

## Meteorological Drought Estimation by Wavelet-Gen Expression Programming: Case Study of Çanakkale, Türkiye

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### ABSTRACT

The differences in duration and amount of precipitation significantly affect the drought due to global climate change in the last decades. Therefore, drought is one of the parameters to be considered for sustainable water resources studies. In this study, firstly, by using historical precipitation records between the years 1975-2010, the drought indices of 3-, 6-, 9- and 12- months of Çanakkale, Bozcaada, and Gökçeada stations were determined with the standardized precipitation index (SPI). Then, gene expression programming (GEP) models were developed in which the drought values of Bozcaada and Gökçeada stations were selected as input parameters for the drought prediction of Çanakkale province. In addition, W-GEP models were developed using a sub-series of the same inputs produced with wavelet transform (W). Examining the developed models, the determination coefficients ( $R^2$ ) for the 6-, 9- and 12-months periods were generally higher than 0.80 for GEP and W-GEP models. In contrast, the  $R^2$  value for the 3- month period was approximately 0.657 and 0.704, respectively. The highest  $R^2$  value was determined as 0.868 for the W-GEP model during the 6- month period. As a result, the GEP and W-GEP approaches were found to be successful in the estimation of drought.

**Keywords:** Çanakkale, drought, GEP, SPI, wavelet transform

## Dalgacık-Gen İfade Programlama ile Meteorolojik Kuraklık Tahmini: Çanakkale Örneği

### ÖZ

Son yıllardaki küresel iklim değişikliğinden dolayı, yağış miktarı ve süresindeki farklılıklar kuraklık üzerinde büyük etkiye sahip olmaktadır. Bu nedenle, sürdürülebilir su kaynakları çalışmalarında kuraklık dikkate alınması gereken parametrelerden biridir. Bu çalışmada, ilk olarak, 1975-2010 yılları arasında bulunan tarihi yağış kayıtları kullanarak Çanakkale, Bozcaada ve Gökçeada istasyonlarının standart yağış indisi (SYİ) ile 3-, 6-, 9- ve 12- aylık kuraklık indisi belirlenmiştir. Daha sonra, Çanakkale ilinin kuraklık tahmini için Bozcaada ve Gökçeada istasyonlarının kuraklık değerlerinin girdi parametreleri olarak seçildiği gen ifade programlama (GEP) modelleri geliştirilmiştir. Ayrıca, aynı girdilerin dalgacık dönüşümü (D) ile üretilen alt serileri kullanılarak D-GEP modelleri üretilmiştir. Geliştirilen modeller incelendiğinde, 6-, 9- ve 12- aylık dönemlere ait belirleyicilik katsayıları ( $R^2$ ), GEP ve D-GEP modelleri için genel olarak 0,80'den yüksek bulunurken, 3- aylık dönem için  $R^2$  değerleri yaklaşık olarak sırasıyla 0,657 ve 0,704 elde edilmiştir. En yüksek  $R^2$  değeri 6- aylık dönemde D-GEP modeli için 0,868 olarak belirlenmiştir. Sonuç olarak, GEP ve D-GEP yaklaşımlarının kuraklık tahmininde başarılı oldukları görülmüştür.

**Anahtar Kelimeler:** Çanakkale, kuraklık, GEP, SYİ, dalgacık dönüşümü

## INTRODUCTION

Meteorological drought caused by the decline of precipitation values below average is one of the main risk factors in developing effective use policies for the existing water potential. The drought, which has a large impact due to global warming and climate change, makes itself seem like a meteorological risk. It causes hydrological drought with decreased groundwater and surface freshwater resources and melting glaciers. As a result of these two serious drought processes, agricultural and socio-economic droughts also may occur (Şen, 2003; Şen, 2009). The Standard Precipitation Index (SPI), frequently used in meteorological drought studies, was first used by McKee et al. (1993). Many researchers prefer this method because only the precipitation parameter is needed (Tsakiris et al., 2007; Efe and Özgür, 2014; Aksever, 2019). Gümüþ et al. (2016) made a drought analysis with SPI using the 78-year precipitation data of the Şanlıurfa station and determined the time intervals in which different drought categories were observed. Arslan et al. (2016) made a drought analysis with SPI using 60-year precipitation data for eight stations in the Kızılırmak Basin. They stated that as the period duration increased, the maximum drought durations were also extended. Bacanlı and Kargı (2019) conducted a drought analysis with SPI after examining the trend of precipitation data for five stations in Bursa with linear regression. They examined the frequencies of drought classes in short and long periods.

