Spatio-temporal analysis of meteorological and hydrological droughts in the Euphrates Basin, Turkey
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ABSTRACT
In this study, the aim was to measure changes in the spatio-temporal distribution of a potential drought hazard area and determine the risk status of various meteorological and hydrological droughts by using the kriging, radial basis function (RBF), and inverse distance weighting (IDW) interpolation methods. With that goal, in monthly, three-month, and 12-month time periods drought indices were calculated. Spatio-temporal distributions of the droughts were determined with each drought index for the years in which the most severe droughts were experienced. According to the results, the basin is under risk of meteorological drought due to the occurrence of severe and extreme droughts in most of the area, and especially in the north, during the monthly and three-month time periods. During the 12-month period, it was found that most of the basin is under risk of hydrological drought due to the occurrence of severe and extreme droughts, especially in the southern parts. The most effective interpolation method for the prediction of meteorological and hydrological droughts was determined as kriging according to the results of the cross-validation test. It was concluded that a drought management plan should be made, and early warnings and precautions should be applied in the study area.

Key words | drought, drought index, drought map, interpolation, precipitation, spatio-temporal analysis

HIGHLIGHTS
- Drought characteristics were determined using five different drought indices.
- Kriging, radial basis function (RBF) and inverse distance weighting (IDW) interpolation methods were compared to find the smallest error rate.
- Spatio-temporal drought patterns are analyzed in Euphrates River Valley, Turkey.
- The maximum meteorological drought was observed in 1989 and between 2012 and 2017 in the Euphrates Basin.

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INTRODUCTION

Droughts, as recurrent natural disasters caused by long-term lack of precipitation, are hard to understand. The main parameters that trigger drought are low humidity and precipitation, high temperature, and wind (Okonkwo et al. 2013; Kazemzadeh & Malekian 2016). Drought is a natural disaster that negatively affects various sectors such as hydroelectricity production, health, industry, tourism, agriculture, livestock, ecological environment and the socioeconomic system (Fang et al. 2019; Guo et al. 2019; Han et al. 2019; Huang et al. 2019). For this reason, it is vital to monitor and determine the spatio-temporal distribution and reduce the effects by taking various measures.

There are three types of drought: meteorological, agricultural and hydrological drought (Wilhite & Glantz 1985). Drought begins as meteorological drought, which is directly affected by precipitation and is considered the most important parameter and progresses as agricultural drought and hydrological drought. In the case of lack of rainfall, meteorological drought is defined as hydrological drought in the case of lack of surface water or groundwater. Agricultural drought is expressed in terms of shortening of agricultural productivity by lack of rainfall, surface water and groundwater (Dai et al. 2020; Özcan 2020).

Drought is a natural phenomenon that can have devastating effects. In order to reduce these destructive effects, it should be determined how often drought occurs and in which regions it is more severe (Gümüş 2017). Taking precautions against drought and being prepared will require determination of drought characteristics (Mishra & Nagarajan 2011). Information such as the area, severity, duration, and frequency of drought can be determined with the help of drought indices used as tools for drought monitoring. This information can be used to create a drought action plan by giving analysts and decision-makers ideas about the character of the drought. Estimating drought saves time for drought measures and helps reduce the negative effects.

Identifying regions at risk of meteorological and hydrological drought is of great importance in terms of management of water resources, agricultural production, hydroelectric energy production, the prosperity and livelihood of society, the economy of the country, and international relations. For these reasons, the drought situation of the study basin was evaluated and recommendations were made for measures to be taken against drought and mitigation policies.

For sustainable drought management, studies involving multiple measures on a basin basis should be undertaken with an integrated approach within the framework of a plan and program. In order to assess drought, the meteorological, agricultural, hydrological, and socio-economic aspects of drought should all be considered as a whole. In this way, sustainable solutions can be developed for every sector affected by drought disasters and economic and social benefits can be obtained. In this sense, it is necessary to implement multiple measures that do not entail structural elements, from public education to afforestation activities (Anonymous 2015).
In order to mitigate the negative effects of droughts and predict them, the spatio-temporal extent of a drought needs to be determined. For this reason, drought maps based on suitable drought indices should be created on a basin basis using various interpolation methods. The most preferred interpolation methods in drought mapping are the kriging, RBF, and IDW methods. The most effective of these methods can be determined by comparing various statistical parameters (Ali et al. 2011; Rahman & Lateh 2016; Yuan et al. 2016).

There are several studies in the literature on determining the spatio-temporal distribution of meteorological droughts through interpolation methods. For example, Ali et al. (2011) used ordinary kriging (OK), IDW, and thin-plate smoothing spline (TPSS) methods to assess the derivation of maps of drought indices at 27 climatic stations in the Boushehr province of Iran. Manikandan et al. (2015) used IDW to determine the spatio-temporal variation of meteorological drought in the Parambikulam-Allyar basin of Tamil Nadu, India. Afzali et al. (2016) used OK, indicator kriging (IK), residual kriging (RK), probability kriging (PK), simple kriging (SK), universal kriging (UK), and IDW methods to assess the derivation of maps of drought indices at 19 climatic stations in the Zayandehroud River Basin of Iran. Rahman & Lateh (2016) used IDW interpolation to determine the spatial pattern of meteorological droughts with a geographic information system (GIS) in Bangladesh. Khazana et al. (2017) used a kriging interpolation method to create a drought map of SPI values in a GIS environment. Cavus & Aksoy (2019) used the IDW interpolation technique for assessing the spatial distribution of precipitation deficit over the Seyhan River basin in Turkey. Amiri & Pourghasemi (2019) used IDW and simple kriging methods to obtain drought maps of SPI values. As a result of the study, it was determined that the IDW method predicts droughts better. Bahrami et al. (2020) employed RD1st values on various time-scales to evaluate the spatio-temporal pattern changes of drought in Iran with different climatic conditions. Drought severity maps were prepared for each year using interpolation methods and the GIS technique.

In the Euphrates Basin, drought has a significant impact on agriculture, water resources and the ecosystem. Water scarcity and droughts increase the impact on water resources day by day. Water resources are very sensitive to climate change and variability. Therefore, changes in drought greatly affect the availability of water. Drought analysis is needed to determine the water potential and requirements in a region. For this, in this study, extreme meteorological and drought characteristics belonging to various drought indices of the Euphrates Basin were investigated.

