Abstract: Remote sensing-based approaches have gained widespread usage in drought monitoring studies. However, relying on single-variable drought indices may be inadequate to provide a comprehensive understanding of drought dynamics. In this study, principal component analysis was employed to derive a combined index, namely, the combined drought index (CDI), from multiple indices such as vegetation condition index, temperature condition index, precipitation condition index, and soil moisture condition index. The CDI was subsequently employed to analyze drought occurrences in the Ergene Basin-Türkiye period from 2001 to 2020 (May to October) using MODIS data. Correlations were computed with standardized precipitation index (SPI) and standardized precipitation evapotranspiration index (SPEI) at 1-, 3-, and 6-month scales and crop yield. The results revealed that drought incidents transpired in the Ergene Basin for at least 1 month annually. May exhibited the wettest, while September stood as the driest month. The severity of drought and its spatial extent displayed an increasing trend followed by a subsequent decline during the aforementioned period. The CDI demonstrated stronger correlations with the 1-month standardized indices than the 3- and 6-month SPI-SPEI. A robust correlation of 0.79 was also observed between the CDI and the crop yield. In general, the CDI performed well in determining the spatial and temporal patterns of the historic droughts. As a result, the CDI could be leveraged to develop effective drought monitoring and management, which could help mitigate the negative impact of drought in the fragile environment of the Ergene Basin.

Keywords: drought, combined drought index, principal component analysis, Ergene Basin, north-west of Türkiye

1 Introduction

Drought is a hydroclimatic natural disaster that has adverse effects on various areas such as agriculture, water resources, natural ecosystems as well as social life [1–3]. It can be categorized into four main types: meteorological, agricultural, hydrological, and socio-economic [3]. Consequently, the monitoring and evaluation of drought hold significant value in light of its wide-ranging adverse impacts. To accomplish this goal, diverse methods have been developed to assess various dimensions of drought, such as intensity, duration, severity, and spatial distribution [4].

When discussing traditional tools, several indices like Deciles, standardized precipitation index (SPI), Palmer drought severity index (PDSI), and surface water supply index depend on climate and meteorological data collected from ground measurement stations [5]. In addition, the standardized precipitation evapotranspiration index (SPEI) was calculated by integrating both potential evapotranspiration (PET) and precipitation data [6]. Nonetheless, since these indices rely on data gathered from ground measurement stations, they may have limitations, incomplete information, and potential errors, and may not be available in real time [7]. On the other hand, an increasing number of observation satellites provide valuable data for monitoring and analyzing vegetation, soil, and water dynamics. These satellites enable the high spatial and temporal resolution monitoring of drought in regions with limited local measurement capabilities [8,9]. Remote sensing-based vegetation, water, and temperature indices are widely used to track the response of plants to climate conditions [9]. Numerous remote sensing-based indices have been developed, including the vegetation condition index (VCI), normalized difference water index,
land surface water index, temperature condition index (TCI), normalized difference temperature index, vegetation health index (VHI), temperature vegetation dryness index, and evapotranspiration drought index [10].

Drought characteristics are too complex to adequately express by a single climate variable [11,12]. Therefore, single-variable drought indices based on precipitation, temperature, streamflow, or soil moisture may fall short in capturing the complex features of drought events [11,12]. In this context, various multivariable drought indices have been proposed, such as the VHI, normalized difference drought index (NDDI), PDSI, and SPEI. However, while VHI and NDDI are primarily used to monitor agricultural drought, PDSI and SPEI are generally preferred to monitor meteorological drought. Therefore, these indices can only be used to monitor one of the four defined drought types [13]. However, different types of drought can occur simultaneously in a given area [14]. Hence, in the assessment of drought in an area, combined indices have been developed by combining various drought indices to account for information about different drought types [13,15].