Since hydrological models containing complex parameters are nonlinear, modelling them with traditional methods is very difficult and time-consuming. Artificial intelligence methods, which facilitate the solution of such problems, have been used by many researchers in drought modelling. In addition, models combined with Wavelet Transform (W), one of the pre-processing techniques, are frequently used in hydrology applications to increase the prediction performance of these methods. Wavelet transforms provide useful decompositions of the main time series. Thus, wavelet-transformed data improves the performance of the prediction model by capturing useful information at various resolution levels (Dadu and Deka, 2016). Belayneh et al. (2016) developed drought models with W, Artificial Neural Networks (ANN), and Support Vector Regression (SVR) after determining drought indices in different periods with SPI for the Awash River Basin in Ethiopia. They stated that the W-ANN model gave the best results in 3- and 6- months periods. Djerbouai and Souag-Gamane (2016) compared ANN and W methods with stochastic models for drought prediction in Al-

geria. They said that the W-ANN model gave good results in short periods. Gene Expression Programming (GEP), one of the other artificial intelligence methods, was proposed by Ferreira (2001). Abbasi et al. (2019) conducted a drought analysis using SPI and Standard Precipitation Evapotranspiration Index (SPEI) for the Urmia station in Iran at different periods. They modelled these drought indices with GEP and obtained the highest correlation coefficient for SPEI in the 48-months. Solgi et al. (2017) developed models with SVR and GEP to estimate daily and monthly flow values of the Gamasiyab River in the Navahand Region of Iran. Then, they determined the most compatible signal of each input with the output by wavelet transform and obtained models with higher predictive performance with W-SVR and W-GEP. In particular, they stated that W-SVR hybrid models are more suitable for the region. Shoaib et al. (2015) developed models to estimate the flow data by using the precipitation and flow data of the stations selected from different parts of the world stated. They found that the W-GEP models developed with the Dmey wavelet are better than the GEP models. Karimi et al. (2016) have tried Auto-Regressive Moving Average (ARMA) and different machine learning methods to estimate Filyos River flows in the West Blacksea region in Turkey. They stated that W-GEP models are suitable for long- and short-term flow estimation.

This study aims to analyze the meteorological drought and develop the drought estimation model of the region by using precipitation data from three stations for Çanakkale province and its surroundings in the semi-arid region. The lack of a drought estimation model developed with wavelet analysis and GEP methods for this region provided the motivation for the study. First, the drought indices were determined using SPI for Çanakkale, Bozcaada and Gökçeada stations. For the drought estimation model of Çanakkale province, GEP models were developed using the drought indices of Bozcaada and Gökçeada stations. Then, to increase the performance of GEP models, W-GEP models were created by decomposing the input parameters into sub-series with wavelet transform. The performances of the models were examined using some statistical parameters. The formula for the most suitable model was extracted.

## MATERIAL AND METHODS

### The Study Region and Data

Çanakkale, as the determined area of this study, is in the northwest of Turkey, including Bozcaada and

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Gökçeada stations, and covers a total area of 9737 km<sup>2</sup> over the continents of Asia and Europe. It is located between 25° 35'- 27° 45' latitude and 39° 30'- 40° 45' longitude (URL-1, 2021). Çanakkale has a semi-humid climate with a long-term mean precipitation height of 591.5 mm. The highest daily measured precipitation height is 137.8 mm (URL-2, 2021). Bozcaada and Gökçeada districts are two islands located in northeast of the Aegean Sea. Bozcaada is cool and dry in the summer months, warm and rainy in the winter months, and influenced by the Mediterranean climate. Gökçeada is hot and warm in the summer months and rainy and cold in the winter months and shows the characteristics of the Mediterranean climate in the south and the Marmara climate in the north. The map showing the study area is given in Figure 1. Monthly total precipitation data for Çanakkale, Gökçeada, and Bozcaada stations used in the study were obtained from the Turkish State Meteorological Service between 1975-2010. Before drought analysis, precipitation data should be subjected to a homogeneity test. Taylan et al. (2021) carried out a homogeneity test for these stations with the double mass curve method on the precipitation data of these stations. When the changes in the curve slope were examined, no breaks were observed in the slopes of the three stations.

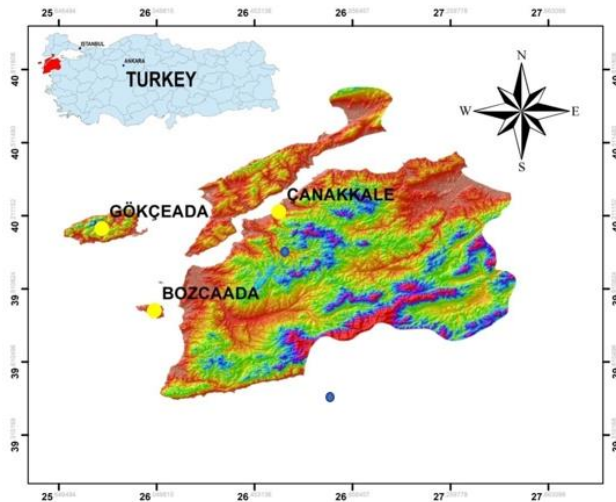


Figure 1. The study region

**Standardized Precipitation Index**

In 1993, the standardized precipitation index (SPI) proposed by McKee et al. was determined according to the deviation of precipitation data from the mean. The negative values of the series obtained by standardized precipitation data of at least 30 years indicate arid processes, while positive values indicate rainy processes.