Assessing drought status and identifying risky areas with maps can provide a starting point for regional drought intervention and can help in the creation of a comprehensive drought management strategy to reduce the effects of drought. In this context, the objective of the present work is to evaluate several spatial interpolation techniques for predicting the spatial distribution of droughts in the Euphrates Basin. In this study, the most appropriate meteorological drought maps were created by comparing the ordinary kriging (OK), radial basis function (RBF), and inverse distance weighting (IDW) interpolation methods with cross-validation testing.

**MATERIALS AND METHODS**

**Study area and data**

In this study, monthly total rainfall data and monthly average air temperature data from 1966 and 2017 belonging to 16 meteorological observation stations (MOSs) in the Euphrates Basin were chosen as meteorological observations. These data were used as input for the calculation of drought indices. The location and spatial characteristics of the stations in the Euphrates Basin are shown in Figure 1 and Table 1.

The Euphrates valley is largely fed from the snow of northern and eastern sections of Turkey with Iran and Iraq’s mountainous area. The Euphrates, which has the largest drainage area of west Asia and Turkey, is the longest river of western Asia. Originating from the mountains in the Ağrı and Erzurum regions in eastern Anatolia, Murat and Karasu, the two main branches, are fed by dozens of tributaries.

According to the spatial distribution of the stations used in the study, they are located in the Continental Mediterranean and Continental Eastern Anatolia precipitation regime regions (Türkeş 1998). The Continental Mediterranean precipitation regime region has quite seasonal semi-arid and arid–semi-humid subtropical features with a moderate rainy winter/spring and a very hot dry summer season. The
Continental Eastern Anatolia precipitation regime region has the characteristics of dry, semi-humid and semi-humid steppe and high land with a moderate rainy spring/summer and a very cold winter with snow.

The main factors that trigger droughts are decrease in rainfall, and increase in temperature and evaporation–transpiration because of climate change in the region. In addition, drought is effective in the study area because it is away from the effects of the sea and the mountains that extend into the country parallel to the coast; in other words, the study area is in an inner part of the country receiving less effect of precipitation.

Drought indices

Drought indices are tools developed to detect, monitor and evaluate drought events. Over the last few decades, more than 150 drought indices have been developed for different locations, targets and applications (Zargar et al. 2011). In

Table 1 | Meteorological stations used in the study

| Station Number/Name | Latitude | Longitude | Altitude (m) | Time period |
|----------------------|----------|-----------|--------------|-------------|
| 17762/ Kangal        | 39.24    | 37.38     | 1,521        | 1960–2017   |
| 17094/ Erzincan      | 39.75    | 39.48     | 1,216        | 1960–2017   |
| 17096/ Erzurum       | 39.95    | 41.19     | 1,758        | 1960–2017   |
| 17740/ Hims          | 39.37    | 41.69     | 1,715        | 1960–2017   |
| 17165/ Tunceli       | 39.11    | 39.54     | 981          | 1960–2017   |
| 17099/ Ağrı           | 39.72    | 43.05     | 1,646        | 1960–2017   |
| 17780/ Malazgirt     | 39.14    | 42.53     | 1,540        | 1961–2017   |
| 17204/ Muş            | 38.75    | 41.50     | 1,322        | 1964–2017   |
| 17776/ Solhan        | 38.96    | 41.05     | 1,366        | 1965–2017   |
| 17203/ Bingöl        | 38.88    | 40.50     | 1,139        | 1961–2017   |
| 17666/ İspir         | 40.48    | 40.99     | 1,223        | 1965–2017   |
| 17688/ Tortum        | 40.30    | 41.54     | 1,576        | 1960–2017   |
| 17692/ Sarıkkamış    | 40.33    | 42.60     | 2,102        | 1960–2017   |
| 17690/ Horasan       | 40.04    | 42.17     | 1,540        | 1968–2017   |
| 17716/ Zara          | 39.89    | 37.75     | 1,338        | 1964–2017   |
| 17265/ Adıyaman      | 37.75    | 38.28     | 672          | 1963–2017   |
general, many drought indices can be calculated using rainfall and temperature data and point or spatial drought evaluation can be made. In this study, five different drought indices (SPI, ZSI, RAI, SPEI, RDI) were used to detect droughts. Katipoglu et al. (2020) should be examined for detailed information about the calculation and evaluation of the drought indices used in this study.

**Standard precipitation index (SPI)**

In the calculation of the SPI index, the time series is determined in the first determined one-month time-scales. The long-term precipitation time series are adapted to a gamma probability distribution and then converted to a standard normal distribution, thus obtaining SPI values with an average of 0 and a standard deviation of 1 (McKee et al. 1993).

**Standard precipitation and evapotranspiration index (SPEI)**

The SPEI was introduced by Vicente-Serrano et al. (2010) to overcome the deficiencies of the SPI. This index can also consider the warming effects on the climate. For calculation of the SPEI, potential evapotranspiration (PET) values are required in addition to precipitation as used in the SPI. Meteorological variables such as average temperature are needed to obtain PET values. For PET calculation, the Thornthwaite equation is recommended, which only needs the monthly average temperature and latitude of the selected station:

$$PET = 16K \left( \frac{10T}{I} \right)^m$$

Here, $T$ is the average temperature (°C) of the selected month, and $K$ is a correlation factor that varies with latitude and month. $I$ is the annual thermal index calculated as the sum of the 12-month $i$ index values. The values of $i$ and $m$ are calculated as follows:

$$m = 0.49 + 0.0179I - 0.0000771I^2 + 0.000000675I^3$$

$$i = \left( \frac{T}{5} \right)^{1.514}$$

when the value of PET is known, the difference ($D$) between precipitation ($P$) and $PET$ in the relevant month is calculated as follows:

$$D_i = P_i - PET_i$$

where $P_i$ is the total precipitation of the $i$-th month (mm), $PET_i$ is the total PET of the $i$-th month (mm), and $D_i$ is a measure of the climatic water balance in the $i$-th month adapted to the three-parameter log-logistic distribution (Vicente-Serrano et al. 2010). After this stage, SPEI values are obtained by converting the distribution to standard normal distribution, like the SPI calculation.