For this purpose, various approaches such as Copula functions [12,13,16], ordered weighted averaging method [17], multivariable linear regression method [18], constrained optimization method [19–21], and principal component analysis (PCA) [15,16,19,22–24], among others, are utilized. PCA is a multivariate approach utilized in this scenario to decrease the complexity of a dataset. It achieves this by generating a set of new perpendicular variables known as principal components (PCs) in a descending order of significance [25]. This approach is widely employed in the analysis of drought [23]. Studies conducted in China and Iran by Karimi et al. [15] and Du et al. [24], respectively, have combined single-variable drought indices (MODIS-based VCI, TCI, TRMM-based precipitation condition index (PCI) and MODIS-based soil water index) using the PCA method to create synthesized drought index and combined drought index (CDI). In studies conducted in Ethiopia and India by Bayissa et al. [26] and Kulkarni et al. [27] respectively, CHIRPS-based SPI and NOAA [27]/MODIS [26]-based LST, MODIS-based NDVI, NOAA-based Soil Moisture data, and in a study conducted in China by Liu et al. [16], in situ station-based precipitation, evapotranspiration, soil moisture of top two layers (SM1 and SM2), and runoff data were used to obtain CDI-E, CDI-M, and ADI (aggregate drought index) using this method. These aforementioned combined indices were then compared with drought indices obtained from in situ meteorological station data (such as SPI and SPEI) and/or crop yield for validation purposes.

The objective of the present study was to develop a combined index that integrates vegetation condition, surface temperature, precipitation, and soil moisture to conduct a comprehensive spatial and temporal analysis of drought in the Ergene Basin, Türkiye. The authors claim that such a CDI approach has never been used before to monitor and analyze drought in Türkiye. The study integrates the MODIS-based VCI, TCI, CHIRPS-based PCI, and ERA-5-based soil moisture condition index (SMCI) to produce CDI in the Google Earth Engine (GEE) platform. Moreover, by utilizing the CDI from the year 2001 to 2020, the spatial distribution and temporal variations of drought within the basin will be evaluated. The effectiveness of the CDI in monitoring and assessing drought events in the basin will be assessed by comparing it with meteorological drought indices (SPI-SPEI) and the crop yield data.

2 Materials and methods

2.1 Study area

The study area, the Ergene Basin, is located in the northwestern section of Türkiye, specifically in the Thrace sub-region, marking the transitional zone from the Marmara region to the European Continent [28]. Geographically, the basin lies between 40°38’ to 42°05’N and 26°03’ to 28°12’E. The Ergene Basin covers a total area of 14,486 km², corresponding to 1.9% of all basins in Türkiye [28,29].

The climate of the Ergene Basin is characterized by a harsh and cold winter and a hot and dry continental climate during summers. However, the basin’s southern part experiences a mild and rainy winter and a hot and dry Mediterranean climate. The annual average temperature for 2001–2020, calculated using monthly total precipitation and monthly average temperature data obtained from meteorological stations in the basin, is 14.3°C, with an annual average precipitation amount of 623.84 mm (Figure S1).

The Ergene Basin is a home to a population of 1,891,878 people [30]. It is an important agricultural region that significantly contributes to agricultural production in Türkiye due to its fertile agricultural land. Agricultural areas cover about 66% of the basin [28], with approximately 48% rainfed cultivable land, 13% continuously irrigated land, and 7% areas with natural vegetation [31]. In 2020, the basin produced 820,736 tons of sunflower (43% of the country's production), 1,739,850 tons of wheat (10% of the coun-
try’s production), and 980,000 tons of rice (paddy) (44% of the annual production) [32].

2.2 Data

Various factors are considered when selecting the study period in drought studies conducted in the literature. For example, in studies conducted by Karimi et al. and Wei et al. [15, 20, 21], the growing seasons of crops were chosen as the study period within a year. In this study, remote sensing and in situ drought index maps and time series specific to the Ergene Basin were generated, and drought analyses were conducted for the period from 2001 to 2020 for each year’s May–October period when the growth and harvest season of crops in the basin and the time of the year when drought is most strongly felt. MOD13A2 1km spatial resolution 16-day composite NDVI, MOD11A1 1km spatial resolution daily LST, CHIRPS pentad 0.05° spatial resolution 30+ year global rainfall data set, and ECMWF ERA5-land monthly averaged by hour of day data with a spatial resolution of 0.1° from GEE platform were used. Furthermore, to compute the meteorological drought indices SPI and SPEI, monthly “total precipitation” and “average temperature” data were obtained from Çorlu, Edirne, Ipsala, Kirkareli, Lüleburgaz-Tigem, Malkara, Tekirdağ, and Uzunköprü Meteorological Stations from 1991 to 2020 (Figure 1). Furthermore, agricultural production statistics (sunflower, rice, maize, wheat, etc.) at the basin level for the period 2004–2020 were obtained from the Turkish Statistical Institute (TURKSTAT) database to calculate the crop yield [32].