Negative processes occur in periods when there is no precipitation or when it is less than average. These negative and positive processes are classified by McKee et al. for different intervals; severe drought (-2 >), moderate drought (-1.99 ~ -1.50), mild, severe drought (-1.49 ~ -1.00), normal (-0.99 ~ 0.99), mild severe precipitation (1.00 ~ 1.49), moderate precipitation (1.50 ~ 1.99) and heavy precipitation (2 <). Equation (1) is used to obtain nondimensional series.

$$SPI = \left( \frac{x_i - x_{ort}}{\sigma} \right) \tag{1}$$

Where  $x_i$  indicates the precipitation data of the month in which the index is calculated,  $x_{ort}$  is the average of precipitation data for long-terms, and  $\sigma$  is the standard deviation of the precipitation data (McKee et. al, 1993).

**Wavelet Transform**

Wavelet analysis is a multi-resolution analysis that depends on the number of repetitions and time. It is of great importance for Fourier transforms. The wavelet function  $\psi(t)$  is the main wavelet that can be reduced to zero. It can be defined as  $\int_{-\infty}^{+\infty} \psi(t) dt = 0$ .  $\psi_{a,b}(t)$  can be obtained by compressing and expanding  $\psi(t)$  (equation (2)):

$$\psi_{a,b}(t) = |a|^{-\frac{1}{2}} \psi \left( \frac{t-b}{a} \right) \quad b \in R, a \in R, a \neq 0 \tag{2}$$

Where  $R$  is the set of real numbers,  $\psi_{a,b}(t)$  is the sequential wavelet,  $a$  is the scale or frequency factor,  $b$  is the time factor. If  $\psi_{a,b}(t)$  satisfies equation (2), the sequential wavelet transform of  $f(t)$  for finite energy signal or time series  $f(t) \in L^2(R)$  is defined as in equation (3).

$$W_{\psi} f(a, b) = \langle f, \psi_{a,b} \rangle \geq |a|^{-\frac{1}{2}} \int_R f(t) \bar{\psi} \left( \frac{t-b}{a} \right) dt \tag{3}$$

where  $\bar{\psi}(t)$  are complex conjugate functions of  $\psi(t)$ . Equation (3) means the decomposition of  $f(t)$  under different resolution levels (scale) of the wavelet transform.

A successive wavelet is usually a discrete structure. If  $a = a_0^j$  ve  $b = kb_0 a_0^j$  ( $a_0 > 1, b_0 \in R, k, j$ ) are integers, the discrete wavelet transform of  $f(t)$  can be written as equation (4):

$$W_{\psi} f(j, k) = a_0^{-\frac{j}{2}} \int_R f(t) \bar{\psi}(a_0^{-j} t - kb_0) dt \tag{4}$$

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If  $a_0 = 2$  and  $b_0 = 1$ , equation (4) becomes the binary wavelet transform (equation 5):

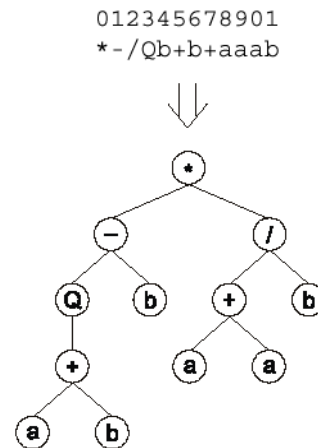
$$W_{\psi}f(j, k) = 2^{-j/2} \int_R f(t) \bar{\psi}(2^{-j}t - k) dt \quad (5)$$

$W_{\psi}f(a, b)$  or  $W_{\psi}f(j, k)$  can simultaneously show the characteristics of the original time series in frequency ( $a$  or  $j$ ) and time domain ( $b$  or  $k$ ). If  $a$  or  $j$  decreases, the frequency resolution of the wavelet transform is low, but the time-domain resolution is high. If  $a$  or  $j$  increases, the frequency resolution of the wavelet transform is high, but the time-domain resolution is low (Wang and Ding, 2003).

**Gene Expression Programming**

Genetic algorithms, one of the evolutionary approaches that facilitate the solution of complex problems, have been used in many fields in recent years (Mehdizadeh et al., 2021; Mehr, 2018; Thakur and Manekar, 2022). Genetic algorithms (GA) are search and optimization methods based on natural selection principles. First introduced by John Holland, genetic algorithms have successful applications in function optimization and machine learning. Genetic algorithms containing probability rules need a particular part of the solution set according to the objective function. Thus, while solving in a shorter time by doing effective searches, they simultaneously examine the population consisting of solutions (Emel and Taşkın, 2002).

Genetic Programming (GP), proposed by Koza (1992), is a search technique that includes computer programs such as mathematical expression, decision trees, polynomial structure, and logical expression (Goldberg, 1989). Gene expression programming (GEP), such as GA and GP, uses the populations of individuals to make a selection according to their suitability. It is similar to the genetic algorithm to introduce genetic variation using one or more genetic operators (Aytek and Kişi, 2008). The main difference between these three algorithms is due to the nature of the individuals. While individuals consist of nonlinear entities of different sizes and shapes in GP, they consist of linear strings of fixed length (chromosomes) in GA. In GEP, individuals are encoded as expression trees and fixed-length linear strings (Ferreira, 2002). An example expression tree showing the genetic information encoded in chromosomes is given in Figure 2.