**Z-score index (ZSI)**

The ZSI is a dimensionless drought index that uses original data; in other words, it uses precipitation data that do not need to conform to the distribution. As can be seen in Equation (5), it is obtained by dividing the difference of precipitation data from the mean by the standard deviation within the specified time period (Wu et al. 2001).

The ZSI has standard deviation (1), standard mean (0), and values below the average are positive and those below are negative.

$$ZSI = \frac{P_i - \bar{P}}{\sigma}$$

Here,

$P_i$: precipitation values,
$\bar{P}$: average of all precipitation data,
$\sigma$: standard deviation of all precipitation data.

**Rainfall anomaly index (RAI)**

The basis of this index is the calculation of the deviation from the normal value of precipitation. For this, after finding the average ($P$) in a long time-series, the average of the ten highest values ($M$) and the average of the ten smallest values ($X$) are obtained. The index value can be calculated using Equations (6) and (7).
\[ P > P \] is anomaly-positive and the index value is:

\[
RAI = +3 \frac{P - P}{M - P} \tag{6}
\]

If \( P < P \), it is anomaly-negative and the index value is:

\[
RAI = -3 \frac{P - P}{X - P} \tag{7}
\]

Here,

\[ P_i \]: precipitation values in monthly and annual time period.

**Reconnaissance drought index (RDI)**

The RDI is a general meteorological index for drought assessment. This index is widely accepted in arid and semi-arid regions. It is evaluated in three ways: initial value (\( \alpha_k \)), normalized RDI (\( RDI_n \)), and standardized RDI (\( RDI_{st} \)). The initial value (\( \alpha_k \)) is within a year for a reference period of \( k \) months. This value (\( \alpha_k \)) can be obtained from the ratio of precipitation values to potential evapotranspiration on a monthly, seasonal, and annual basis. Equation (8) is used to calculate these values (Tsakiris & Vangelis 2005; Zarch et al. 2014):

\[
\alpha_k = \frac{\sum_{j=1}^{j=k} P_j}{\sum_{j=1}^{j=k} \text{PET}_j} \tag{8}
\]

Here, \( P_j \) is the precipitation value of month \( j \) and \( \text{PET}_j \) is the evapotranspiration value of month \( j \). Normalized RDI values (\( KKI_n \)) can be calculated by Equation (9). In this equation, \( \bar{\alpha}_k \) is the average of the initial values.

\[
RDI_n(k) = \frac{\bar{\alpha}_k - \bar{\alpha}_k}{\sigma_k} \tag{9}
\]

Standardized RDI values (\( RDI_{st} \)) can be calculated by Equation (10). Here, \( y_k = KKI_k \). Moreover, \( \bar{y}_k \) is the arithmetic mean of values of \( y_k \) and \( \sigma_k \) is the standard deviation (Tsakiris & Vangelis 2005).

\[
RDI_{st}(k) = \frac{y_k - \bar{y}_k}{\sigma_k} \tag{10}
\]

Threshold values and corresponding categories of all drought indices used in the study are shown in Table 2.

**Inverse distance weighting**

Inverse distance weighting interpolation is the method that applies the assumption that the points close to each other are more similar than the distant ones. It uses the known values surrounding the prediction point to estimate the value of any point that has not been measured. Values closest to the prediction point will have more impact than distant ones. Thus, it assumes that each measured point has a local effect that decreases with distance. This method is called the reverse distance weighting method because it places more weight on closer points to the prediction (Johnston et al. 2001).

The general formula of the method:

\[
W_i = \frac{1}{\sqrt{\sum_{i=1}^{n} \frac{1}{d_i^2(x_i)}}} \tag{11}
\]

\[
\tilde{Z}(x_0) = \sum_{i=1}^{n} W_i \cdot Z(x_i) \tag{12}
\]

\[
\sum_{i=1}^{n} W_i = 1 \tag{13}
\]

Here,

\( x_0 \): point to be estimated,

\( \tilde{Z}(x_0) \): the value of the estimate at the point \( x_0 \).

**Table 2** | Classification of drought indices (McKee et al. 1993; Keyantash & Dracup 2002; Tsakiris et al. 2007)

| SPI-SPEI-ZSI-RDI                                                                 | RAI          | Category          |
|---------------------------------------------------------------------------------|--------------|-------------------|
| \( \leq 0 \) Index                                                             | \( 0 \) Index | Wet               |
| \(-1 < \) Index \( \leq 0 \)                                                    | \(-1.2 < \) Index \( \leq 0 \) | Mild              |
| \(-1.5 < \) Index \( \leq -1.0 \)                                              | \(-2.1 < \) Index \( \leq -1.2 \) | Medium            |
| \(-2 < \) Index \( \leq -1.5 \)                                               | \(-3 < \) Index \( \leq -2.1 \) | Severe            |
| Index \( \leq -2.0 \)                                                          | Index \( \leq -3 \) | Extreme           |
$Z(x_i)$: the value of the sample point at point $x_i$,
$W_i$: inverse distance weight of the sample at point $x_i$ relative to point $x_0$,
$d$: the distance between the sample point and the point to be estimated,
$p$: power parameter,
n: the number of measured sample points surrounding the prediction location to be used in the estimation.

Radial basis functions (RBF)

In this study, five different interpolation methods were used as RBF methods, and these are: thin-plate spline, spline with tension, completely regularized spline, multiquadric function and inverse multiquadric function methods. Each method produces different results and different surfaces. The basis of these methods is to create a flexible surface according to the examined values of the points throughout the study area from every known point (Johnston et al. 2001). The real values are the same as the estimates made for the locations of the sample points used with RBF methods. However, estimates for points other than the locations of the sample points may be below the minimum value of actual values above the maximum value (Johnston et al. 2001). The completely regularized spline method can produce softer surfaces than they actually are for fast changing variations. The spline with tension method, compared with the completely regularized spline method, creates a smoother and rough surface. The thin-plate spline method creates smoother surfaces using a softening average locally, unlike the extreme values resulting from other methods (Lilly 2006). The multiquadric function method was designed by Ronald Hardy in 1968 to create topographic maps (Chenoweth & Sarra 2009). According to the Chenoweth & Sarra (2009) study, this method produces favorable results with spatially scattered points. The inverse multiquadric function method is more dependent on data values.