2.3 Methods

The study aimed to investigate the spatial and temporal patterns of drought in the Ergene Basin between May and October from 2001 to 2020 using the CDI. In addition, the performance of CDI in monitoring drought was assessed. To produce CDI, various remote sensing-based drought indices such as VCI, TCI, SMCI, and PCI were computed. In addition, in situ SPI-SPEI for different periods and detrended crop yield data were utilized.

Figure 1: Study area and meteorological stations.
Subsequently, the remote sensing-based CDI was compared to in situ drought indices and detrended crop yield measurements (Figure 2).

2.3.1 Calculation of drought indices

In this research, two categories of drought indices were calculated and analyzed: remote sensing-based drought indices and in situ drought indices.

2.3.1.1 Remote sensing-based indices

The remote sensing-based indices were examined under two categories: single remote sensing drought indices and CDI. The GEE platform was utilized to carry out all mapping, time series analysis, and preprocessing of remote sensing data associated with these indices [24].

2.3.1.1.1 Single remote sensing drought index

Over the past few years, remote sensing systems have been extensively employed to monitor environmental phenomena, including drought, at different scales. In the field of drought research, commonly used indices such as VCI, TCI, PCI, and SMCI are utilized. These indices offer valuable insights into vegetation conditions, surface temperature, precipitation patterns, and soil moisture content [24,33,34]. The equations used to compute these indices are presented in Table 1. The index values are standardized on a scale of 0–100. The changes in these index values from 0 to 100 correspond to the transition from unfavorable to optimal conditions [10,35]. In the equations presented in Table 1, \( i \) represents the values for the corresponding month, and min and max correspond to the multi-year minimum and maximum NDVI, LST, precipitation, and soil moisture values.

For the calculation of the VCI, the MOD13A2 1 km spatial resolution 16-day composite NDVI data were utilized, and the cloud-affected pixels were either weighted or

<table>
<thead>
<tr>
<th>Drought index</th>
<th>Data source</th>
<th>Formula</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>VCI</td>
<td>MODIS</td>
<td>[VCI = \frac{100 \times (NDVI - NDVI_{min})}{NDVI_{max} - NDVI_{min}}]</td>
<td>[33]</td>
</tr>
<tr>
<td>TCI</td>
<td>MODIS</td>
<td>[TCI = \frac{100 \times (LST_{max} - LST)}{LST_{max} - LST_{min}}]</td>
<td>[33]</td>
</tr>
<tr>
<td>PCI</td>
<td>CHIRPS</td>
<td>[PCI = \frac{100 \times (Pr - Pr_{min})}{Pr_{min} - Pr_{max}}]</td>
<td>[35]</td>
</tr>
<tr>
<td>SMCI</td>
<td>ERA-5</td>
<td>[SMCI = 100 \times \frac{SM_{max} - SM}{SM_{min} - SM_{max}}]</td>
<td>[35]</td>
</tr>
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Figure 2: Flowchart of the study.
removed based on the pixel reliability band “SummaryQA flags” of the MOD13A2. No additional geometric correction was performed for the MOD13A2 and MOD11A1 datasets [36]. In contrast, to calculate the PCI and SMCI, the CHIRPS precipitation and ERA-5 soil moisture data were adjusted to a spatial resolution of 1 km using the bilinear resampling technique [36].

2.3.1.2 CDI and PCA

The mixture of diverse datasets, considering the differential contributions of variables and components, is facilitated by adopting the combined index approach [37]. One of these approaches, PCA is widely used to identify dominant patterns in datasets in climate and drought studies [23,24,27]. The primary objective of PCA is to extract valuable insights from a multivariate dataset by constructing a fresh set of variables known as PCs. These components adeptly encapsulate the inherent variability in the original dataset while simultaneously reducing its dimensionality [25].