**Figure 2.** An example of the expression tree

However, owing to simple rules determining the structure and interactions of expression trees, it is possible to infer the phenotype from a set of genes and vice versa. This bilingual and imprecise system is called the Karva language (Ferreira, 2002).

**FINDINGS AND DISCUSSION**

In the study, after performing meteorological drought analysis with standard precipitation index (SPI), drought estimation models were developed for Çanakkale province with gene expression programming (GEP) using the meteorological drought values of Bozcaada and Gökçeada stations as input parameters. Then, sub-series were obtained from the standard series of Bozcaada and Gökçeada stations by wavelet transform ( $W$ ). These sub-series were modelled using GEP to estimate the standard series of Çanakkale province, and  $W$ -GEP models were created.

Firstly, for meteorological drought analysis, the SPI values for 3-, 6-, 9- and 12- months periods were calculated using 36-year precipitation data of these three stations between 1975-2010. For the standard series calculated for each station in different periods, the correlation values between the stations are given in Table 1 to see the compatibility of Çanakkale province with Bozcaada and Gökçeada. From Table 1, correlation values show a good relationship between the drought values of the stations. In this context, it was found appropriate to estimate the drought values of Çanakkale station, which was selected as an output in the modelling phase with GEP and  $W$ -GEP, by using the drought values of the other two stations.



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**Table 1.** The correlation values between Çanakkale station and other stations

Periods	Bozcaada	Gökçeada
3- month	0,64	0,70
6- month	0,81	0,85
9- month	0,83	0,85
12- month	0,82	0,86

According to the historical record, the first 80% of the data is used as a training set in GEP and W-GEP models, and the remaining 20% is reserved as a testing set. While developing the models, the SPI values of Bozcaada and Gökçeada stations were used in the terminal (input) set, which is the first of five basic steps. In the second step, which is the determination of functions, arithmetic, exponential and logarithmic operators such as \*, /, -, +, √, ^, ln, 10<sup>x</sup>, and log were tested. In the third step, the head length is eight, and the number of genes per chromosome is 3 in the chromosome architecture. Total (+), the connection function type, is selected in the fourth step. In the fifth step, the chromosome number is 50; the mutation rate is 0.044; the single point recombination ratio is 0.3; the recombination ratio at two points is 0.3; the gene recombination rate was taken as 0.1 and the gene transfer rate as 0.1. After applying these steps, the suitability of developed drought prediction models was determined using the determination coefficient (R<sup>2</sup>) and root means square error (MSE) values. The R<sup>2</sup> and MSE values of the training and testing sets of the developed GEP and W-GEP models are given in Table 2. When Table 2 is examined, the high R<sup>2</sup> values have been obtained for models in 6-, 9- and 12- months periods, in which mainly seasonal changes can be observed.

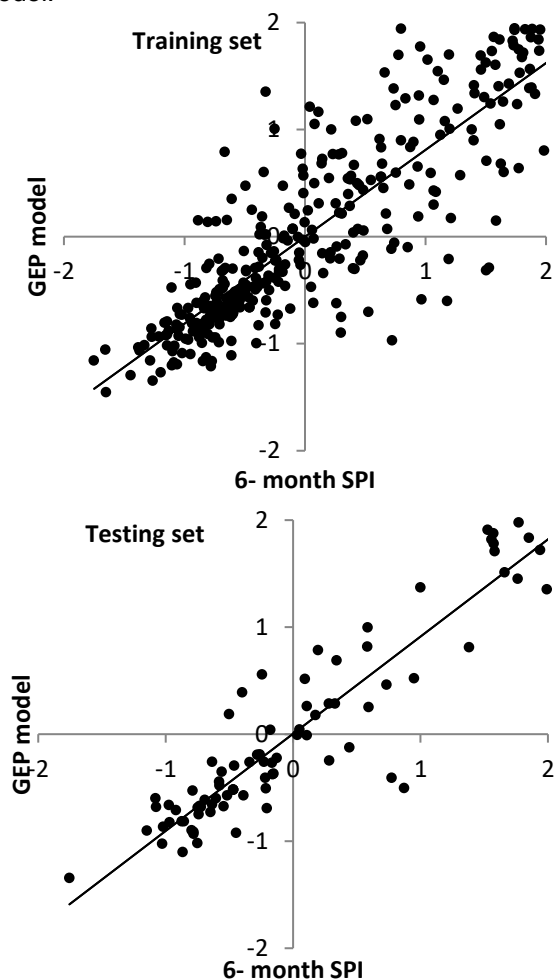
**Table 2.** The drought estimation models

Models	Training set		Testing set		
	MSE	R <sup>2</sup>	MSE	R <sup>2</sup>	
3- month	GEP	0.594	0.470	0.481	0.657
	W-GEP	0.681	0.304	0.444	0.704
6- month	GEP	0.486	0.716	0.350	0.856
	W -GEP	0.491	0.710	0.334	0.868
9- month	GEP	0.488	0.731	0.375	0.846
	W -GEP	0.525	0.689	0.409	0.815
12- month	GEP	0.476	0.754	0.494	0.789
	W-GEP	0.499	0.729	0.649	0.636