Kriging

Kriging is a statistical method based on estimating unknown points by the weighted sum of known points within a given radius. Kriging is used for advanced prediction surface modeling and also takes into account errors or estimation uncertainty (Bajjali 2017). Kriging is similar to IDW, because weights of the measured values in the environment are adjusted to get an estimate for each location. However, the weights are based not only on the distance between the measured points and the forecast location, but also on the general spatial arrangement between the measured points. Spatial autocorrelation is measured to use spatial regulation in weights. Natural physical events (precipitation, temperature, soil properties, etc.) generally have areal autocorrelation. In other words, this autocorrelation is determined by assuming that the sampling points that are close to each other have similar values and the difference in value between the samples that are far apart from each other is large. While this autocorrelation can be calculated with a specific model in methods such as kriging, there is no apparent autocorrelation calculation in methods such as IDW, and its determination is tried only by the weighting coefficient according to the distance.

Kriging consists of five different parts: simple kriging, ordinary kriging, universal kriging, co-kriging, indicator kriging. Different kriging methods are suggested according to the characteristics of the data. In this study, the ordinary kriging method was used, which is suitable for drought analysis and does not require a normal distribution assumption:

$$Z(x_0) = \sum_{i=1}^{N} W_i Z(x_i)$$  \hspace{1cm} (14)

Here, $Z(x_i)$ represents the measured value at location $i$, $W_i$ the unknown weight of measured values at location $i$, $x_0$, the estimated location, and $N$ is the number of measured values.

The sum of the weights must be equal to 1 to ensure the estimate is noncommittal:

$$\sum_{i=1}^{n} W_i = 1$$ \hspace{1cm} (15)

The difference between the estimated value of the estimated point and the random variable is expected to be 0:

$$E[\hat{z}(x_0) - Z(x_0)] = 0$$ \hspace{1cm} (16)
Each kriging prediction is associated with a kriging variance. There are weights for the kriging process that will then minimize the kriging variance, and the sum of the weights must be 1 as in Equation (15).

In the kriging method, the weighting process varies according to the size of the working area, the distribution of the stations, the distances and directions of each sample point according to the estimated regional variable, the distances between the sample points, the anisotropic or isotropic variation and the semivariogram model parameters (Oliver 2010; Sen 2016).

**Semivariogram function**

Kriging uses a semivariogram function to determine unknown values. The semivariogram provides information about the scale and structure of spatial change and is used to investigate the magnitude of spatial change and autocorrelation of the study region in case the stationary hypothesis is valid. Semivariograms show the spatial variation of regional variables (random variables whose positions in time or space are known) (Curran 1988).

The function expressing the spatial relationship between regional variables is illustrated by Equation (17) (Matheron 1963). Using Equation (17), the semivariogram function is obtained in the form of Equation (18) (Sarma 2010):

\[
\gamma(h) = \text{Var}[z(x+h) - z(x)] \\
\hat{\gamma}(h) = \frac{1}{2N} \sum_{i=1}^{N} (z(x_i + h) - z(x_i))^2
\]

(17) (18)

Here, \(N\) is the number of sample pairs compared, \(h\) is the step range, and \(z(x_i + h)\) is the expected value of the regionalized variable at position \(x_i + h\). The variogram function is expressed as the variance of the difference between two regional variables as far away as \(h\) from each other (Uyar 2005). Thus, spatial relationship and dependence between regional variables are expressed. While the variance between the sample pairs close to each other is expected to be low, it is likely that the variance will increase and the similarity will decrease with increasing distance (Uzunlar 2006).

**Selection of the most suitable interpolation method**

Spatio-temporal analysis of drought is of great importance in terms of assessing drought risk status. Drought index values depend on meteorological parameters such as precipitation, temperature, PET and hydrological parameters such as flow. It is not possible to measure meteorological and hydrological data from all points in an area in terms of both cost and technique. For this, drought values in the whole area were estimated by using interpolation methods to determine the spatial distribution of droughts at various time intervals. Thus, drought values at other points were estimated by making use of previously measured data. The geostatistical analysis tool of Arcmap 10.5 Software was used for spatial drought interpolation.

In this study, raster surfaces are estimated from the vector data defined on point geometries using kriging, RBF and IDW methods under geostatistical analysis. There are different statistics parameters in the literature to determine the accuracy of the predicted surface. In general terms, the most widely used method is the root mean square error (RMSE) value obtained by cross-validation test. Therefore, this method was used in model comparison.

The kriging model contains several model parameters such as semivariogram models, kernel functions, and neighborhood types (Table 5). In order to determine the best fit among these parameters, various variations were tried and the kriging model was applied, giving the smallest RMSE value by trial and error and cross-validation methods.

In the application of radial-based function interpolation, kernel functions, neighborhood and sector types were selected by trial and error, and the model with the lowest valuation method was applied with the cross-valuation method (Table 4). Neighborhood and sector types of the IDW method are the same as those of RBF.

According to the calculated drought index values, Euphrates Basin drought maps were created for the driest dates. The point drought values of the stations in the study area are colored by the interpolation method, the distribution of the area according to the drought classes, and the drought hazard is mapped. The drought maps are colored according to the class ranges (0, −1, −1.5, −2) of the various drought indices (McKee et al. 1993).
Cross-validation is an effective method used to estimate semivariogram model parameters. This method examines the relationship between predicted and actual values using the information available in the sample dataset. In this method, the value at one location is temporarily removed from the dataset and an estimate is made for that location, which is extracted using the remaining values (one-leave-out). This process is repeated for all the remaining samples (Isaaks & Srivastava 1989). For example, in Figure 2 below, ten randomly distributed data points are shown. Cross-validation ignores a point (red dot) and calculates the value of that location using the remaining nine dots (blue dots). Predicted and actual values are compared with the position of the ignored point. This procedure is repeated for a second point and so on (Johnston et al. 2001). Thus, the observed values are estimated and the difference (error value) between the real values is determined. Various error criteria can be used when testing the accuracy of the predicted maps. In this study, it was made by comparing RMSE values in evaluating the predicted maps.

