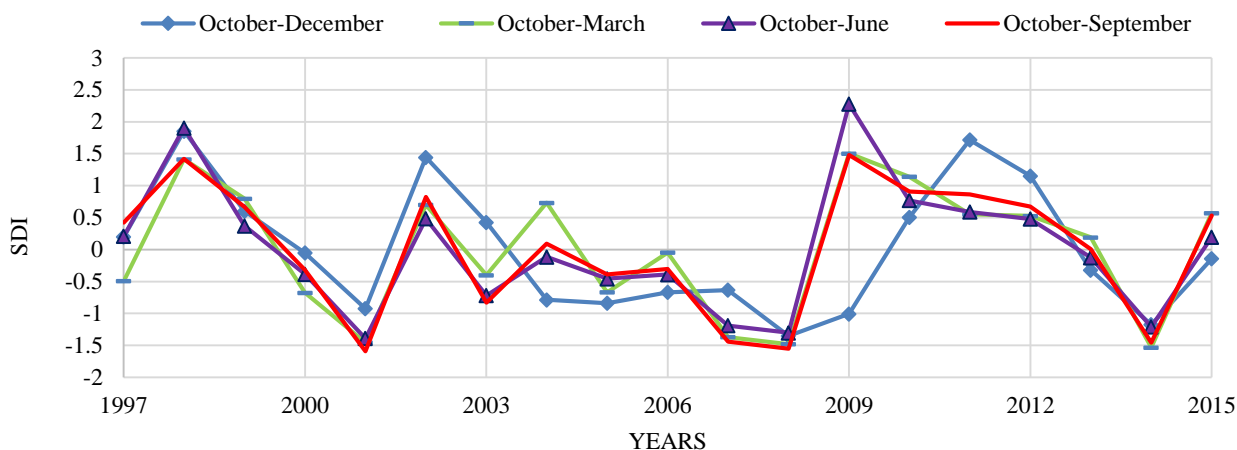Figure 6. Cumulative Forecasted Flow Data for the 2016-2030 Period
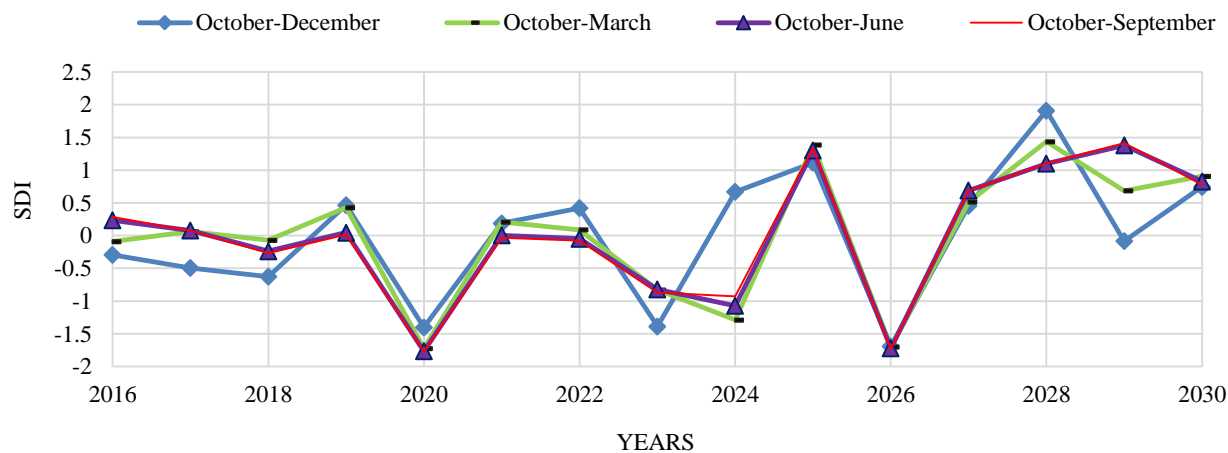
Figure 7. SDI values for the 1997-2015 Period

Figure 8. SDI values for the 2016-2030 Period

The transformed cumulative flow data, mean and standard deviations of these data were calculated according to the normal distributions for the period 1997-2030 and SDI drought index values were obtained using equation 2 and the results are given in Figures 7 and 8.

It is seen that drought values are very close to each other and follow a similar trend in 9-month (October-June) and 12-month (October-September) periods. Accordingly, it can be said that July, August and September do not affect annual drought very much.

The drought trend was similar for the 3, 6, 9 and 12-month periods until 2002, while the similarity continued for the 6, 9 and 12-month periods between 2004 and 2011, and the tendency of the 3-month period varied. This difference shows that especially between 2004-2010 the October-December period was less rainy than the previous years.

After 2012, the tendency of all four periods showed similarity again. The year 2009 was the wettest year out of a 3-month period, while a dry period was entered after 2012. Between 1997 and 2015, mild droughts were experienced, moderate to severe droughts, but no extreme

dry periods. It can be said that the dry and wet periods alternate with an average of 3 years interval.

During the October-December period, there were 8 wet periods, 8 mild droughts and 3 moderate droughts. During the October-March period, there were 10 wet periods and 5 mild droughts, 3 moderate droughts and 1 severe drought. During the October-June period, there were 9 wet periods, 6 mild droughts and 4 moderate droughts. During the October-September period there were 11 wet periods, 4 mild droughts, 2 moderate droughts and 2 severe droughts. The longer the period time scales, the higher the number of moderate and severe dry periods. The higher number of wettest period was observed in the 12-month period of October-September. The longest dry periods were experienced between 2003 and 2008 and as the duration increased, the drought severity increased.

When the results of drought forecasts between 2016-2030 are considered, it is seen that dry periods are expected in the region until 2024, and that after 2027, a markedly wet period will be entered. The drought trend between 3, 6, 9 and 12 monthly time scales between 2016-2030 is very close. Severe droughts are expected in the region in 2020

and 2026. According to forecast results, the 8 wet periods, 4 mild drought, 2 moderate and 1 severe drought are expected in 3 months period. 9 wet periods, 3 mild drought, 1 medium severe and 2 severe drought are expected in in 6 and 9 month periods, 8 wet periods, 5 light droughts and 2 severe droughts are expected in 12 months period.

Conclusion

In this study, the drought in Nallihan region was predicted by using SDI and ANN method which is a part of artificial intelligence approaches. The meteorological data recorded at 8 different stations in Sakarya Basin between 1996 and 2015 and daily streamflow data observed from Nallihan station were used. The ANN method used for the prediction of future stream data has yielded quite good results. Average monthly streamflow data were calculated from input data and cumulative flow for 3, 6, 9 and 12 monthly time scales for reference periods (k1, October-December; k2, October-March; k3, October-June; k4, October-September) series were obtained.

SDI values were calculated by determining the optimal distribution for each series. When the drought index results obtained by using observed data between 1997-2015 and forecast data between 2016-2030 were evaluated, mild drought was observed more in both periods, but the number of moderate and severe droughts has gradually increased with time. It is predicted that in the future, it may be seen in extreme arid periods in the region. Drought in the 6-month period between October and March is similar to the average of all periods for 1997-2015 and 2016-2030. The use of 6-month drought data for the SDI index is expected to be useful in predicting future drought. It may be suggested to prepare a regional drought action plan in order to monitor drought in the region and to take precautions for possible meteorological, agricultural and socioeconomic drought.

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