The highest R<sup>2</sup> values in both GEP and W-GEP models were found as 0.856 and 0.868 for the testing set

in 6-month drought models, respectively. Also, especially in 3- and 6- months models, the performance improvement was observed for testing sets after applying wavelet transform, while a decrease was observed in 9- and 12- months models. A decrease was observed in MSE values as consistent with the increase in model performances. For the 6-month GEP and W-GEP models, the scatter plots of the training and testing sets and the time series showing the compatibility of models with SPI values for the testing set are given in Figures 3, 4, and 5, respectively.

Similar to this study, Terzi et al. (2019) developed the drought models of Çanakkale for 3-, 6-, 9-, 12- and 24-months periods with data mining. They found R<sup>2</sup> value of the drought model developed for the 6-month period as 0.808 for the test set (Terzi et al., 2019). In this study, it was seen that the preprocessing technique increased the model performance with the W-GEP model.



**Figure 3.** The scattering diagrams of 6- the month GEP model

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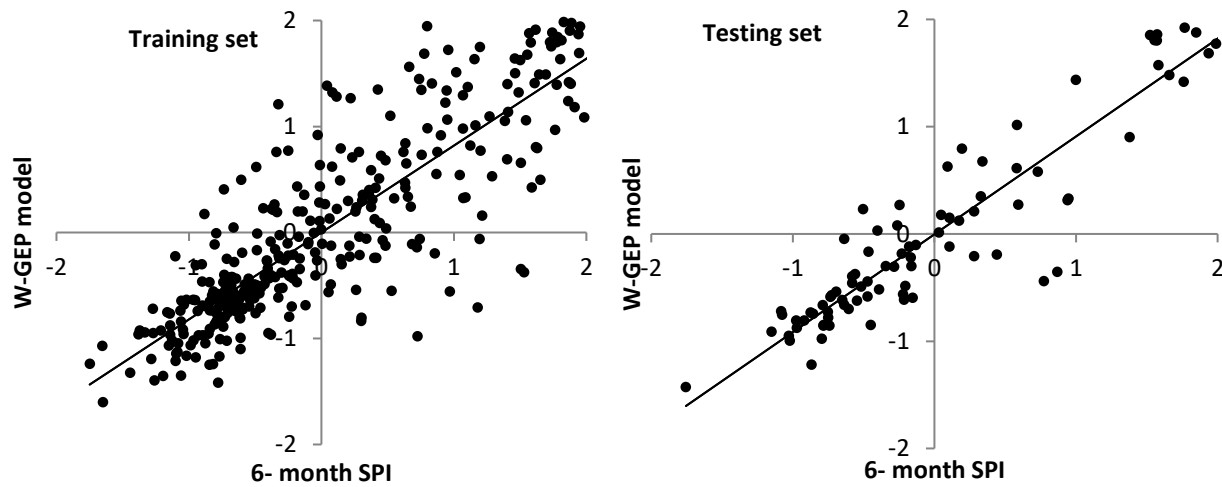


Figure 4. The scattering diagrams of 6- the month W-GEP model

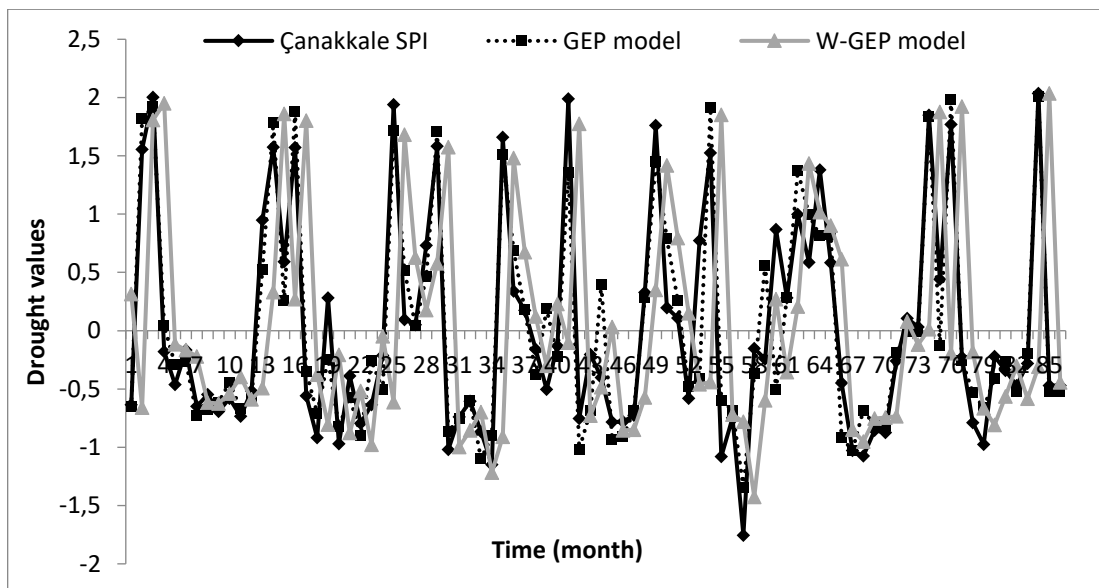


Figure 5. The time series of 6-month GEP and W-GEP models for the testing set

The equations obtained for 6- month GEP and W-GEP models developed using the GEP, which provides the advantage of obtaining mathematical expression and expression trees, are given in equations (6) and (7), respectively.