**Evaluation of models**

The performances of the established models have been tested with the help of different statistical criteria. In this study, Pearson correlation coefficient \( R \), determination coefficient \( R^2 \) and root mean square error (RMSE) criteria were used. These statistical calculations can be made with the help of Equations (19) and (20), respectively. RMSE is a statistical measure that measures the predictive accuracy by determining the differences between the predicted values and the observed values. The determination coefficient \( R^2 \) is a statistical measure that shows how close the data is to the fitted regression line.

\[
R^2 = 1 - \frac{\sum_{i=1}^{N} (x_i - y_i)^2}{\sum_{i=1}^{N} (x_i - \bar{x})^2} \tag{19}
\]

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - y_i)^2} \tag{20}
\]

Here, \( x_i \) is the expected (observed) values of models, \( y_i \) is the outputs (estimation values), and \( N \) is the number of data. The models for which the \( R^2 \) value is the largest (close to 1)
and which have the lowest error rates (close to 0) are evaluated as the best.

RESULTS AND DISCUSSION

Preliminary analysis of extreme drought characteristics

In this study, the aim was to obtain drought maps by the interpolation method. Accordingly, preliminary analysis of the years with the highest and most frequent droughts was made by analyzing the dry periods. Thus, it was chosen which year of drought should be mapped.

RAI is more sensitive to extreme droughts in the monthly and 12-month time periods, while SPEI is more effective in the three-month time period. RDI has been found to be almost as sensitive as RAI. In addition, it was found that SPI and ZSI were ineffective in the monitoring of extreme drought compared with other indices (Table 5).

When the results of the monthly, three-month and 12-month meteorological drought indices outcome analyses were compared, it was found that the maximum drought was observed in the same years. However, the effect can be felt more since SPI, SPEI and RDI show maximum drought in a wider time period (Table 6). In addition, the years in which the most severe droughts were identified were taken as critical years in drawing drought risk maps in the later stages of the study.

Meteorological and hydrological drought interpolation

In this section, the spatial distributions of the drought classes on the basin were determined by kriging RBF and IDW methods according to the drought intensity determined by each drought index and drought risk maps were created. While one- and three-month indices show meteorological drought, 12-month indices give information about hydrological drought status.

Table 5 | Analysis of maximum drought characteristics in the Euphrates Basin

| Index | Station | Time period | Drought number | Onset       | End         | Time (Months) | Severity |
|-------|---------|-------------|----------------|-------------|-------------|---------------|----------|
| SPI   | Ispir   | Monthly     | 142            | 2013 March  | 2014 March  | 13            | −19.05   |
|       | Şirkanı   | 3 Months    | 72             | 2011 October| 2014 August | 35            | −47.15   |
|       | Şirkanı   | 12 Months   | 33             | 2012 April  | 2017 December| 69            | −114.58  |
| SPEI  | Ispir   | Monthly     | 137            | 2013 March  | 2014 August | 18            | −21.37   |
|       | Şirkanı   | 3 Months    | 72             | 2011 October| 2016 May    | 56            | −79.16*  |
|       | Şirkanı   | 12 Months   | 26             | 2012 April  | 2017 December| 69            | −109.69  |
| ZSI   | Ispir   | Monthly     | 137            | 2013 March  | 2014 April  | 14            | −15.77   |
|       | Şirkanı   | 3 Months    | 71             | 2011 October| 2014 August | 35            | −45.12   |
|       | Şirkanı   | 12 Months   | 32             | 2012 April  | 2017 December| 69            | −118.31  |
| RAI   | Ispir   | Monthly     | 126            | 2013 March  | 2014 March  | 13            | −29.29*  |
|       | Şirkanı   | 3 Months    | 66             | 2013 July   | 2016 April  | 34            | −59.60   |
|       | Şirkanı   | 12 Months   | 33             | 2012 April  | 2017 December| 69            | −143.57* |
| RDI   | Şirkanı   | 12 Months   | 26             | 2012 April  | 2017 December| 69            | −137.64  |

Note: * sign represents the maximum value.

Table 6 | The most severe droughts in the Euphrates Basin

| Time period | SPI          | ZSI          | RAI          | SPEI          | RDI          |
|-------------|--------------|--------------|--------------|---------------|--------------|
| Monthly     | 1989, 2013–2014 | 1989         | 1989         | 1988, 1989, 2012–2014 | -            |
| 3 Months    | 2011–2016    | 2013–2014    | 2012–2014    | 1989, 2012–2017 | -            |
| 12 Months   | 2012–2017    | 2012–2015    | 2012–2015    | 2012–2017     | 2012–2017    |
In our country, while mild climate characteristics are seen in the coastal regions with the effect of the seas, the North Anatolian Mountains and Taurus Mountains prevent the sea effects from entering the inner parts. For this reason, severe droughts are observed in the Euphrates Basin in the inner parts due to low precipitation. In this study, the drought risk maps of the 5-difference drought index of May 1989, which is one of the years with the most severe drought, are shown (Figures 3–5).

Similar results were encountered when the meteorological drought maps produced by kriging of the monthly SPI, ZSI and RAI values of May 1989 were examined. According to these indices, severe and extreme droughts were observed in most of the basin. In the drought map obtained by the IDW method of SPEI values, severe and moderate drought was encountered throughout the basin (Figure 3). In this situation, it has been determined that there is some difference according to the interpolation method and drought index selected in the study of areal change of drought. Unlike other indices, the use of PET values is one of the important factors in SPI calculation.

When the meteorological drought maps obtained by kriging of the 3-month SPI, SPEI and ZSI values of May 1989 were analyzed, similar results were encountered. According to these indices, severe and extreme droughts were observed in most of the basin. In the drought map obtained by IDW of the RAI values, severe and moderate droughts dominate the basin. According to these results, different conditions may occur according to the interpolation method and drought index selected in the study of the spatial variation of droughts. When using the RAI and IDW methods, some decrease in areal distribution intensity of droughts was encountered. This is due to the evaluation of the RAI according to different cut levels and to the IDW method being only a distance-dependent deterministic method. In other words, the kriging
method is determined to be a more reliable and powerful method compared with the IDW method.

When the hydrological drought maps obtained by the 12-month drought index values of May 1989 were analyzed, similar results were encountered. According to these indices, severe and extreme droughts were observed in most of the basin. However, there was some difference in the drought classes of some points according to the drought index. In the drought maps obtained by SPI, SPEI, RAI and RDI, severe droughts dominated in the southern parts of the basin, whereas in the drought map obtained with ZSI, severe droughts shifted to the north of the basin.

In accordance with the cross-validity results of drought indices, the most suitable interpolation model was determined as kriging. This situation shows us that the kriging method is the most effective method in determining the areal change of droughts.

The selection of the most suitable interpolation method and the high number of stations in the study area and its good representation of the basin boundaries have a major impact on the error value of the interpolation applied. In this study, it is thought that there is some deviation in the estimations due to the low number of stations in the southern parts of the basin. The low number of stations in the study area is due to the large amount of missing data in the meteorological measurement network. The meteorological measurement network needs to be developed in order to make a more effective drought map.

The best result in the interpolation of drought indices, the smallest error rate, was obtained by using kriging type (ordinary), semivariogram model (hole effect, J-Bessel), kernel function (exponential, polynomial) and neighborhood type (smooth). In the selection of the appropriate model, the optimized model option was applied and the
second-degree trend effects were removed. By removing the trend, the semivariogram will model spatial autocorrelation between data points without having to take into account the trend in the data. The trend is automatically added to the calculations before the final surface is produced.

The type of sector selected is determined by the number of neighboring points to be estimated and the proximity of the neighboring points to the forecast point. In this study, when the standard neighborhood type is used, four sectors with 45° offset is selected and the maximum number of neighborhoods is limited to 12.

In the radial basis function (RBF) method, it was determined that the most suitable estimation surface was obtained by using a multiquadric kernel function, sector
type with four sectors with 45° offset and standard neighborhood type. The most appropriate model was chosen as the model that gives the smallest RMSE value with the cross-validation method. In addition, optimum power parameter and smooth neighborhood are used to obtain the most suitable IDW model.

Deterministic interpolation methods are mostly used due to their flexibility and reliability. These methods make estimates based on the distance between points. However, this method does not work well when the distribution of the stations is not very good (Gidey et al. 2018). In this study, the stations used cause some deviations from the estimate because they are not randomly distributed (not homogeneous or clustered). For this reason, the kriging interpolation, which can be adjusted with the semivariogram model, gave more effective results instead of determining the weights as a function of distance only. As a result of cross-validation tests, it can be seen from the obtained RMSE values that the kriging method is more effective in meteorological drought prediction than the IDW and RBF methods (Tables 7–8).

Current research has determined that geostatistical interpolation methods perform better than deterministic interpolation methods in sparsely distributed stations and regions where the altitude varies greatly in a short distance, namely in mountainous regions, due to the sudden change

| Index     | Kriging | IDW | RBF |
|-----------|---------|-----|-----|
| SPI-1     | 0.56    | 0.57| 0.57|
| SPEI-1    | 0.47    | 0.43| 0.48|
| ZSI-1     | 0.23    | 0.42| 0.39|
| RAI-1     | 0.70    | 0.96| 0.81|
| SPI-3     | 0.55    | 0.58| 0.56|
| SPEI-3    | 0.38    | 0.40| 0.77|
| ZSI-3     | 0.41    | 0.50| 0.55|
| RAI-3     | 0.48    | 0.81| 0.69|
| SPI-12    | 0.63    | 0.75| 0.65|
| SPEI-12   | 0.87    | 0.73| **0.60**|
| ZSI-12    | 0.25    | 0.65| 0.55|
| RAI-12    | 0.97    | 0.95| **0.74**|
| RDI-12    | 0.58    | 0.71| **0.51**|

Table 8 | Number and percentage of interpolation methods that best fit May 1989

| Interpolation method | Monthly | 3 Months | 12 Months | Total |
|----------------------|---------|----------|-----------|-------|
| Kriging              | 3       | 4        | 2         | 9     | (69.23%) |
| IDW                  | 1       | –        | –         | 1     | (7.69%)  |
| RBF                  | –       | –        | 3         | 3     | (23.08%) |

in precipitation (Goovaerts 2000; Kuzucu 2016; Subedi et al. 2019). In other words, the kriging method, which is a geostatistical method, gives better results than the deterministic RBF and IDW methods. Since this study was conducted in the Euphrates Basin, which is a mountainous basin, and the stations do not have a dense distribution, the fact that the kriging method shows more consistent prediction results supports the existing studies.

Güngen (2019) made a drought analysis and map of the Southeastern Anatolia Region using SPI values in 3–6–12 and 24-month time periods, which were developed to determine and monitor meteorological drought. As a result of the mapping of three-month SPI values of 1989, when the most severe droughts were observed, it was determined that while extreme droughts prevailed in Adıyaman province, moderate wetness was dominant in Şanlıurfa and Gaziantep provinces. In the six- and 12-month time periods, severe and very severe wetness prevails in the province of Adıyaman, while moderate and mild droughts are dominant in the southern parts. While the study was similar to our study in the three-month time period, different results were obtained in the six- and 12-month time periods. The reason for this difference can be explained by the interpolation method used and the number and distribution of stations.

Tanahto et al. (2012) found that there was an increase in temperature and a decrease in precipitation in most of the Middle East in the previous decade. Mathbout et al. (2018) investigated the spatio-temporal variation of drought trends and severities in Syria using SPI and SPEI values. As a result of that study, it was found that drought severity increased in all time periods. Sensoy et al. (2013) found that while the annual total precipitation trend increased in the northern parts of Turkey, it decreased in the Southeastern Anatolia, Mediterranean, and Aegean regions. The present study shows that the increase in drought severity in the Euphrates Basin changes on a large scale with...
Climatic factors, that evaporation/transpiration-based indices measure droughts more sensitively, and that the drought risk in the basin will gradually increase.

**CONCLUSIONS**

In this study, the aim was to determine drought levels according to various meteorological drought indices at the basin level, to compare the maps according to the drought indices, to determine the spatio-temporal variation of drought severity, to compare the kriging, RBF and IDW interpolation methods, to identify the risky areas in terms of drought in the basin and to manage the drought. The scope of the outputs obtained in the study basin drought management and planning of water resources in Turkey are qualities that would benefit decision makers and public institutions.

In this study, the kriging, RBF, and IDW methods were compared for the prediction of meteorological and hydrological droughts. The comparison process was performed according to the RMSE values obtained as a result of cross-validation testing. Since the meteorological stations in the basin are not distributed uniformly, they performed better than deterministic interpolation methods such as kriging, IDW, and RBF, which are geostatistical methods, for the prediction of meteorological droughts. In addition, in this study, risky areas were determined with drought maps and it was emphasized that the effects of droughts that might reoccur in the region should be reduced.

Risky areas were identified with drought maps and it was emphasized that the effects of droughts that are likely to repeat should be reduced by taking measures in these regions. It was determined that the meteorology stations of Kangal, Erzincan, Tunceli, Erzurum, Bingöl, Muş, Hınıs, Ağrı, and Malazgirt, especially in the northern parts of the basin, are under risk due to severe and extreme droughts in monthly and three-month time periods. In the 12-month period, it was determined that the southern parts of the basin were at risk, especially at the Adıyaman station, due to severe and extreme droughts.

In the Euphrates Basin, which is a mountainous basin, multiple quadratic kernel functions for interpolation of droughts with RTF and exponential or polynomial kernel functions for interpolation of droughts with kriging have been proposed.

As a result of the analysis run within the scope of this study, the maximum meteorological drought was observed in 1989 and between 2012 and 2017. This indicates that droughts have become more frequent in recent years. In addition, the occurrence of prolonged and very severe droughts in the basin reveals the need for more effective use of water resources and drought management plans.

As a continuation of this study, it is suggested to study the relationships between drought indices and atmospheric oscillations (NAO, SO,…), the relationships between meteorological droughts and hydrological droughts, and the recurrence intervals of meteorological and hydrological droughts. In addition, in this study, it is suggested that the models established can be improved by increasing the number of meteorological and hydrological measurement stations and their more homogeneous distribution.

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**DATA AVAILABILITY STATEMENT**

Data cannot be made publicly available readers should contact the corresponding author for details.

**REFERENCES**

Afzali, A., Keshkar, H., Pakzad, S., Moazami, N., Azizabadi Farahani, E., Golpaygani, A., Khosrojerdi, E., Yousefi, Z. & TaghiNaghilou, M. 2016 Spatio-temporal analysis of drought severity using drought indices and deterministic and geostatistical methods (case study: Zayandehroud River Basin). *Desert* 21 (2), 165–172.

Ali, M. G., Younes, K., Esmaeil, A. & Fatemeh. T. 2017 Assessment of geostatistical methods for spatial analysis of SPI and EDI.
drought indices. *World Applied Sciences Journal* **15** (4), 474–482.

Amiri, M. & Pourghasemi, H. R. 2019. Investigation of the relationship between hydrological and meteorological droughts at Maharloo Watershed, Fars Province. *Watershed Engineering and Management* **11** (3), 725–738.

Anonymous. 2015. *Drought Management Plan of Konya Basin.* The Republic of Turkey Ministry of Water Affairs and Forestry, General Directorate of Water Management Flood and Drought Management Department, Ankara, Turkey.

Bahrami, M., Bazkar, S. & Zarei, A. R. 2020. Spatiotemporal investigation of drought pattern in Iran via statistical analysis and GIS technique. *Theoretical and Applied Climatology,* doi: 10.1007/s00704-020-03480-1.

Bajjali, W. 2017. *ArcGIS for Environmental and Water Issues.* Springer, Cham, Switzerland.

Cavus, Y. & Aksoy, H. 2019. Spatial drought characterization for Seyhan River basin in the Mediterranean region of Turkey. *Water* **11** (1), 1331.

Chenoweth, M. E. & Sarra, S. A. 2009. A numerical study of generalized multiquadric radial basis function interpolation. *SIAM Undergraduate Research Online* **2** (2), 58–70.

Curran, P. J. 1988. The semivariogram in remote sensing: an introduction. *Remote Sensing of Environment* **24** (3), 493–507.

Dai, M., Huang, S., Huang, Q., Leng, G., Guo, Y., Wang, L. & Zheng, X. 2020. Assessing agricultural drought risk and its dynamic evolution characteristics. *Agricultural Water Management* **231**, 106003.

Fang, W., Huang, S., Huang, Q., Wang, H., Leng, G., Wang, L. & Guo, Y. 2019. Probabilistic assessment of remote sensing-based terrestrial vegetation vulnerability to drought stress of the Loess Plateau in China. *Remote Sensing of Environment* **232**, 111290.

Gidey, E., Dikinya, O., Sebego, R., Segosebe, E. & Zenebe, A. 2018. Modeling the spatio-temporal meteorological drought characteristics using the standardized precipitation index (SPI) in Raya and its environs, Northern Ethiopia. *Earth Systems and Environment* **2** (2), 281–292.

Goovaerts, P. 2000. Geostatistical approaches for incorporating elevation into the spatial interpolation of rainfall. *Journal of Hydrology* **228** (1–2), 113–129.

Gümüş, V. 2017. Hydrological drought analysis of Asi River Basin with streamflow drought index. *Gazi University Journal of Science Part C: Design and Technology* **5** (1), 65–73.

Güngen, Y. 2019. Drought Analysis of Southeastern Anatolia Region by Standardized Precipitation Index (SPI). MSc thesis, Manisa Celal Bayar University Institute of Science and Technology, Manisa, Turkey.

Guo, Y., Huang, S., Huang, Q., Wang, H., Fang, W., Yang, Y. & Wang, L. 2019. Assessing socioeconomic drought based on an improved Multivariate Standardized Reliability and Resilience Index. *Journal of Hydrology* **568**, 904–918.

Han, Z., Huang, S., Huang, Q., Leng, G., Wang, H., He, L. & Li, P. 2019. Assessing GRACE-based terrestrial water storage anomalies dynamics at multi-timescales and their correlations with teleconnection factors in Yunnan Province, China. *Journal of Hydrology* **574**, 836–850.

Huang, S., Wang, L., Wang, H., Huang, Q., Leng, G., Fang, W. & Zhang, Y. 2019. Spatiotemporal characteristics of drought structure across China using an integrated drought index. *Agricultural Water Management* **218**, 182–192.

Isaaks, E. & Srivastava, R. 1989. *An Introduction to Applied Geostatistics.* Oxford University Press, New York, USA.

Johnston, K., Ver Hoef, J. M., Krivoruchko, K. & Lucas, N. 2001. Using ArcGIS Geostatistical Analyst. ESRI, Redlands, CA, USA.

Katipoglu, O. M., Acar, R. & Şengül, S. 2020. Comparison of meteorological indices for drought monitoring and evaluating: a case study from Euphrates basin, Turkey. *Journal of Water and Climate Change* **11** (S1), 29–43.

Kazemzadeh, M. & Malekian, A. 2016. Spatial characteristics and temporal trends of meteorological and hydrological droughts in northwestern Iran. *Natural Hazards* **80** (1), 191–210.

Keyantash, J. & Dracup, J. A. 2002. The quantification of drought: an evaluation of drought indices. *Bulletin of the American Meteorological Society* **83** (8), 1167–1180.

Khezzama, A., Amarchi, H., Derdous, O. & Bousakhrira, F. 2017. Drought monitoring in the Seyrouse basin (Algeria) over the last decades. *Journal of Water and Land Development* **33** (1), 79–88.

Kuzucu, A. 2016. Investigation of Temporal and Spatial Changes of Drought in Seyhan Basin. MSc thesis, Dokuz Eylul University, Izmir, Turkey.

Lilly, J. O. 2016. A GIS Approach to Modeling Groundwater Levels in the Mississippi River Valley Alluvial Aquifer. MSc thesis, University of Arkansas, Fayetteville, AR, USA.

Manikandan, M., Tamilmani, D., Anandanaraj, N. & Thiagarajan, G. 2015. Evaluation of meteorological drought parameters in the Parambikulam-Aliyar basin, Tamil Nadu. *Environment and Ecology* **35** (4), 1547–1552.

Mathboub, S., Lopez-Bustins, J. A., Martin-Vide, J., Bech, J. & Rodrigo, F. S. 2018. Spatial and temporal analysis of drought variability at several time scales in Syria during 1961–2012. *Atmospheric Research* **200**, 153–168.

Matheron, G. 1965. Principles of geostatistics. *Economic Geology* **58** (8), 1246–1266.

McKee, T. B., Doesken, N. J. & Kleist, J. 1993. The relationship of drought frequency and duration to time scales. In: *Proceedings of the 8th Conference on Applied Climatology*, American Meteorological Society, Boston, MA, USA, pp. 179–183.

Mishra, S. S. & Nagarajan, R. 2011. Spatio-temporal drought assessment in Tel river basin using standardized precipitation index (SPI) and GIS. *Geomatics, Natural Hazards and Risk* **2** (1), 79–93.

Okonkwo, C., Demoz, B. & Onyeukwu, K. 2013. Characteristics of drought indices and rainfall in Lake Chad Basin. *International Journal of Remote Sensing* **34** (22), 7945–7961.
Oliver, M. A. 2010 The variogram and kriging. In: Handbook of Applied Spatial Analysis (M. M. Fischer & A. Getis, eds), Springer, Berlin, Germany, pp. 319–352.

Özcan, M. 2020 Spatial and Temporal Drought Analysis of Tigris Basin. MSc thesis, Harran University Institute of Science and Civil Engineering Department, Şanlıurfa, Turkey.

Rahman, M. R. & Lateh, H. 2016 Meteorological drought in Bangladesh: assessing, analysing and hazard mapping using SPI, GIS and monthly rainfall data. Environmental Earth Sciences 75 (12), 1026.

Sarma, D. D. 2010 Geostatistics with Applications in Earth Sciences. Springer Science & Business Media, Dordrecht, The Netherlands.

Sen, Z. 2010 Spatial Modeling Principles in Earth Sciences. Springer, Cham, Switzerland.

Sensoy, S., Türkoglu, N., Akçakaya, A., Ekici, M., Demircan, M., Ulupinay, Y., Atay, H., Tüvan, A. & Demirbaş, H. 2013 Trends in Turkey climate indices from 1960 to 2010. In: 6th International Atmospheric Science Symposium, Istanbul, Turkey.

Subedi, M. R., Xi, W., Edgar, C. B., Rideout-Hanzak, S. & Hedquist, B. C. 2019 Assessment of geostatistical methods for spatiotemporal analysis of drought patterns in East Texas, USA. Spatial Information Research 27 (1), 11–21.

Tanarhte, M., Hadjinicolaou, P. & Lelieveld, J. 2012 Intercomparison of temperature and precipitation data sets based on observations in the Mediterranean and the Middle East. Journal of Geophysical Research: Atmospheres 117, D12102.

Tsakiris, G. & Vangelis, H. 2005 Establishing a drought index incorporating evapotranspiration. European Water 9, 3–11.

Tsakiris, G., Pangalou, D., Tigkas, D. & Vangelis, H. 2007 Assessing the areal extent of drought. In: Water Resources Management: New Approaches and Technologies, European Water Resources Association, 14–16 June 2007, Chania, Crete, Greece.

Türkeş, M. 1998 Influence of geopotential heights, cyclone frequency and southern oscillation on rainfall variations in Turkey. International Journal of Climatology 18 (6), 649–680.

Uyar, H. 2005 Geovar3: Computer Software of Geostatistical Variogram Analyses and Kriging Techniques. MSc thesis, Department of Geological Engineering, Institute of Science, Hacettepe University, Ankara, Turkey.

Uzunlar, Z. 2006 Determining the Geothermal Gradient Distribution in Turkey Using Variogram Analysis on Deep Well Temperature Data. MSc thesis, Institute of Science and Technology, Istanbul Technical University, Istanbul, Turkey.

Vicente-Serrano, S. M., Beguería, S. & López-Moreno, J. I. 2010 A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. Journal of Climate 23, 1696–1718.

Wilhite, D. A. & Glantz, M. H. 1985 Understanding: the drought phenomenon: the role of definitions. Water International 10 (3), 111–120.

Wu, H., Hayes, M. J., Weiss, A. & Hu, Q. 2001 An evaluation of the standardized precipitation index, the China-Z index and the statistical Z-score. International Journal of Climatology 21, 745–758.

Yuan, S., Quiring, S. & Patil, S. 2016 Spatial and temporal variations in the accuracy of meteorological drought indices. Cuadernos de Investigación Geográfica 42 (1), 167–183.

Zarch, M. A. A., Malekinezhad, H., Mobin, M. H., Dastorani, M. T. & Kousari, M. R. 2011 Drought monitoring by reconnaissance drought index (RDI) in Iran. Water Resources Management 25, 3485.

Zargar, A., Sadiq, R., Naser, B. & Khan, F. I. 2011 A review of drought indices. Environmental Reviews 19, 333–349.