PCA is a statistical method that employs an orthogonal transformation to convert a set of observations into a new dataset. This transformation aims to filter the components of the original dataset while preserving the maximum variability [22].

Equation (1) provides the mathematical formula for CDI and outlines the fundamental structure that links the PCs to the original data [22,26].

\[ Z = X \cdot E, \]

where \( Z \) is the \( n \times p \) matrix of PCs, in which \( p \) is the number of variables (e.g., VCI, TCI, SMCI, and PCI), \( n \) is the number of observations (e.g., number of years for a specific month), \( X \) is the \( n \times p \) matrix of standardized observational data (the column mean subtracted from each element and divided by the column standard deviation), and \( E \) is the \( p \times p \) matrix of eigen vectors. Nonetheless, in the case of orthogonal treatments, PCs are essentially independent vectors, and it is inappropriate to merge all of them into a single numerical representation [16]. According to the study by Keyantash and Dracup [22], it is recommended to utilize the first PC (PCI), as it preserves the maximum variability of the original datasets. In particular, if the eigenvector \( E_1 = [e_{1,1}, e_{1,2}, ..., e_{p,1}] \) corresponds to the initial component of \( Z \), the primary component of \( Z \) can be explicitly stated as equation (2) [14,38]:

\[ Z_1 = \sum_{k=1}^{p} e_{k,1}X_k \quad k = 1, 2, ..., p. \] (2)

The CDI values were normalized by dividing them by their standard deviation (equation (3)) [26]. Normalization is necessary to prevent significant spikes in the time series values of CDI caused by months with higher degrees of variability [26].

\[ \text{CDI}_{ij} = \frac{Z_{ij}}{\sigma}, \] (3)

where CDI\(_{ij}\) is the CDI value, \( Z_{ij} \) is the PCI for month \( j \) in year \( i \), and \( \sigma \) is the sample standard deviation of \( Z_{ij} \) over all years.

In this study, PCA was applied to extract the key information from the VCI, TCI, SMCI, and PCI. The previously calculated values of these indices were used as input for the PCA. It was observed that the PCI consistently captured over 79% of the information contained in the VCI, TCI, SMCI, and PCI (Table S1). Therefore, PCI was identified as the CDI [22]. By using the PCA method, CDI maps and time series were generated for the period of May to October from 2001 to 2020 in the Ergene Basin. In addition, in this study, the drought index values were divided into five categories based on conducted studies [15,24]. These drought categories are presented in Table S2.

2.3.1.2 In situ meteorological station measurement-based indices

The SPI and SPEI are widely used in drought studies, either derived solely from precipitation data or calculated using precipitation and temperature data [39].

The SPI, developed by [40], is calculated by dividing the difference between the precipitation in a specified period and the average of the same period across all historical years by the standard deviation. The SPEI, presented by [6], serves as an essential indicator of the climatological water balance, obtained by utilizing data on precipitation (\( P \)) and PET across diverse time intervals [41]. Moreover, these indices can be calculated for various time frames, including 1, 3, 6, 9, 12, 24, and 48 months.

In this study, the methodologies put forth by the studies by McKee et al. [40] and Vicente-Serrano et al. [6] were utilized to compute the SPI and SPEI, which were subsequently compared to the CDI as reference values.

Monthly average temperature and total precipitation data were obtained from the MGM for the meteorological stations situated within the basin, covering the period from 1991 to 2020. Following data acquisition, the obtained data underwent processing, and calculations were performed to compute the SPI and SPEI at 1-, 3-, and 6-month time scales. These calculations were carried out utilizing the “SPEI Package” within the RStudio environment. To calculate SPI and SPEI with a spatial resolution of 1 km, the inverse distance weighted interpolation method was employed by...
utilizing of the QGIS software. Subsequently, these raster datasets were uploaded onto the GEE platform to generate drought maps and time series encompassing the entire study period for the Ergene Basin.