$$D_C = (D_B + D_G) + (-\ln \sqrt{e^{(D_B+D_G)}}) \tag{6}$$

Where  $D_C$ ,  $D_B$  and  $D_G$  show the drought indices of Çanakkale, Bozcaada and Gökçeada, respectively.

$$D_C = W1_G + W2_G + W3_G + \log^4 \sqrt{e^{(W1+W2)_B - (W1+W2+W3)_G}} + \log^4 \sqrt{e^{W3_B}} \tag{7}$$

In Equation 3,  $W_i$  ( $i = 1,2,3$ ) values represent the sub-series obtained by wavelet transform for each station, and the indices of B and G indicate Bozcaada and Gökçeada stations. Also, expression trees of 6- month GEP and W-GEP models among the developed models are given in Figures 6 and 7, respectively.

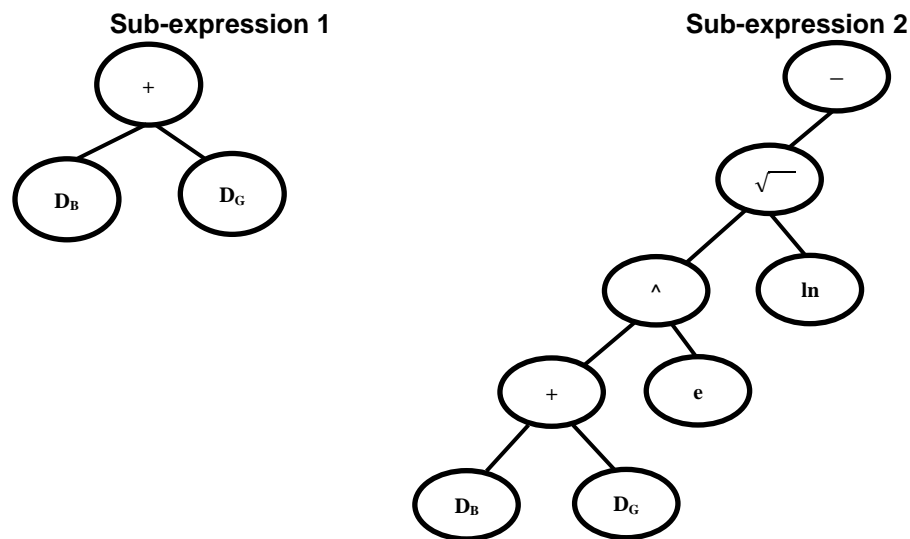


Figure 6. The expression tree of the 6-month GEP model

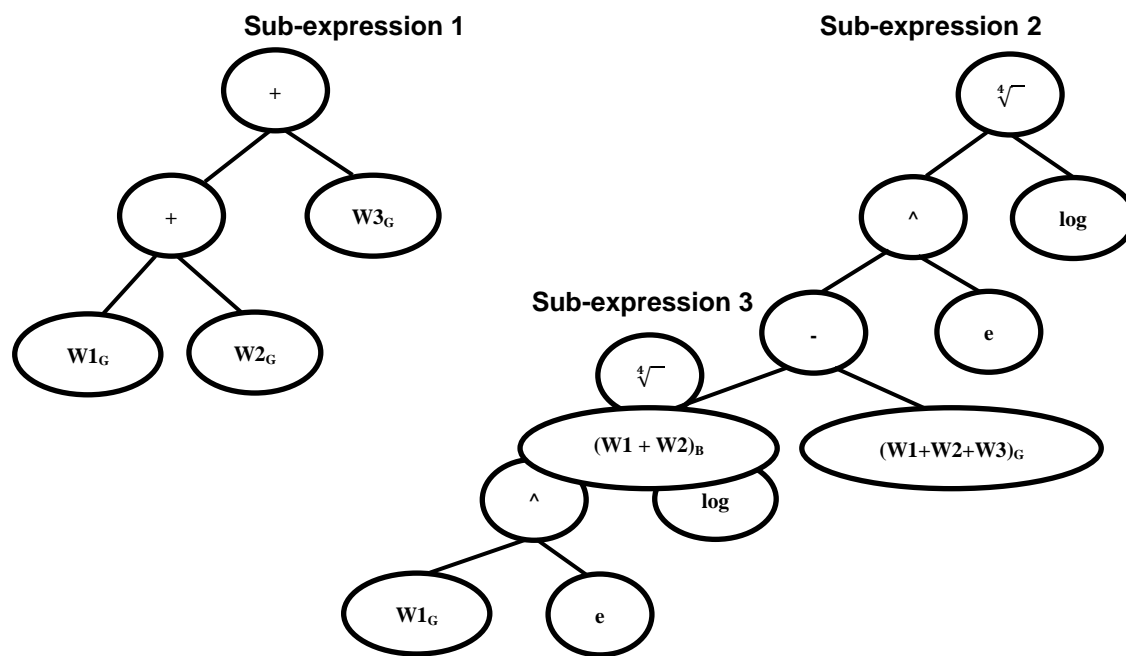


Figure 7. The expression tree of the 6-month W-GEP model

Mehdizadeh et al. (2021) modeled the standardized precipitation evapotranspiration index (SPEI) for the SPEI-3, SPEI-6 and SPEI-12 periods from six meteorological stations in Turkey. They stated that W-GEP performed better in estimating SPEI-3 and SPEI-6 compared to GEP model. Belayneh et al. (2014) developed ANN, SVR, W-ANN and W-SVR models to estimate SPI (6- and 12- months) values for Awash River Basin of Ethiopia. They said that W-ANN model has

higher accuracy than other models. According to Mehdizadeh et al. (2021), Belayneh et al. (2014), Karimi et al. (2016), Solgi et al. (2017) and Terzi et al. (2019), it was shown that the use of artificial intelligence models together with preprocessing techniques improves model performance. In addition, all W-GEP models provide superior performances compared to stand-alone GEP. Wavelet transform is a procedure that removes the trend component and periodicity by decomposing the original time series data into subseries.

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Therefore, wavelet, which is a successful pre-processing technique, is useful to improve model performance in developing a predictive model.

## CONCLUSION

Meteorological drought is one of the fundamental studies in planning water resources and predicting hydrological and agricultural droughts that may occur over a long time by using meteorological data. In the study, firstly, drought indices using SPI for Bozcaada, Gökçeada, and Çanakkale stations in 3-, 6-, 9- and 12-months periods were determined for the meteorological drought analysis of Çanakkale, which has a climate between the Mediterranean and the Black Sea climate. Then, GEP and W-GEP models were developed using the SPI values of Bozcaada and Gökçeada stations to estimate the drought indices of Çanakkale province. According to the results, there was an increase in the performances of models where seasonal changes could be seen in the long term. Among the GEP models, the drought series obtained with the model developed for the 6- months period provided the closest drought predictions. However, a decrease was observed in the 3- months period.

Similarly, W-GEP models developed by using wavelet transform, one of the pre-processing techniques used to increase the performance of estimation methods, obtained the highest performance for 6- month period. In general, it has been observed that the wavelet transform method improves the performance of the estimation model. When the data mining models developed for the same region in study of Terzi et al. (2019) were compared with the GEP and W-GEP models in this study, it was seen that both GEP and W-GEP models gave higher performance. Also, GEP models, which can be used in drought prediction, have an advantage according to other artificial intelligence methods because they can show the relationship between variables with expression trees or mathematical correlations. Wavelet transform, which is seen as an advance in signal processing, can reliably eliminate artificial intelligence model shortcomings.

