TRENDS ANALYSIS OF AGRICULTURAL DROUGHT IN CENTRAL ANATOLIAN BASIN, TURKEY

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ABSTRACT:

Drought is a natural disaster that can have devastating economic, environmental, and social impacts on a global, national, and regional scale. Remote sensing technology is the most powerful tool to determine of drought categories and analyse drought severity, vulnerability and its trends. Because data that is temporal, quick, wide-area, and repeating can be obtained via remote sensing technologies. The calculation of drought indices with the use of remote sensing technology is crucial for assessing the severity of the drought and its evolution over time. In this study, the Central Anatolian Basin, one of Turkey's agricultural basins, was subjected to a temporal and spatial drought analysis between 2000 and 2023. In order to analyze the agricultural drought in the Central Anatolian Basin, drought indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Drought Index (NDDI), Vegetation Condition Index (VCI), Temperature condition index (TCI), Vegetation Health Index (VHI), Precipitation Condition Index (PCI), and Scaled Drought Condition Index (SDCI) were calculated. Moderate resolution Imaging Spectroradiometer (MODIS) data collection were used to calculate the NDVI, NDWI, NDDI VCI and TCI drought indices and PCI was calculated using the Climate Hazards Group Infrared Precipitation with Station CHIRPS data set. With the results obtained, the change in drought severity in the Central Anatolian Basin over the years was observed and drought severity, plant health status and surface temperature were compared. Additionally Temporal trend and Spatial trend of agricultural drought were determine using Sen's slope and The Mann – Kendal non parametric test

1. INTRODUCTION

A natural calamity like a drought can have catastrophic effects on the environment, economy, and society at large as well as locally, nationally, and internationally. Drought can be classified into four main categories: hydrological, agricultural, social, and meteorological. A notable drop in average precipitation is indicative of a meteorological drought; a deficiency of surface and groundwater is indicative of a hydrological drought; and a combination of meteorological and hydrological droughts results in an agricultural drought that lowers plant moisture content.

A drought is a complex, protracted calamity marked by a sustained lack of water. Droughts can have a negative impact on the environment's ability to sustain itself, particularly on socioeconomic and agricultural activities and resource development. Agricultural drought monitoring is linked to global food security. Scientists worldwide are thus paying more and more attention to the problem of how to achieve the accurate and timely estimation of agricultural drought. Policymakers and scientists have given quantitative drought evaluation and prediction a lot of scientific attention during the last few decades (Tao et al., 2023). Historically, weather station data have been used for drought monitoring. However, these observations do not offer the continuous spatial coverage needed to accurately identify and track the precise spatial pattern of drought conditions. Wide spatial coverage, time domain repeatability, and cost-effectiveness are just a few benefits of using remote sensing data. Compared with the conventional methods, the remote sensing technique is regarded as an effective way to monitor drought conditions. It can be applied to monitor land surface parameters, for example, albedo, vegetation indices (VIs) and land surface temperature (LST), etc. These models typically use different optical bands to compute LST and VIs from satellite data (Tao et al., 2023). Using remote sensing indices, the dynamics of the drought and its effects can be quickly evaluated.

The Normalized Difference Drought Index (NDDI) can be useful for long-term drought monitoring, especially for agricultural drought, as it integrates vegetation greenness (NDVI- Normalized Difference Vegetation Index) and wetness conditions (NDWI- Normalized Difference Water Index). Trinh L.H. and Vu D.T. studied on drought assessment in Bac Binh district, Binh Thuan province using LANDSAT multispectral imagery based on normalized difference drought index (NDDI). Besides; Vegetation Condition Index (VCI), Temperature Condition Index (TCI) and Vegetation Health Index (VHI), which have been widely used to monitor and detect drought-related vegetation conditions. The satellite-based Vegetation Health Indices (VHIs) have been used to characterize drought and vegetation productivity in many previous studies around the world (Jiang et al., 2021). For example, Kogan et al. studied the trends of global and regional drought area for several drought intensities based on the satellite-based vegetation health indices during the warmest decade, especially, two recent strongest droughts happened in Russia and USA in 2010 and 2011, respectively (Jiang et al., 2021). Precipitation Condition Index (PCI) was used in various studies (Farooq et al., 2009; Gago et al., 2015; Pérez Blanco et al., 2016) showed that water stress has been proven to be a major cause for the occurrence of agricultural drought and PCI can be used to identify a

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precipitation deficit (Badamassi M. B. M. et al., 2019). Scaled Drought Condition Index (SDCI) is designed to be not only applicable to both arid and humid regions but also flexible in terms of the multiple timescales of precipitation. It combines thermal stress (TCI), water stress (PCI), and vegetation stress (VCI) (Park S. et al., 2020). Park et al. studied drought-forecasting models that were developed considering the temporal patterns of satellite-based drought indices (SDCI and SPI) and numerical model outputs through the synergistic use of convolutional long short-term memory (ConvLSTM) and random forest (RF) approaches over a part of East Asia.

In the Central Anatolian basin, Altın T. B. et al. 2023 were analysed using the annual and seasonal precipitation totals, Aridity Index (AI) and Standardized Precipitation Index (SPI), along with the long-term trends (1970-2020) and trends in precipitation totals, 12-month SPI and annual AI series were statistically determined by applying the Mann–Kendall rank correlation test (M–K test). According to the M–K test, they obtained statistically significant decreasing trends were determined for annual total precipitation and the 12-month SPI series in Keskin, Pınarbaşı, Sarız, Ürgüp and Akşehir. Nonsignificant and statistically significant decreasing trends in spring precipitation were determined at approximately 67% of the stations and at Ilgaz, Kulu, Eskişehir, Keskin, Zara, Ürgüp and Sarız stations, respectively.