2.3.2 Evaluation of CDI

Correlation analysis is a statistical methodology used to examine the degree of correlation between variables [20]. In the context of drought studies, Pearson correlation coefficients are frequently employed to explore the relationships and reliability of various indices [20].

In this study, the effectiveness of the CDI was assessed through the utilization of two separate datasets: standardized indices and crop yield data. Pearson correlation coefficients were employed to establish the relationship between CDI and the standardized indices, as well as CDI and crop yield. The objective was to evaluate the degree of agreement between CDI and the standardized indices, as well as CDI and crop yield.

2.3.2.1 Evaluation of CDI with in situ meteorological station measurement-based indices

SPI-SPEI are commonly used reference indices for the validation of drought indices [20]. In this regard, correlations between drought indices and these reference indices are utilized. In this study, standardized indices for the 1-, 3-, and 6-month time scales were generated for the May to October periods of the 20-year period. Subsequently, spatial correlation coefficient maps were produced to examine the relationship between these indices and CDI.

2.3.2.2 Evaluation of CDI with crop yield

Crop yield is often used to assess the performance of combined indices. This study focused on the relationship between CDI and the crop yield using sunflower cultivation data in the basin.

In the basin, primary crops include wheat, sunflower, corn, canola, and rice. Wheat and canola have growth periods from October to June, while rice and corn are often irrigated. This makes monitoring drought through satellite data for them challenging. Conversely, sunflower cultivation is particularly practiced during drought-prone months, often in rainfed or under limited irrigation conditions [42,43]. The cultivation of this plant under such conditions increases its sensitivity to extreme environmental conditions such as heat and drought [44,45]. This characteristic turns sunflower into an indicator where signs of climate changes can be observed earlier [46]. Sunflower cultivation covers about 40–45% of the arable land in the basin and is practiced on a rotating basis under rainfed conditions from April until October [32]. This cultivation period aligns with the May to October timeframe, which is the focus of this study’s seasonal investigation. This synchronization allows for a direct comparison between annual sunflower production data and the annual CDI values calculated for the May to October period.

The sunflower is a suitable crop to reflect the agricultural characteristics of the basin. Its growing period closely aligns with the seasonal study period, and its extensive and continuous cultivation in broad rainfed agricultural areas enhances the significance of this plant in representing the basin. Considering its sensitivity to climate changes, the use of sunflower production data specific to the basin is found to be highly meaningful when assessing the effectiveness of the CDI in evaluating agricultural drought in the basin.

Figure 3: Crop yield pattern of sunflower cultivation in the basin before and after detrending.
In this context, the crop yield data for sunflower in the basin has been calculated as the ratio of production (tons) to the total cultivable area (hectares) [26,27]. It is influenced by factors such as technology, policy, and diseases [24]. However, the present study focuses on objectively assessing the impact of climatic conditions on sunflower yield. Non-climatic trends were eliminated, and the detrended yield data were analyzed in relation to the annual CDI values [26]. The crop yield time series for sunflower is shown in Figure 3.

3 Result and discussion

3.1 Temporal and spatial distribution characteristics of CDI

Time series of monthly CDI generated by using PCA is shown in Figure 4. According to Figure 4, at least 1 dry month occurs every year in the basin during this period. Moreover, CDI generally exhibited a similar pattern each year from May to October, fluctuating between values of 35 and 79. In addition, it was found that the peak and trough values of CDI varied according to the drought conditions experienced in the basin. According to Figure 4, the driest month in the basin was September 2001, while the wettest month was May 2011. The CDI time series for the May to October periods from 2001 to 2020 is illustrated in Figure 4.