## REFERENCES

- Abbasi, A., Khalili, K., Behmanesh, J., Shirzad, A. (2019). Drought monitoring and prediction using SPEI index and gene expression programming model in the west of Urmia Lake. *Theoretical and Applied Climatology*, 138(1): 553-567.
- Aksever, F. (2019). Drought analysis with standard precipitation index (SPI) method and groundwater exchange in the Kaklik (Honaz-Denizli) Plain. *Journal of Engineering Sciences and Design*, 7(1): 152-160.
- Arslan, O., Bilgil, A., Veske, O. (2016). Meteorological drought analysis in Kızılırmak Basin using standardized precipitation index method. *Nigde University Journal of Engineering Sciences*, 5(2): 188-194.
- Aytek, A., Kisi., O. (2008). A genetic programming approach to suspended sediment modelling. *Journal of Hydrology*, 351(3): 288-298.
- Bacanlı, Ü.G., Kargı, P.G. (2019). Drought analysis in long and short term periods: Bursa case. *Journal of Natural Hazards and Environment*, 5(1): 166-174.
- Belayneh, A., Adamowski, J., Khalil, B., Ozga-Zielinski, B. (2014). Long-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet neural network and wavelet support vector regression models. *Journal of Hydrology*, 508, 418-429.
- Belayneh, A., Adamowski, J., Khalil, B. (2016). Short-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet transforms and machine learning methods. *Sustainable Water Resources Management*, 2(1): 87-101.
- Dadu, K. S., Deka, P. C. (2016). Applications of wavelet transform technique in hydrology—a brief review. In: *Urban Hydrology, Watershed Management and Socio-Economic Aspects*. Sarma, A.K., Singh, V.P., Kartha, S.A., Bhattachariya, R.K. (eds.), Springer Cham, Switzerland, 241-253.
- Djerbouai, S., Souag-Gamane, D. (2016). Drought forecasting using neural networks, wavelet neural networks, and stochastic models: case of the Algerois Basin in North Algeria. *Water Resources Management*, 30(7): 2445-2464.
- Efe, B., Özgür, E. (2014). Drought analysis of Konya and surroundings by standardized precipitation index (SPI) percent of normal index (PNI). 2<sup>nd</sup> International Drought and Desertification Symposium, September 16-18, 2014, Konya, Turkey, Book of Proceedings, 1-6.
- Emel, G.G., Taşkın, Ç. (2002). Genetic algorithms and application areas. *Bursa Uludağ Journal of Economy and Society*, 21(1): 129-152.
- Ferreira C. (2002). *Gene expression programming in problem solving*. In: *Soft Computing and Industry*. Roy, R., Köppen, M., Ovaska, S., Furuhashi, T., Hoffmann, F. (eds), 635-653, Springer, London: DOI:10.1007/978-1-4471-0123-9\_54.
- Ferreira, C. (2001). Gene expression programming: A new adaptive algorithm for solving problems. *Complex Systems*, 13(2): 87-129.
- Goldberg, D.E. (1989). *Genetic algorithms in search, optimization and machine learning*. Addison-Wesley Publishing Company, Boston, United States.
- Gümüş, V., Başak, A., Oruç, N. (2016). Drought analysis of Şanlıurfa Station with standard precipitation index (SPI). *Harran University Journal of Engineering*, 1(1): 36-44.
- Karimi, S., Shiri, J., Kisi, O., Shiri, A.A. (2016). Short-term and long-term streamflow prediction by using 'wavelet-gene expression' programming approach. *ISH Journal of Hydraulic Engineering*, 22(2): 148-162.



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- Koza, J.R. (1992). *Genetic programming: On the programming of computers by means of natural selection*. A Bradford Book, Massachusetts London, England.
- Malakiya, A.D., Suryanarayana, T.M.V. (2016). Assessment of drought using standardized precipitation index (SPI) and reconnaissance drought index (RDI): A Case Study of Amreli District. *International Journal of Science and Research*, 5(8): 1995-2002.
- McKee, T.B., Doesken, N.J., Kleist, J. (1993). The relationship of drought frequency and duration to time scale. 8<sup>th</sup> Conference on Applied Climatology. January 17-22, 1993, Anaheim, CA, USA, Book of Proceeding, 1-6.
- Mehdizadeh, S., Ahmadi, F., Mehr, A.D., Safari, M.J.S. (2020). Drought modeling using classic time series and hybrid wavelet-gene expression programming models. *Journal of Hydrology*, 587, 125017; DOI:10.1016/j.jhydrol.2020.125017.
- Mehr, A.D. (2018). An improved gene expression programming model for streamflow forecasting in intermittent streams. *Journal of Hydrology*, 563: 669-678.
- Shoib, M., Shamseldin, A.Y., Melville, B.W., Khan, M.M. (2015). Runoff forecasting using hybrid wavelet gene expression programming (WGEP) approach. *Journal of Hydrology*, 527: 326-344.
- Solgi, A., Pourhaghi, A., Bahmani, R., Zarei, H. (2017). Pre-processing data using wavelet transform and PCA based on support vector regression and gene expression programming for river flow simulation. *Journal of Earth System Science*, 126(5): 65; DOI:10.1007/s12040-017-0850-y
- Şen, Z. (2003). *Su bilimi ve yöntemleri*. Su Vakfı Yayınları, İstanbul, Türkiye.
- Şen, Z. (2009). *Kuraklık afet ve modern hesaplama yöntemleri*. Su Vakfı Yayınları, İstanbul, Türkiye.
- Taylan, E.D., Terzi, Ö., Baykal, T. (2021). Hybrid wavelet-artificial intelligence models in meteorological drought estimation. *Journal of Earth System Science*, 130(1): 1-13; DOI: 10.1007/s12040-020-01488-9
- Terzi, Ö., Taylan, E. D., Özcanoğlu, O., Baykal, T. (2019). Drought estimation of Çanakkale with data mining. *Düzce University Journal of Science & Technology*, 7(1): 124-135.
- Thakur, R., Manekar, V.L. (2022). Artificial intelligence-based image classification techniques for hydrologic applications. *Applied Artificial Intelligence*, 36(1): 2014185; DOI: 10.1080/08839514.2021.2014185
- Tsakiris, G., Pangalou, D., Vangelis, H. (2007). Regional drought assessment based on the Reconnaissance Drought Index (RDI). *Water Resources Management*, 21(5): 821-833.
- URL-1 (2021). Coğrafi yapı <https://www.canakkale.bel.tr/tr/sayfa/1125-cograf-yapi> (Access Date: 18.05.2021)
- URL-2 (2021). İzmir Meteorology Directorate, [http://izmir.mgm.gov.tr/FILES/iklim/canakkale\\_iklim.pdf](http://izmir.mgm.gov.tr/FILES/iklim/canakkale_iklim.pdf) (Access Date: 18.05.2021)
- Wang, W., Ding, J. (2003). Wavelet network model and its application to the prediction of hydrology. *Nature and Science*, 1(1): 67-71.
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