Şorman A.Ü. et.al. (2018) were analysed the meteorological drought represented by Standardized Precipitation Evapotranspiration Index (SPEI) and agriculture drought represented by Vegetation Condition Index (VCI) in seven regions over Turkey. The regional correlation showed that, the highest correlation between two parameters is obtained for all the regions with SPEI 12 during summer, then followed by Autumn, and Spring months, the maximum values are recorded for the Central Anatolia (0.656) and Mediterranean (0.625) in Summer, and Aegean (0.643) in Autumn respectively; rather lower correlation values did occur in Marmara (0.515) in Autumn, Eastern Anatolia (0.501), SE Anatolia (0.375) and Black Sea (0.297) regions in Summer. The provincial investigation between seasonal VCI and SPEI indicated that the presence of a positive correlation in general in most of the provinces in all seasons with several exceptions in the Eastern Anatolia, South eastern Anatolia, Black sea, and Marmara.

In this study, the NDVI, NDWI, NDDI, VCI, TCI, VHI, PCI, and SDCI remote sensing indices were calculated between 2000 and 2023 in order to examine the temporal and spatial agricultural drought of the Central Anatolian Basin, one of Turkey's agricultural basins. Moderate-resolution Imaging Spectroradiometer (MODIS) data collection was used to calculate the NDVI, NDWI, NDDI VCI, and TCI drought indices, and PCI was calculated using the Climate Hazards Group Infrared Precipitation with Station CHIRPS data set. The results allowed for the comparison of surface temperature, plant health status, and drought severity as well as the observation of changes in drought severity over time in the Central Anatolian Basin. Furthermore, Sen's slope and the Mann-Kendal non-parametric test were used to identify the Temporal and Spatial trends of the agricultural drought.

2. MATERIALS AND METHODOLOGY

2.1 Study Area

Turkey's Ministry of Agriculture and Forestry has designated thirty agricultural basins in 2009. The Central Anatolian basin that is one of the these agricultural basins, was selected in this study to analyze agricultural drought. Figure 1 illustrates it.

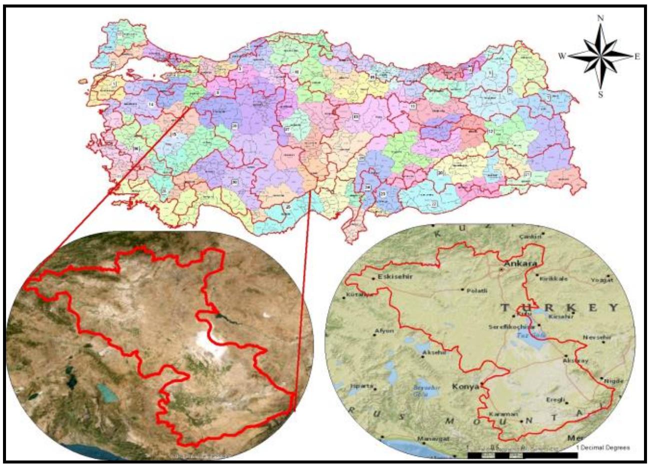

Figure 1. Study Area : Thirty agricultural basins in Turkey and Central Anatolian Basin (URL1) .

The Central Anatolian agricultural basin is located between 36-40 north latitude and 29-34 east longitude. The altitude of the study area varies between 1,889 m and 874 m. and the study area is approximately 71750.43 km² and the surrounding is 1973 km. Central Anatolia agricultural basin consists of 7 provinces and 52 districts. The average annual rainfall of the study area is 300 mm. The climate characteristic of the region is semi-dry.

2.2 Data Sets

Semi-global daily rainfall data is provided by the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset, which extend more than 30 years and uses satellite images with a resolution of 0.05°. Gridded rainfall time series and a precipitation condition index (PCI) were produced using the daily CHIRPS data acquired through the Google Earth Engine (GEE) platform for every month from 2000 to 2023. The CHIRPS data with 0.05° resolution was transformed to a monthly time scale by considering the number of days in the composite data. Precipitation data were reprojected onto MODIS imagery for spatial resolution.

The TCI for the months 2000–2023 was created using MOD11A2.061 Terra LST and Emissivity 8-Day Global 1 km product. NDVI data were calculated using The MOD13A2 product's surface reflectance b02 and surface reflectance b01 from MODIS image collections for every months between 2000 and 2023. Every month from 2000 to 2023, the Normalized Difference Water Index (NDWI) was calculated using the MOD13A2 product's surface reflectance b02 and surface reflectance b07 from MODIS image collections.

DATA	Data Utility	Spatial Resolution	Temporal Resolution	Source
Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)	PCI	0.05°	Daily	CHIRPS packages in GEE
MODIS MOD11A1.061 Terra Land Surface Temperature and Emissivity	TCI	1km	Daily	MODIS packages in GEE
MODIS MOD13A2.061 Terra Vegetation Indices (bands 1, 2, 7)	NDVI NDWI	1km	16 Day	MODIS packages in GEE

Table 1. Data sets used in the study.

2.3 Methodology

The agricultural drought is monitored using the remote sensing based indices. The remote sensing (RS) indices used in the study are Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Drought Index (NDDI), Vegetation Condition Index (VCI), Temperature Condition Index (TCI), Vegetation Health Index (VHI), Precipitation Condition Index (PCI) and Scaled Drought Condition Index (SDCI). Remote Sensing indices results obtained monthly between 2000 and 2023, were compared each other as annually and seasonally.

Moreover, Sen's slope and the Mann–Kendal non-parametric test were also used to determine the Temporal and Spatial trends of the agricultural drought.