The examination of the drought behavior during the May to October period in the basin over a 20-year time-frame indicated a decrease in CDI values from May to September, followed by a slight increase from September to October, in conjunction with increasing temperatures and decreasing rainfall (Figure S1) (Figure 5a). The driest month in the basin was September, while the wettest month was May (Figure 5a). CDI values remained in the mild drought class for 3 months starting from August (Figure 5a). Furthermore, the spatial extent impacted by
drought in the basin exhibited an upward trend until September, followed by a slight decline thereafter. Notably, in September, approximately 73% of the basin experienced drought, which decreased to 71% in October (as illustrated in Figure 5b). In May, merely 1% of the basin encountered extreme drought conditions, while this figure rose to 4% in August and reached 6% in September and October. Conversely, no areas exhibited extreme drought in June and July. Severe drought affected 1% of the basin in May and June, with the affected areas expanding from June to September before contracting in October. Moderate drought areas demonstrated an increase until September, followed by a marginal decrease in October. In addition, the extent of mild drought areas rose until July, then decreased in August and September, and again experienced an increase in October. Despite the reduction observed in August and September, there was an expansion in the geographical coverage of areas impacted by extreme, severe, and moderate drought.

Figure 6 illustrates the average monthly drought map from May to October. In May, the drought-affected areas were concentrated in the southwestern part of the basin.
(Figure 6a). In June, most of these areas showed no signs of drought, except for some mild droughts in the northern region (Figure 6b). By July, the basin experienced mild drought conditions, which intensified in August with the emergence of severe and extreme droughts (Figure 6c and d). In September and October, the eastern and southern parts of the basin were particularly affected by severe and extreme droughts (Figure 6e and f). The average monthly drought maps provided an overview of the drought patterns in the basin.

As shown in Figure 4, although CDI values generally followed a similar pattern throughout the study period, the peak and trough values varied depending on the drought conditions. While it was observed that at least 1 month of drought occurred in each year from 2001 to 2020 (Figure 4), the overall drought situation in the basin during the May to October period varied from year to year. This variability was reflected in the annual average CDI values, showing fluctuations between 44 and 59 (Figure 7a). Specifically, the CDI values for 2001, 2003, 2007, 2008, 2012, and 2016 indicated drought events in the basin (Figure 7a). The CDI values for 2009, 2013, and 2020 were on the threshold. It can be observed that drought events occurred approximately every 4 years in the basin since 2003, and the intensity of droughts decreased toward the end of the 20-year period (Figure 7a). The drought event in 2001 was the most severe and widespread among the mentioned years. Moreover, the wettest year was identified as 2014. In 2001, approximately 65% of the basin area was affected by drought, with over 11% classified as extreme, 17% as severe, 21% as moderate, and 16% as mild. In contrast, in 2014, about 69% of the basin area did not experience drought conditions (Figure 7b).

In 2001, the basin experienced the most widespread and intense drought, affecting 65% of the area during the 20-year period. The following year, in 2002, was significantly wetter. However, drought occurred again in 2003. After the drought in 2003, there was a recovery trend in the basin until 2006. However, the rate of recovery decreased from 2004 onward. Following this relatively wet period of 3 years, the basin was affected by drought again in 2007. The intensity of the drought in 2007 was equal to that of the drought in 2003. Despite a slight improvement after the drought in 2007, the basin continued to be affected by drought in 2008.

The drought impact in the basin decreased after the drought in 2007 and continued to decline until 2010. However, dry conditions intensified again in the basin after 2010, leading to the drought event in 2012. The drought in 2012 was the second most severe drought in the basin. Following a 2-year recovery period, the basin experienced its wettest year in 2014. After 2014, the basin became progressively drier each year until 2016. This trend culminated in the drought event of 2016. Subsequently, 2017 was wetter than 2016, 2018 was drier than 2017, and 2019 was wetter than 2018. 2020, on the other hand, was the driest year since 2016. The annual CDI change maps for the basin are shown in Figure S2.

Figure 8 displays the spatial distribution of the average CDI value (a) and the corresponding classifications (b) for the period from 2001 to 2020. The CDI values indicated that the majority of the study area predominantly encountered moderate and mild drought conditions (Figure 8a and b). Approximately 45% of the area fell within the CDI range of 30–50 (Figure 8c). Furthermore, the CDI values tended to be higher in areas where rainfed agriculture is practiced, as well as in forested regions. It was observed that areas most sensitive to drought were clustered in a crescent shape.
In summary, over the course of the 20-year study period from 2001 to 2020, approximately six drought events occurred, exhibiting a frequency of approximately one event every 4 years. Notably, the intensity of these drought events gradually declined as the study period progressed. The most severe and extensive drought event transpired in 2001, while the wettest year within the 20-year timeframe was observed in 2014. In addition, a decline in CDI values was observed from May onward during the May to October period, primarily due to rising temperatures and reduced precipitation. It was discerned that May represents the month with the wettest condition, while September is characterized as the driest month within the study area. Furthermore, it was revealed that areas most susceptible to drought are spatially concentrated in a crescent shape within the basin.