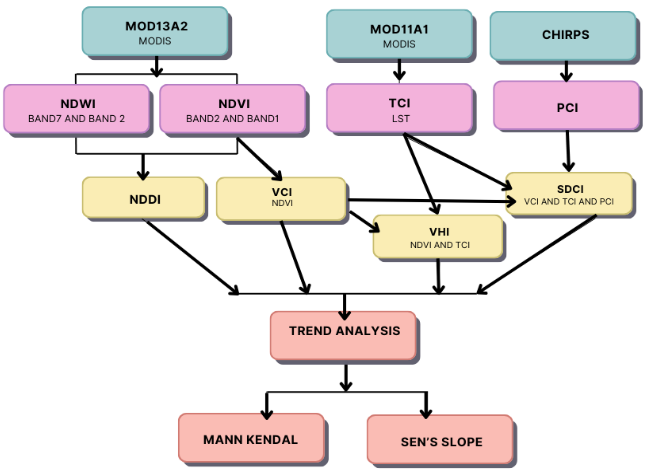

Figure 2. Flowchart of Methodology

2.4 Remote Sensing Indices

Remote sensing indices; It is a useful tool for detecting and analyzing long-term agricultural drought due to its ability to cover large areas quickly and repeatedly and provide the needed spatial and temporal information. In this study, NDVI, NDWI, NDDI, VCI, TCI, PCI and SDCI remote sensing indices, which are frequently used in the literature, were used to detect agricultural drought.

NDVI and NDWI is calculated using MODIS MOD13A2 product via Google Earth Engine. NDVI and NDWI proposed by Rouse et al.(1974) and Gao et al. (1996), The NDVI and NDWI were defined by the following formula is shown in equation (1) and (2) and it is shown in Table 3 respectively. In formula, R(Red), R(NIR) and R(SWIR) are the reflectance for MODIS MOD13A2 product, respectively A vegetation drought indicator, the NDDI combines information from both the NDVI and NDWI following Gu et al. (2007). NDDI were defined by the following formula is shown in equation (3) and it is shown in Table 3 respectively. In the formula, NDVIj and NDWIj are based on the monthly scales. NDDI Drought Categories are shown in Table 2.

Drought	**Values**
Non Drought	-1<NDDI<0.2
Mild Drought	0.2<NDDI<0.3
Moderate Drought	0.3<NDDI<0.4
Severe Drought	0.4<NDDI<0.5
Extreme Drought	0.5<NDDI<1

Table 2. Classification of Drought by calculated the NDDI

REMOTE SENSING INDICES	FORMULA	NUMBER
NDVI	$\frac{R(NIR) - R(red)}{R(NIR) + R(red)}$	(1)
NDWI	$\frac{R(NIR) - R(SWIR)}{R(NIR) + R(SWIR)}$	(2)
NDDI	$\frac{NDVIj - NDWIj}{NDVIj + NDWIj}$	(3)
VCI	$\frac{NDVIi - NDVImin}{NDVImax - NDVImin} * 100$	(4)
TCI	$\frac{LSTmax - LSTj}{LSTmax - LSTmin} * 100$	(5)
VHI	a VCI + (1-a) TCI	(6)
PCI	$\frac{CHIRPS\ i - CHIRPS\ min}{CHIRPS\ max - CHIRPS\ min} * 100$	(7)
SDCI	$\alpha * VCI + \beta * TCI + \gamma * PCI$	(8)

Table 3. Equations of Remote Sensing Indices

The VCIi is utilized for the evaluation of vegetation in drought conditions affecting agriculture. The VCIi compares the NDVIi data for a given period with the highest and lowest values of the NDVI data for the whole period. Equation (4) is used to calculate the VCIi. and it is shown in Table 3. In the formula the NDVIi is the smoothed 16-day NDVIi, NDVI min and NDVI max defined as minimum and maximum values of NDVIi for all pixels and periods and i is based on the monthly scales (Jalayer s. et al 2023). VCI Drought Categories are shown in Table 4.

The land surface temperature (LST) is strongly associated with drought, and the temperature rise is the initial indication of the crops being treated with moisture stress and drought. The increase of temperature and the closure of leaf stomata can reduce the water loss caused by transpiration, reduce the surface latent heat flux, increase the surface sensible heat flux, and then cause the increase of temperature (Cai S. et al, 2023). Based on this principle, Kogan (1995a) proposed the Temperature Condition Index (TCI), and its calculation formula is shown equation (5) and it is shown in Table 3. In the formula, LSTj is the smoothed monthly LST; LST max and LST min represent maximum and minimum LST, respectively, calculated by multiyear smoothed monthly LST series for each pixel during the period 2000–2023 (Cai S. et al, 2023). TCI Drought Categories are shown in Table 4.

The Vegetation Health Index was defined as combination of VCI and TCI. It has been widely used to detect drought in many Places (Cai S. et al.,2018). VHI was proposed to address the limitations of VCI in areas with excessive soil wetness and/or long periods of cloudiness (Kogan F.N. et al, 1995), under which conditions NDVI is normally very depressed and VCI has low values, which can be interpreted as drought in error. The VHI was defined by the following formula is shown in equation (6) and it is shown in Table 3. In VHI formula; a and (1-a) is 0.5 that are the weight of monthly VCI and TCI; on the other hand, plus of a and (1-a) equal to 1. Generally, α is set as 0.5 because it is difficult distinguish the contribution of crop surface temperature and NDVI when measuring drought stress. VHI Drought Categories are shown in Table 4.

Precipitation Condition Index: The PCI which normalized by the CHIRPS data is described for the recognition of the deficit in precipitation during a period from climate signal. Equation (7) is used to calculate the PCIi. and it is shown in Table 3. In the formula; CHIRPSmax, and CHIRPSmin are the pixel values of rainfall, maximum and minimum of it, respectively, and i is based on the monthly scales (Jalayer S. et al.,2023). PCI Drought Categories are shown in Table 4.

The SDCI is made to be variable with regard to the various precipitation timescales and to work in both humid and dry environments. It includes the effects of water stress (PCI), vegetation stress (VCI), and heat stress (TCI). Formula of SDCI is shown in equation 8. (Rhee, J. et al 2010) and it is shown in Table 3. In formula α is 0.25, β is 0.25 and γ is 0.50 that are the weights of monthly VCI, TCI and PCI, and plus both α and β and γ is equal to 1. SDCI Drought Categories are shown in Table 4.

Drought Categories	SDCI,TCI,VCI,VHI Values	PCI Value
Extreme Drought	0<SDCI,TCI,VCI,VHI<10	0<PCI<10
Severe Drought	10<SDCI,TCI,VCI,VHI<20	10<PCI<20
Moderate Drought	20<SDCI,TCI,VCI,VHI<30	20<PCI<30
Mild Drought	30<SDCI,TCI,VCI,VHI<40	30<PCI<40
Near Normal	40<SDCI,TCI,VCI,VHI<60	40<PCI<50
Non Drought	60<SDCI,TCI,VCI,VHI<100	50<PCI<100

Table 4. Classification of Drought by calculated the SDCI,TCI,VCI,VHI, PCI

2.5 Trend Analysis

Mann Kendal and Sen's slope non parametric methods was chosen for to understand the trends in the agricultural drought in Central Anatolian Basin.

2.5.1 Mann Kendal

Mann-Kendall (MK) test is the most preferred non-parametric test to determine the trend of time series where there is no distributional fit.

For a given time series X (x1; x2; x3;... xn), the null hypothesis (H0) indicates no trend, but the alternative hypothesis (Ha) indicates either a steady growing or decreasing trend. The approach for analyzing MK trends is detailed below. Using the following equation, we can get the test statistic for the series, which we will refer to as “S” is shown in equation (9) (Bambang I. et al,2023).

$$S=\sum_{j=1}^{n-1}\sum_{j=i+1}^{n}\operatorname{sgn}(x_j-x_i) \tag{9}$$

In formula; n is number of data, xi and xj are the values of remote sensing indices that correspond to the years i and j (j=i+1), respectively. As shown with “sgn” formula in equation (10) and Variasion

$$\operatorname{sgn}(x_j-x_i)=\begin{cases}+1 & x_j>x_i\\ 0 \;\; if & x_j=x_i\\ -1 & x_j<x_i\end{cases} \tag{10}$$

Var(s), which shows the variance of the variable S, is calculated with the formula shown in equation 11. In the Var(S) formula, ti represents the total number of bonds found in the sample analysis.

$$Var(S)=\{n(n-1)(2n+5)-\sum_{i=1}^{n}ti(i-1)(2i+5)\}/18 \tag{11}$$

The statistics for the standardized test, which are denoted by the letter Z, are computed as follows equation 12. A rising trend is indicated by a positive Z value, whereas a declining trend is shown by a negative Z value. The significance threshold for the test was set at 5% throughout its execution (Bambang I. et al,2023).

$$Z=\begin{cases}S-1/\sqrt{Var(S)} & S>0\\ 0 & S=0\\ S+1/\sqrt{Var(S)} & S<0\end{cases} \tag{12}$$

2.5.2 Sen’s Slope

Sen created this test first in order to verify statistical linear correlations in the long-term temporal data, that is employed to compute the magnitude of trends. Due to its insensitivity to data outliers, Sen's slope is seen to be a superior method for identifying linear relationships. In this study, the trend magnitude for remote sensing drought indicators is determined using Sen's slope.

All slope pairs are ranked from smallest to largest, and if the calculated number of slopes (n) is odd, the median slope gives the slope S. If n is even, the two median slopes are averaged. Here, Q represents data, n is the length of the data, and T is time. The slope of n pair of data is predicted as follows equations 13 and 14 (Esit M., et al,).

$$S = \frac{Q_2 - Q_1}{T_2 - T_1} \tag{13}$$

$$S = \begin{cases} S_{\frac{n+1}{2}} & n = even \\ S_{\frac{n}{2}} & n = odd \end{cases} \tag{14}$$

3. RESULTS AND DISCUSSIONS

3.1 Agricultural Drought Monitoring with Remote Sensing Indices

Remote sensing based indices like NDVI, NDWI, NDDI, VCI, TCI, VHI, PCI and SDCI were used for the agricultural drought monitoring in Central Anatolian Agricultural Basin. The indices were calculated on monthly and yearly for the period of 2000 to 2023 via Google Earth Engine (GEE). Due to lack of data, January 2000 and November and December 2023 were not calculated for all indices.

NDDI is calculated using NDVI and NDWI indices as yearly and seasonally. The annual and seasonal distribution of NDDI values between 2000 and 2023 is shown with Figure 3 and NDDI Drought Categories are shown in Table 2. An increased trend had been detected for the temporal trend of Winter NDDI values.(R=0.4354) According to NDDI values, there was no agricultural drought in the winter months, but it increased to a mild drought between 2000 and 2023. When annual NDDI values are analyzed, the highest value of 0.567 indicates the year 2016, and the lowest value of 0.144 indicates the year 2002. As Table 2 NDDI shows Extreme Drought in 2016 and non drought in 2002. The spatial characteristics of the NDDI drought index, in 2002 and 2016 were shown in Figure 4.

In order to assess the spatial patterns of PCI throughout the Central Anatolian Basin between 2000 and 2023 as a sign of climate change, this study used the CHIRPS dataset, which contains daily rainfall data from 2000 to 2023. PCI is calculated as yearly and seasonally. The annual and seasonal distribution of PCI values between 2000 and 2023 is shown with Figure 5 and PCI Drought Categories are shown in Table 3.

The temporal trend of Winter PCI values is R=0.2646 and according to PCI values, there is a decrease in rainfall conditions in winter season between 2000 and 2023. When annual PCI values are analyzed, the highest value of 49.495 indicates the year 2005, and the lowest value of 26.600 indicates the year 2022. As Table 3, PCI shows Near Normal Drought in 2005 and Moderate Drought in 2022. The spatial characteristics of the PCI drought index, in 2005 and 2022 were shown in Figure 6.

TCI was calculated using Land Surface Temperature from MOD11A1.061 Terra Land Surface Temperature and Emissivity product via Google Earth Engine (GEE). TCI is calculated as yearly and seasonally. The annual and seasonal distribution of TCI values between 2000 and 2023 is shown with figure 7 and TCI Drought Categories are shown in Table 3.

The temporal trend of Winter TCI values is R=0.2105 and according to TCI values, there is a decrease in temperature conditions in winter season between 2000 and 2023. When annual TCI values are analyzed, the highest value of 48.652 indicates the year 2005, and the lowest value of 27.438 indicates the year 2021. As Table 3, TCI shows Near Normal Drought in 2005 and Moderate Drought in 2021. The spatial characteristics of the TCI drought index, in 2005 and 2021 were shown in Figure 8.

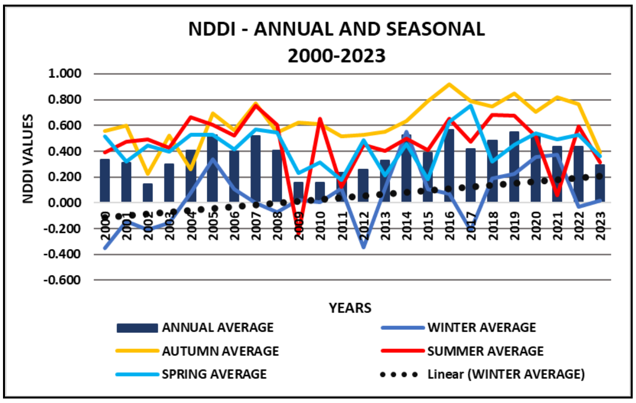

Figure 3. NDDI Values as annual and seasonal between 2000 and 2023

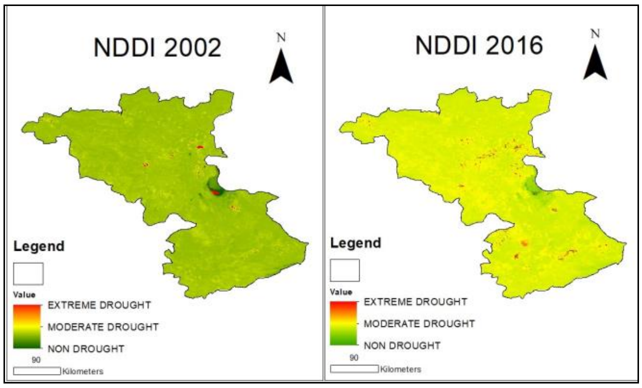

Figure 4. The temporal spatial pattern of NDDI in 2002 and 2016

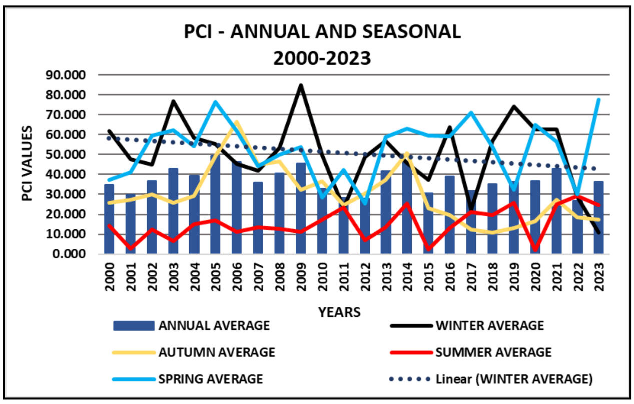

Figure 5. PCI Values as annual and seasonal between 2000 and 2023

VCI was calculated using NDVI that is obtained from MOD13A2.061 Terra Vegetation Indices product via Google Earth Engine (GEE). VCI is calculated as yearly and seasonally. The annual and seasonal distribution of VCI values between 2000 and 2023 is shown with figure 9 and VCI Drought Categories are shown in Table 3.

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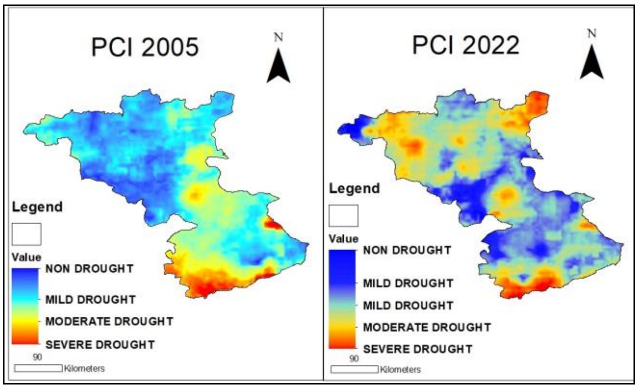

Figure 6. The temporal spatial pattern of PCI in 2005 and 2022

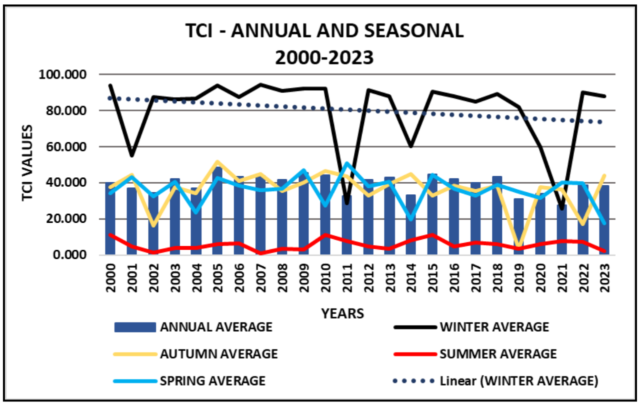

Figure 7. TCI Values as annual and seasonal between 2000 and 2023

An increased trend had been detected for The temporal trend of annual VCI values.(R=0.2855) However, since there was not aggressive increasing, according to VHI values the agricultural drought category did not change and it is detected as Mild Drought between 2000 and 2023. On the other hand, when the VCI is examined seasonally, it shows that the VCI in 2008 and 2011 had the lowest drought rates in the spring with average values of 64.73, 72, and 75, respectively, indicating that it was not drought in this case. The lowest VCI values were recorded as 4.8 and 8 in the spring of 2019 and the summer of 2014 and 2018, respectively, indicating extreme drought.

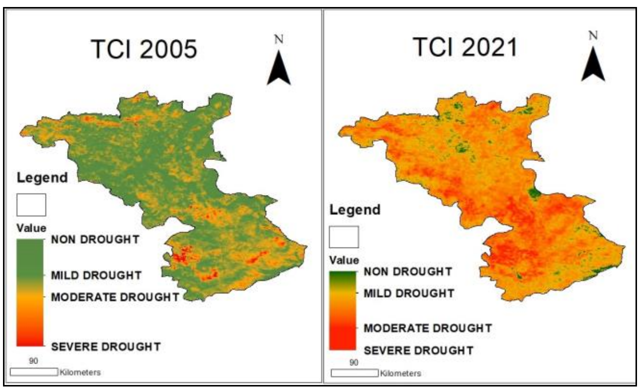

Figure 8. The temporal spatial pattern of TCI in 2005 and 2021

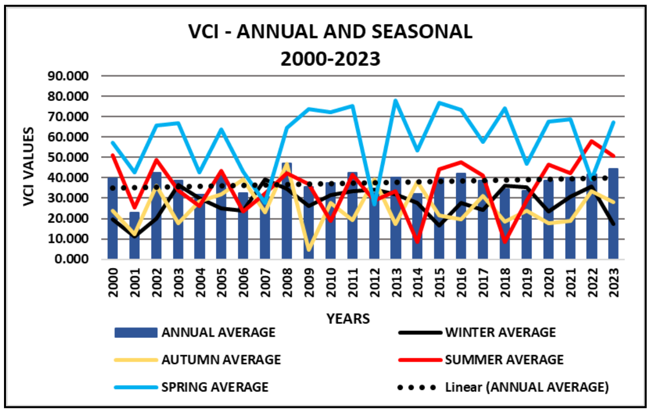

Figure 9. TCI Values as annual and seasonal between 2000 and 2023

VHI is calculated using VCI and TCI indices as yearly and seasonally. The annual and seasonal distribution of VHI values between 2000 and 2023 is shown with figure 10 and VHI Drought Categories are shown in Table 3. The temporal trend of annual VHI values is R=0.1982 and according to VHI values, there is a minimal decrease in vegetation health between 2000 and 2023. However, when the 23-year time series was analyzed, the decreasing and increasing situation of VHI values over time provided a balance. Therefore, the drought category in terms of vegetation health did not change on average between 2000 and 2023. The drought category of the Central Anatolia Basin according to VHI was generally determined as Mild Drought between 2000 and 2023..

The highest drought rates, with average values of 66 and 67 in the winter of 2007 and 2010, respectively, are determined in a seasonally-assisted analysis of the VHI, indicating that this is not a case of drought. The lowest recorded VHI readings in the summers of 2006, 2020, and 2021 were 9, 13, and 1, respectively, indicating an extreme drought.

The SDCI evaluated the agricultural drought in the Central Anatolian Basin from 2000 to 2023 based on the PCI, VCI, and TCI calculations. Figure 11 displayed the temporal variation of the agricultural drought at the yearly and monthly levels. SDCI Drought Categories are shown in Table 3. According to the temporal trend of annual SDCI values that is R=0.01, the agricultural drought category did not change and it is detected as Mild Drought between 2000 and 2023.

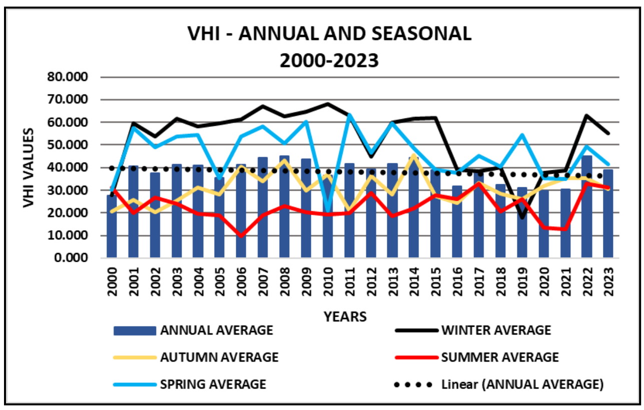

Figure 10. VHI Values as annual and seasonal between 2000 and 2023

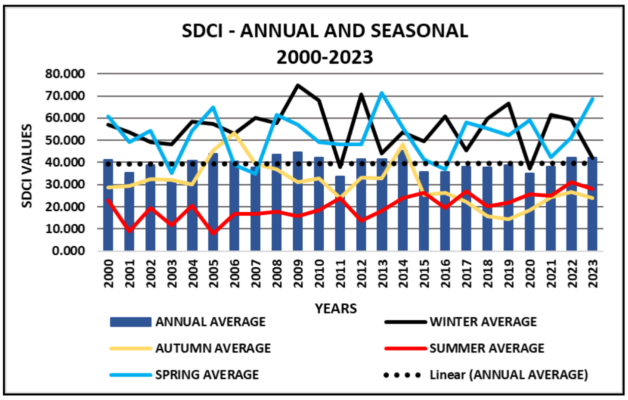

Figure 11. SDCI Values as annual and seasonal between 2000 and 2023

However, a seasonally-assisted analysis of the SDCI reveals that the highest drought rates are found in the spring of 2013 and the winter of 2019, with average values of 71 and 74, respectively, suggesting that this is not a case of drought. In the summers of 2001, 2003, and 2005, the lowest SDCI values were recorded as 8, 11, and 7, respectively, suggesting an extreme drought.

3.2 Trend Analysis

The direction of change resulting from the increase or decrease of parameter values in a time series is expressed as a trend. Predicting future trends using historical data is the primary goal of trend analysis, particularly with regard to time series data. In this study, the confidence interval was chosen as 95 percent when calculating the Mann Kendal and Sen's Slope methods. The Z value for the significance level at the 95 percent confidence interval from the standard normal distribution table was determined as 1.96. If the Z values obtained by the Mann Kendall test are outside the range of ±1.96, H_0 is rejected at the significance level and indicates the presence of a trend. In the Sen's slope test results, negative values indicate a decreasing trend and positive values indicate an increasing trend.

Mann Kendal and Sen's slope were calculated using R Studio programme. The statistical results of Remote Sensing Indices as annually and seasonally between 2000 and 2023 is shown in Table 5. As seen in Table 5, there is no trend test results, and the increasing and decreasing trend results are compatible with each other in the Mann Kendal and Sen's slope.

Mann Kendal and Sen's slope test results of the calculated agricultural drought indices show that there is not statistically significant trend on an annual basis. When the test results are evaluated from a seasonal perspective, it is seen that there is a statistically significant decreasing trend in the PCI autumn season and SDCI autumn season. In addition, it is seen that NDDI autumn and winter seasons, PCI summer seasons and SDCI summer seasons have a statistically significant increasing trend.

Since there is a negative relationship between PCI and drought, it can be said that the PCI autumn season, which is in a statistically significant decreasing trend, shows the increasing drought severity, and the PCI summer season, which is in a statistically significant increasing trend, shows the decreasing drought severity.

		ANNUAL	AUTUMN	WINTER	SPRING	SUMMER
NDDI	MK Values	1.7611	2.3564	2.2572	0.2233	0.1489
	Sen's slope	0.0069	0.0138	0.0179	0.0007	0.0007
	Trend	↔	↑	↑	↔	↔
PCI	MK Values	-0.7193	-2.3564	-0.7689	0.6201	2.2572
	Sen's slope	-0.1589	-0.7897	-0.7489	0.3042	0.6347
	Trend	↔	↓	↔	↔	↑
TCI	MK Values	-1.1658	-1.0170	-1.2154	-0.6697	0.5209
	Sen's slope	-0.2225	-0.2372	-0.2667	-0.1592	0.0376
	Trend	↔	↔	↔	↔	↔
VCI	MK Values	1.1658	-0.1736	0.6697	1.0666	0.7689
	Sen's slope	0.1759	-0.0757	0.2112	0.3312	0.3911
	Trend	↔	↔	↔	↔	↔
VHI	MK Values	-0.9178	1.3146	-0.9178	-1.2154	0.5705
	Sen's slope	-0.2249	0.2953	-0.4224	-0.5850	0.1202
	Trend	↔	↔	↔	↔	↔
SDCI	MK Values	0.2232	-2.5052	0.0744	0.3225	3.5470
	Sen's slope	0.0361	-0.6603	0.0315	0.1369	0.6113
	Trend	↔	↓	↔	↔	↑

Tablo 5. Mann Kendal and Sen's slope statistical result of Remote Sensing Indices as annually and seasonally

Besides, NDDI and SDCI are indices calculated directly for the prediction of agricultural drought, there is a positive relationship between them and drought. Therefore, it can be said that the SDCI autumn season, which has a statistically significant decreasing trend, shows the decreasing drought severity, and the statistically significant increasing NDDI autumn and winter seasons and the SDCI summer season show the increasing drought severity.

3.3 Conclusion

When the remote sensing indices calculated in spatial and temporal terms are examined, the decrease in PCI and TCI values shows that the severity of drought has increased in the Central Anatolian agricultural basin. However, according to the calculated VCI and VHI values, since the drought category has not changed between 2000 and 2023, it can be said that decreasing precipitation and temperature have not yet negatively affected plant health.

As precipitation increases and temperatures decrease in winter, drought severity is expected to be less than in summer. When long-term annual data are examined, it is predicted that an increase in drought in the winter months will cause an increase in agricultural drought in the spring and summer months.

According to Mann Kendal and Sen's slope test results, SDCI values show that there is increasing agricultural drought severity in summer, and NDDI values show that there is increasing agricultural drought severity in autumn and winter.

REFERENCES

Altın T. B., Türkeş M., Altın B. N., Evolution of Drought Climatology and Variability in the Central Anatolia Region, Turkey, for the Period 1970–2020 (2023), Pure and apllied Geophysics, Volume 180, pages 3105–3129.

Badamassi M. B. M., Ahmed E. A., Gbetkom P. G., 2019, A New Agricultural Drought Index to Better Detect and Monitor Millet Crop by Remote Sensing in West Africa: Case of Niger. Journal of Advanced Research in Dynamical and Control Systems, 11, 11-Special Issue, pp.1023-1033.

Bambang I., Saravanan S., Reddy N.M., Abijith D., An investigation of the changing patterns of rainfall in the Indravathi subbasin utilizing the Mann–Kendall and Sen's slope Methods, 2023, IOP Conf. Ser.: Earth Environ. Sci. 1173 012036, doi:10.1088/1755-1315/1173/1/012036

Cai S., Zuo D., Wang H., Xu Z., Wang G., Yang H., Assessment of agricultural drought based on multi-source remote sensing data in a major grain producing area of Northwest China, 2023, Agricultural Water Management 278, 108142

Cai S., Zuo D., Xu Z., Han X., Gao X., Spatiotemporal variability and assessment of drought in the Wei River basin of China, 2018, PIAHS, 8th International Water Resources Management Conference of ICWRS, Beijing, China, 13–15 June 2018 Proc. IAHS, 379, 73–82, doi.org/10.5194/ piahs-379-73-2018

Dinha N., Haa N. T. T., Thaoa N. T. P.,Linha N. T., 30 Years Monitoring Spatial - Temporal Dynamics Of Agricultural Drought In The Central Highlands Using Landsat Data, 2019, The International Conference on Geo-Spatial Technologies and Earth Resources At: Hanoi, Vietnam

Esit M., Yüce M. I.;2022, Comprehensive evaluation of trend analysis of extreme drought events in the Ceyhan River Basin, Turkey, doi: 10.26491/mhwm/154573

Farooq, M., Wahid, A., Kobayashi, N., Fujita, D., Basra, S.M.A., 2009. Plant drought stress: effects, mechanisms and management. Agron. Sustain. Dev. 29, 185–212. doi.org/10.1051/agro:2008021

Gago, J., Douthe, C., Coopman, R.E., Gallego, P.P., Ribas-Carbo, M., Flexas, J., Escalona, J., Medrano, H., 2015. UAVs challenge to assess water stress for sustainable agriculture. Agric. Water Manag. 153, 9–19.

Gao B., 1996. NDWI - A normalized difference water index for remote sensing of vegetation liquid water from space, Remote Sens. Environ., 58, p. 257- 266.

Gu, Y; Brown, J. F; Verdin, J.P; Wardlow, B., 2007. A five year analysis of MODIS NDVI and NDWI for grassland drought assessment over the central Great Plains of the United States. Geophysical Research Letters, 34, L06407.

Jalayer S., Sharifi A., Abbasi-Moghadam D., Tariq A., Qin S., Assessment of Spatiotemporal Characteristic of Droughts Using In Situ and Remote Sensing-Based Drought Indices,2023, IEEE Journal Of Selected Topics In Applied Earth Observations And Remote Sensing, Vol. 16, 1483-1502

Jiang R., Liang J., Zhao Y., Wang H., Xie J., Lu X., Li F., 2021, Assessment of vegetation growth and drought conditions using satellite-based vegetation health indices in Jing-Jin-Ji region of China. Nature Portfolio, Scientifc Reports, 11:13775. doi.org/10.1038/s41598-021-93328-z

Kogan, F. N.: Droughts of the late 1980s in the United States as derived from NOAA polar-orbiting satellite data, B. Am. Meteorol. Soc., 76, 655–668, 1995

Kogan, F., Adamenko, T. & Guo, W., 2013, Global and regional drought dynamics in the climate warming era. Remote Sens. Lett. 4, 364–372.

Park S. , Im J. , Han D., Rhee J., 2020, Short-Term Forecasting of Satellite-Based Drought Indices Using Their Temporal Patterns and Numerical Model Output, Remote Sens., 12, 3499; doi:10.3390/rs12213499

Pérez-Blanco, C.D., Standardi, G., Mysiak, J., Parrado, R., Gutiérrez-Martín, C., 2016. Incremental Water Charging in Agriculture. A Case Study of the Regione Emilia Romagna in Italy. Environ. Model. Softw. 78, 202–215.

Rhee, J.; Im, J.; Carbone, G.J. Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data. Remote Sens. Environ. 2010, 114, 2875–2887

Rouse, J. W., Jr., H. R. Haas, D. W. Deering, J. A. Schell, and J. C. Harlan, 1974. Monitoring the vernal advancement and retro gradation (green wave effect) of natural vegetation, NASA/GSFC Type III Final Report, p. 371, Greenbelt, Md

Şorman A. Ü., Mehr A. D., Hadi S.J., Study on spatial-temporal variations of Meteorological-Agricultural droughts in Turkey (2018) The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLII-3/W4, GeoInformation For Disaster Management (Gi4DM), 18–21 March 2018, Istanbul, Turkey

Tao, L.; Di, Y.; Wang, Y.; Ryu, D., 2023, Normalized Temperature Drought Index (NTDI) for Soil Moisture Monitoring Using MODIS and Landsat-8 Data. Remote Sens., 15, 2830. doi.org/ 10.3390/rs15112830

Trinh L.H.; Vu D.T., 2019, Application of remote sensing technique for drought assessment based on normalized difference drought index, a case study of Bac Binh district, Binh Thuan province (Vietnam). Russ. J. Earth. Sci., Vol.19, ES2003, doi:10.2205/2018ES000647.

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URL1:https://www.tarimorman.gov.tr/Sayfalar/Icerikler.aspx?IcerikId=296c5dc2-2d3f-427d-af9a-70c4a2f131a6 (18 December 2023)