3.2 Evaluation of CDI with standardized indices

SPI and SPEI are commonly used meteorological drought indices to assess drought conditions across different time scales [20]. In the Ergene basin, the performance of CDI in drought monitoring was evaluated by comparing the time series of CDI with SPI-SPEI at various time scales from 2001 to 2020. As shown in Figures S3 and S6, CDI exhibited good consistency in fluctuation with the standardized indices at a 1-month time scale. The temporal fluctuations of the 1-month indices and CDI are particularly consistent, especially from 2010 onward. With the 3-month indices, CDI showed consistent fluctuations in some periods (Figures S4 and S7). The time series of CDI and the meteorological indices at a 3-month scale demonstrated strong

Figure 8: The spatial distribution of the average CDI values (a) and the classifications (b) from 2001 to 2020 and the statistical histogram of CDI values (c).
consistency, especially from 2003 to 2006, 2012 to 2014, and 2018 to 2020, although generally weaker consistency compared to the 1-month indices. However, with the 6-month SPI-SPEI, CDI showed consistency only in a few periods (Figures S5 and S8). In conclusion, the change trends of CDI and the 1-month meteorological indices appear to be similar. Figures S3–S8 present the temporal variations of CDI and SPI-SPEI at various time scales (1, 3, and 6 months).

On the other hand, to better evaluate CDI’s drought monitoring capability, the correlations between CDI and multitemporal SPI-SPEI were assessed spatially. The highest correlation and consistency were observed between CDI and 1-month meteorological indices, covering the largest area (Figure 9). The correlation values between CDI and 1-month indices concentrated between 0.5 and 1. Nevertheless, the correlation values in the southwestern part of the basin demonstrated lower values. Moreover, as the time scale expanded, the breadth of areas displaying high correlation and strong consistency diminished. CDI displayed a substantial correlation with 3-month indices, with correlation values varying from 0.4 to 0.7. Conversely, the correlation values between CDI and 6-month SPI-SPEI predominantly fell within

**Figure 9:** CDI correlation maps: (a) SPI-1, (b) SPI-3, (c) SPI-6, (d) SPEI-1, (e) SPEI-3, and (f) SPEI-6.
the range of 0.2–0.5, indicating significant areas with limited correlation. Furthermore, when SPI and SPEI were compared separately with CDI, SPEI showed higher correlations with CDI compared to SPI for the same period. Maps depicting the spatial distribution of correlations between CDI and meteorological indices are shown in Figure 9.

The correlation analysis between CDI and 1-month SPI-SPEI revealed a more robust relationship in comparison to other time scales, consistent with prior studies [15,17,19,20,55,56]. Interestingly, when comparing the SPI and SPEI for the same period, the correlation between CDI and SPEI was higher than that of SPI. This finding contradicts the results of previous studies [19,56].

3.3 Evaluation of CDI with crop yield

The crop yield is often used as an independent variable for assessing the CDIs. In this research, the correlation coefficient analysis was employed to examine the connection between the detrended crop yield and the CDI. It became evident that the sunflower crop directly reflects the impacts of agricultural drought in the basin. Therefore, a year-to-year comparison was made using the annual detrended data of sunflower crop yield and the annual CDI (averaged for the May to October study period) values of the basin [20,27]. As a result of this comparison, a strong and linear statistical relationship ($r = 0.79$) was found between CDI values and detrended crop yield data of sunflower. This indicates that the fluctuations in CDI can reflect the changes in crop yield in the basin. This finding is consistent with the results of previous studies [20,27,57,58], which contrast with the studies by Du et al. [24] and Bayissa et al. [26] that characterized this relationship as weak. The time series of the data used in the comparison is shown in Figure 10.

In conclusion, the CDI exhibited a stronger correlation with 1-month SPI-SPEI compared to other time scales of meteorological indices. In additionally, it showed a high correlation with crop yield data. These findings suggest that CDI has the potential to serve as a reliable indicator for monitoring meteorological and agricultural drought in the examined region. Moreover, it is anticipated that the Mediterranean region, encompassing Türkiye as well, will endure significant drought repercussions as a consequence of climate change. This, in turn, will adversely affect agricultural output [59]. In this context, sunflower can be considered as an indicator plant for detecting drought in this region.

4 Conclusions

Drought, a natural occurrence with negative impacts across multiple domains, necessitates sustainable and effective monitoring due to its harmful effects on society and the ecosystem. Remote sensing methodologies, renowned for their extensive coverage and frequent temporal observations, are extensively employed to fulfill this purpose.

In this study, a detailed and accurate drought analysis was conducted in the Ergene Basin, and a new combined index incorporating vegetation condition, surface temperature, precipitation, and soil moisture was proposed. The CDI was derived by combining the VCI, TCI, PCI, and SMCI by using PCA. This combined index was then used to analyze the spatial distribution and temporal drought changes in the Ergene Basin from 2001 to 2020. In addition, the performance of CDI in monitoring and assessing drought was evaluated by comparing it with standardized indices and crop yield data. The study utilized not only remote sensing data but also in situ observations. The MODIS 1 km spatial
resolution 16-day NDVI, 1km spatial resolution daily LST, 0.05° spatial resolution CHIRPS precipitation dataset, and 0.1° spatial resolution ERA-5 Soil Moisture data were used as the remote sensing datasets. In addition, precipitation and temperature data from meteorological stations in Çorlu, Edirne, Ipıla, Kırklareli, Lüleburgaz-Tigem, Malkara, and Tekirdağ were utilized to calculate SPI and SPEI.

According to the analysis, it was found that there was at least one drought month in the basin every year from 2001 to 2020. CDI values ranged from 35 to 79, indicating varying degrees of drought in the basin. It was determined that the wettest month in the May to October period is May, while the driest month is September. The degree of drought and the affected area in the basin showed an increasing trend followed by a decreasing trend during this period.

Based on the annual variations in CDI, the most intense and widespread drought in the basin occurred in 2001. Furthermore, these changes indicate that a drought event occurred on average every 4 years in the basin from 2003 to 2020, with drought intensity decreasing toward the end of the 20 years.

In addition, the CDI demonstrates the strongest correlation with 1-month SPI-SPEI when comparing CDI to other time scales. When assessing CDI in comparison to SPI-SPEI individually, it becomes apparent that SPEI exhibits a higher correlation with CDI than SPI for the corresponding period. Moreover, there is a substantial correlation ($r = 0.79$) between CDI values and sunflower crop yield data. The CDI maps also reveal a remarkable consistency in the spatial distribution of drought, revealing clusters of heightened vulnerability arranged in a crescent-like pattern.

Briefly, the high correlation of CDI’s SPI-SPEI in short periods (1 and 3 months) and crop yield demonstrates its effectiveness in monitoring meteorological and agricultural droughts. In addition, the alignment between the drought years identified by the annual CDI for the period 2001–2020 and the documented drought years in Türkiye and the southeastern European countries adjacent to the northwest border of Türkiye further validates the competence of CDI in drought studies.

This study highlights how PCA-based CDI can contribute to improved drought management practices, more accurate crop yield estimation, and the creation of customized drought mitigation strategies in the Ergene Basin.

Drought monitoring is still the main challenge in a relatively changing environment. It is worth mentioning that the input parameters used in this study were available in different spatial resolutions. While some datasets were only available in a coarse resolution, they still represent spatial variability. However, for future research, it is recommended to use high-resolution input data to enhance the accuracy of the results.

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References


[41] Stagge JH, Tallaksen LM, Gudmundsson L, Van Loon AF, Stahl K. Possible impacts of climate change on sunlight yield in Turkey. In:


