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Drought Monitoring on Google Earth Engine with Remote Sensing: A Case Study of Şanlıurfa

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ABSTRACT

Drought is a natural disaster disrupting provision of ecosystem services, causing degradation of agricultural lands and leading migration of people living mostly in arid and semi-arid regions of the world. Regional and country-level drought monitoring are needed to adopt agricultural production systems and people living in rural areas and minimize the adverse impacts. The drought indices using different climate or vegetation variables have been used to obtain a comprehensive understanding for drought analysis and decision-making. The purpose of this study was to evaluate agricultural drought in Şanlıurfa province of Turkey using Normalized Difference Vegetation Index NDVI and precipitation data, and to investigate the relationship between the indices and the temporal interaction of the factors active in the drought process. NDVI dataset produced from MODIS/006/MCD43A4 surface reflection composites of Google was used in the study. Google Earth Engine cloud computing platform and JavaScript coding language were employed in drought analysis. The NDVI anomaly data between 2004 and 2020 showed that the highest negative deviation -0.208 was in April 2008. The largest negative rainfall anomaly -9.372 was calculated in February 2017. The rainfall anomaly amplitude, which had negative and cumulative rainfall anomaly from mid-2007 to late 2009, was also reflected in the NDVI anomaly with a low latency. Moderate positive correlation was obtained between NDVI and rainfall anomaly $r=0.35$, $p\leq0.05$. The results show that agricultural drought in large areas where annual precipitation is less than the precipitation threshold required for the NDVI temporal response, can be monitored rapidly and efficiently using the anomaly values calculated with big remote sensing data.

1. Introduction

Drought is a general term including meteorological, hydrological, agricultural and socioeconomic drought (Wilhite et al., 1986). Meteorological drought, which has many definitions, is generally defined by the magnitude and duration of precipitation deficiency (American Meteorological Society, 2013). Hydrological drought is associated with the effects of insufficient precipitation on surface or groundwater resources and is generally defined as a period of continued water scarcity due to the precipitation anomalies (National Drought Mitigation Center, 2022). The term agricultural drought is used to define the period in which the available soil water content is not sufficient for healthy plant growth, plants cannot grow well and the yield significantly decreases. The agricultural drought is defined as a lack of soil moisture in relation to climate and impact of water deficiency on agricultural production as well as economic profitability (Mannocchi et al., 2004). Socio-economic drought is related to the impact of other three drought types on various socio-economic activities (Wilhite et al., 1986). This study aimed to evaluate precipitation and vegetation performance together and to discuss agricultural drought.

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The drought is monitored and evaluated using ground-based point observation data and spatial interpolation techniques for meteorological and agricultural purposes (AghaKouchak, 2015; Wilhelmi et al., 2002). However, the information obtained with ground-based observations such as long-term reliable precipitation, soil surface temperature, wind speed, atmospheric water vapor and relative humidity of the agricultural lands is not yet at the desired level. In addition, current observations do not have sufficient continuity to reveal the spatial and temporal variability of drought-related data such as precipitation (Easterling, 2013). Therefore, recent studies have focused on remote sensing datasets for climate parameters and vegetation. In this context, the advantages of satellite-based sensors over traditional ground-based observations are providing consistent data records on a global scale and having enhanced spatial and temporal resolution (Jiao et al. 2021). In addition, the diversity and volume of data combined with the increased satellite observations have provided opportunities to improve drought-monitoring capabilities. However, managing the high volume with the diversity of data causes difficulties such as evaluating multiple data sets together (AghaKouchak et al., 2015). The Google Earth Engine (GEE) is a platform established to process geospatial data. Environmental monitoring for large areas can be carried out using GEE and the geospatial data is analyzed to overcome aforementioned challenges with the opportunity provided by the GEE. Everyone can access to huge remote sensing imageries with no cost using the GEE. The JavaScript and Python languages are used in the GEE as well as machine learning algorithms, along with high-speed parallel processing capability using computing infrastructure of Google. Therefore, the GEE enables to analyze and visualize large size geospatial data (Tamiminia et al., 2020).

Several vegetation indices have been developed using the data from the electromagnetic spectrum. The Normalized Difference Vegetation Index NDVI is the simplest, efficient and commonly employed vegetation index among the researcher (Liu and Huete, 1995). The NDVI was proposed by Tucker et al. (1982) as an indicator of plant density and health, which suggests overall vegetative health. The vegetation changes and frequency of agricultural drought in an area can be determined and monitored using the NDVI data (Sruthi and Aslam, 2014). Since the NDVI provides information on the effects of moisture deficiency on plant growth, the moisture deficiency determined using NDVI does not allow correction by intervention (Ji and Peters, 2003). Precipitation and other meteorological parameters monitored over a long period reveal that the drought is a temporal problem (Wilhite et al., 1986). Therefore, NDVI anomaly NDVIA, which provides information on the difference between the values of current NDVI and the average NDVI for a specific period, is a useful and more accurate measure of drought compared to the NDVI. In addition, the NDVIA has the ability to reveal the negative impacts of moisture economy caused by precipitation anomalies on vegetation due to the temporal monitoring of drought.

The overall aim of this study was to evaluate agricultural drought based on a conceptual framework that synthesizes NDVI and precipitation data based on dynamic monitoring. In this context, the relationships between the indices and the temporal interaction of the factors in the drought process were examined. The NDVIA evaluates the relationships between temporal precipitation anomalies and crop yield, with a focus on water deficit accumulation and time lag, to assess agricultural drought over a long-term period.

2. Material and Method

2.1. Study Area

The study covers Şanlıurfa province, located in the Southeastern Anatolia Region of Turkey. The study area is located between 37°40'0"-40°20'0" East longitudes and 37°40'0"- 38°00'0" North latitudes (Figure 1). The coverage area of province is 3668.76 km^2 which is larger than Georgia 2642 km^2, Luxemburg 2586 km^2 and many other small countries of the Europe. Agriculture is the main source of income in the province which is the eighth most crowded city in Turkey. Rainfed agriculture is carried out in the northern part, while irrigation is used in the plains located on the south, southeast and southwest parts of the province (Aydogdu, 2019). The precipitation occurs mostly as rain in winter and spring and snow occurs only in the high altitudes around the province. The annual average temperature of the study area, which is under the influence of Basra Low Pressure zone in summer, varies between 11 ºC and 19 ºC (Caglak et al., 2016). The annual average rainfall in Şanlıurfa is 462 mm. Annual average temperature is 18.6 °C, evaporation is 2048 mm, wind speed is 2.8 m/s (Anonymous, 2021).

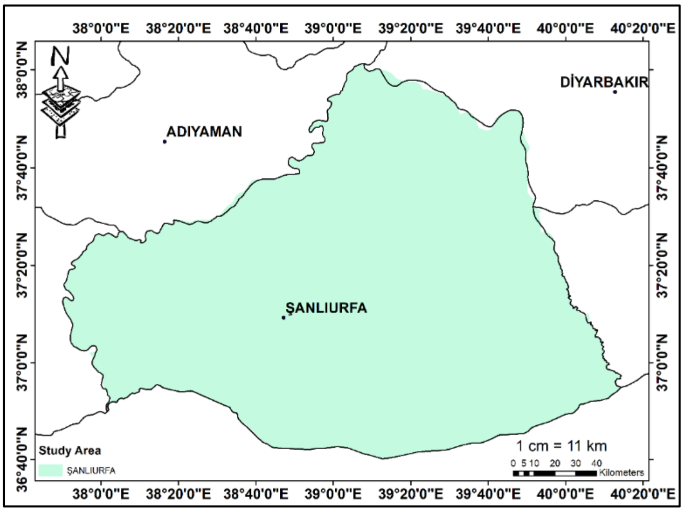


Figure 1. Geographical location of Şanlıurfa province

2.2. Remote Sensing Data

The NDVI was calculated using data from the Near-IR NIR and Red bands and ranges from -1.0 to 1.0 Equation 1.

$$NDVI = NIR - Red / NIR + Red$$

The NDVI dataset produced from Google's MODIS/006/MCD43A4 surface reflection composites was used. The data of Terra MODIS was used between the years 2004-2020 (Anonymous, 2022). The spatial and temporal resolution of Terra MODIS are 250 m and 16 days, respectively. The precipitation data of the study area were obtained from the

Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). The CHIRPS has a quasi-global rainfall data set for more than 35 years. A precipitation dataset of 2004-2020 containing the study area boundaries was selected from the CHIRPS 30-year global data catalog. The CHIRPS contains terrestrial station data and 0.05° resolution satellite imagery. The data in the CHIRPS can be used in trend analysis and seasonal drought monitoring creating rainfall time series (Funk et al., 2015).

2.3. Drought Assessment using NDVI and Rainfall Anomaly

Drought analysis was carried out using the GEE cloud computing platform and JavaScript coding language. The GEE is a cloud-based computing platform developed to store and process petabyte scale datasets for analysis and to conclude the final decision (Kumar and Mutanga, 2018). The Google archived all the datasets following the public release of the Landsat dataset in 2008, and linked the data to the cloud computing engine of Google for free use of researchers. The GIS-based vector datasets, social, demographic, climate, digital elevation model data layers and data from other satellites have been stored in the archive. The large number of datasets used range from spatial data with low resolution such as MODIS Medium Resolution Imaging Spector radiometry to datasets with very high spatial resolution such as Worldview-2 (Mutanga and Kumar, 2019).

NDVI anomaly NDVIA is the most commonly used and user friendly plant indices used to determine and map drought. The NDVIA uses the long-term average values of a small area or a large region for a specific time (Anyamba and Compton, 2012). A positive change of NDVI value indicates natural conditions with no problems, in contrast, a NDVI negative value is a sign for a severe drought condition (Vaani and Porchelvan, 2017). The NDVIA was calculated using equation 2 (Anyamba et al., 2001).

$$NDVIA_{\ t} = \frac{NDVI_{mean} - \overline{NDVI}}{\overline{NDVI}} \times 100 \tag{2}$$

In the equation; NDVIA is a growing season anomaly during year t; $NDVI_{mean}$ is the mean NDVI values for the first 16 days of the month and the NDVI values for the last 16 days of the months covering the growing season period during the year t, divided by the total number of months of the growing season period during the year t; $\overline{NDVI}$ is the value obtained by ratio of the mean NDVI values to t years.

The rainfall anomaly of the study area was defined as the deviation from the 20-year long-term average (World Meteorological Organization, 2017). The deviation of the t-year growing season period from the long-term rainfall average was calculated using equations 2a and 2b (World Meteorological Organization, 2017).

$$OY_i = Y_i - Y_{mean} \tag{2a}$$

In Equation 2a; Oy_{ti} is the mean anomaly in month i; Y_i is the average rainfall value of month i; Y_{mean} is the average long-term rainfall. The average rainfall anomaly of the growing season period was calculated by equation 2b.

$$OY_{i_B - i_S} = Y_{i_B - i_S} - Yort \tag{2b}$$

In equation 2b; $OY_{i_B - i_S}$, is the mean rainfall anomaly during the growing season; $_{iB}$ is the beginning of the growing season period, $_{iS}$ is the end of the growing season period months: $Y_{i_B - i_S}$, is the mean rainfall value between the first and last days of the growing period; Y_{mean} is the long-term average rainfall value during the growing season period.

2.4. Statistical Assessment

The correlation between the yields of rainfed agriculture crops between 2004-2020 and the NDVIA and rainfall anomalies in the study area was evaluated. Barley and lentil yields were obtained from the open access database of Turkish Statistical Institute (Anonymous, 2022a).

Coefficient of Pearson correlation shows the strength and direction of the relationship between two quantitative and continuous variables. The coefficients of Pearson correlation were calculated to test the degree of the linear relationship between 17 years of NDVIA, rainfall anomaly and crop yield for Şanlıurfa province using equation 3.

$$r_{x,y} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{3}$$

In the equation; $r_{x,y}$ is the coefficient of Pearson correlation, the length of time series is shown with the n and i indicates the number of years from 2004 to 2020. x_i and y_i are NDVIA and rainfall anomalies, respectively. $\bar{x}$ and $\bar{y}$ and mean values of NDVIA and rainfall anomalies from 2004 to 2020 (Tong et al., 2017).

3. Results and Discussion

3.1. Descriptive Statistics

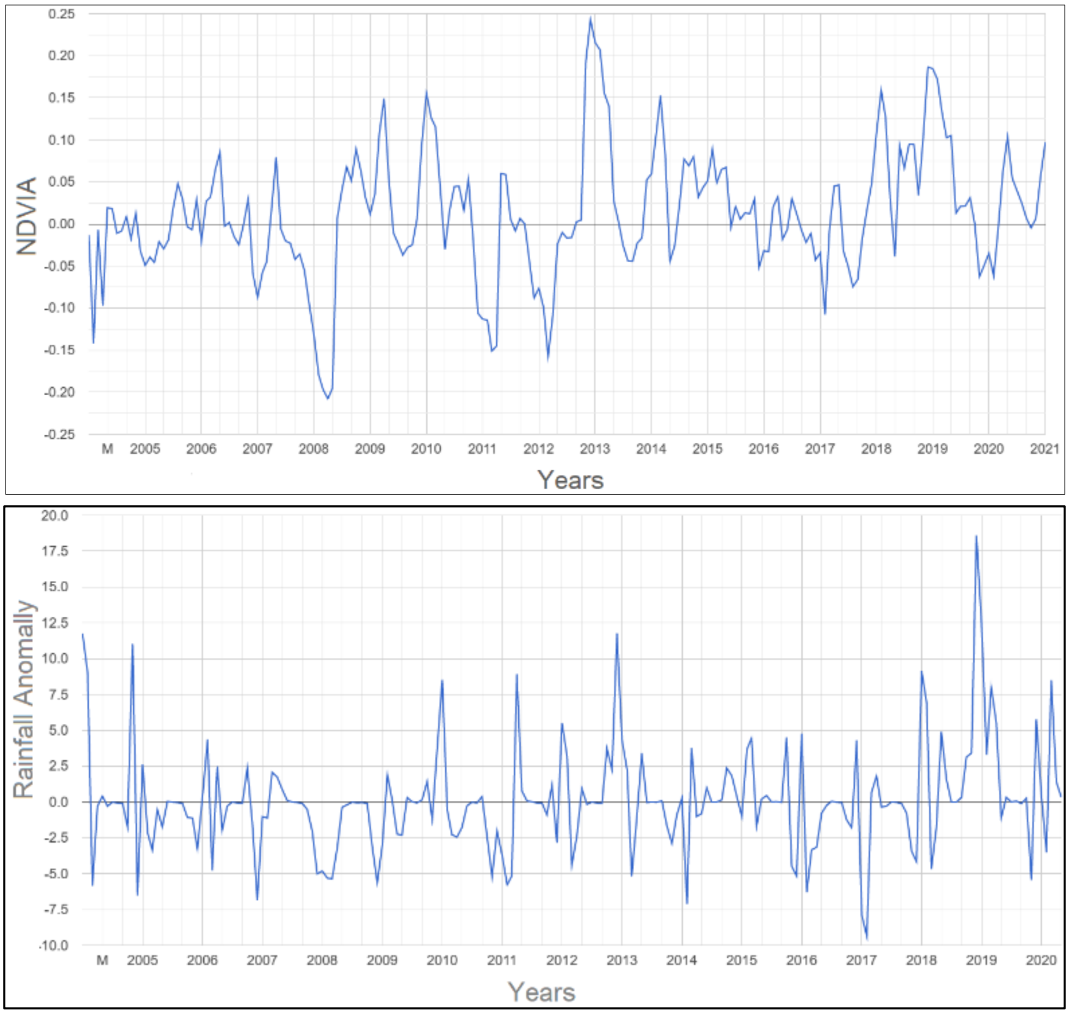
The statistics of annual NDVI and precipitation anomalies, and lentil and barley yields in rainfed farming are given in Table 1. The largest negative deviation in the NDVI anomaly between 2004 and 2020 is -0.208, that was recorded in April 2008 Figure 1a. The largest negative deviation during the 17-year period was in the average NDVI trend in all April months. The largest positive deviation occurred in December 2012 Figure 1a. The rainfall anomalies between the years 2004-2020 indicated that the largest negative rainfall deviation -9.372 was in February 2017, and the largest positive rainfall deviation 18.601 was recorded in January 2019 Table 1 and Figure 1b. Barley and lentil were chosen to show the effect of drought on crop yield. The lowest rainfed barley yield 1110 kg ha^{-1} was obtained in 2016, and the highest yield 3170 kg ha^{-1} was obtained in 2007. The lowest 810 kg ha^{-1} and highest and 1940 kg ha^{-1} lentil yields were recorded in 2008 and 2011, respectively (Anonymous, 2022a).

3.2. Evaluation of Anomalies

In addition to the lowest annual anomaly values, accumulated negative anomaly values are also useful to determine long-term effect of drought severity on vegetation (Chávez et al., 2023; Udelhoven et al., 2009). In this context, monthly deviations from the long-term average trend of anomalies and the amplitude of this deviation throughout the year are also very important in revealing the effects of climatic factors on vegetation (Bianchi et al., 2020). Negative and cumulative rainfall anomaly amplitude were observed from mid-2007 to late 2009 Figure 2b. Similar negative anomaly amplitude was also determined in the NDVIA plot Figure 2a. Trigo et al. (2010) investigated the effects of drought recurrences between 2007-2009 on grain production in the so-called Fertile Crescent area of Syria, Iraq and Iran. The researchers noted that the two-year drought is relatively similar to the drought between 1998-2000. In addition, this two-year drought was considered the driest period for the study areas since 1940. The negative NDVIA and rainfall anomaly amplitude of 2007-2009 in our study area and the significant lentil yield decrease in 2009 are consistent with the findings of Trigo et al. (2010) (Table 1 and Figure 2).

Table 1. Descriptive statistics for NDVI Anomaly, Precipitation Anomaly, Annual Wheat and Lentil Yield

Years	**NDVIA**		**Rainfall Anomaly**		**Barley**	**Lentil**
	Min.	**Max.**	**Min.**	**Max.**	**kg ha^{-1}**	
2004	-0.142	0.019	-6.531	11.745	2090	1330
2005	-0.049	0.048	-3.353	2.632	2880	1530
2006	-0.059	0.085	-6.844	4.365	2950	1630
2007	-0.094	0.079	-5.008	2.074	**3170**	1630
2008	**-0.208**	0.089	-5.631	-0.012	1760	**810**
2009	-0.037	0.149	-3.017	3.660	2600	1620
2010	-0.106	0.155	-5.210	8.526	2170	1800
2011	-0.151	0.060	-5.771	8.922	2280	**1940**
2012	-0.158	**0.243**	-4.400	11.765	2980	1860
2013	0.155	0.216	-5.191	4.302	2670	1390
2014	-0.044	0.153	-7.106	3.764	1400	940
2015	-0.045	0.089	-1.016	4.451	2440	1310
2016	-0.051	0.067	-6.302	4.776	**1110**	940
2017	-0.108	0.033	**-9.372**	4.313	2650	1130
2018	-0.075	0.159	-4.673	9.146	1930	890
2019	-0.039	0.186	-1.770	**18.601**	2080	960
2020	-0.063	0.105	-5.455	8.508	2370	1290



a)

b)

Figure 2. Illustration of annual NVIDIA and rainfall anomaly

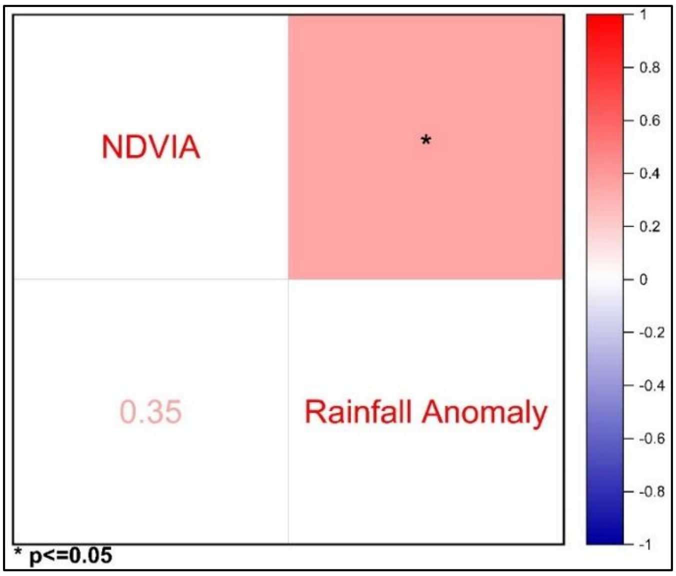


Figure 3. Correlation between NDVIA and precipitation anomaly

A moderate positive correlation was obtained between long-term NDVIA and rainfall anomaly r=0.35, p≤0.05 Figure 3. (Naga Rajesh et al., 2022) determined the relationship between NDVI and other hydrological parameters in Gangetic Plains of India affected by monsoon droughts. Unlike our findings, a weak positive correlation was recorded between NDVI and Rainfall. In our study, NDVIA and rainfall anomaly were calculated to eliminate the effect of delayed relationship between vegetation and rainfall. Therefore, unlike Naga Rajesh et al. (2022), a moderate positive correlation was recorded. Similarly, Lakshmi et al. (2016) reported a strong statistical relationship between NDVI and rainfall for four to six weeks of accumulated precipitation. Udelhoven et al. (2009) conducted a regression analysis for NDVI and monthly and annual precipitation in Spain to eliminate the effect of seasonal components on autocorrelation, which is one of the problems in dealing with the biomass-precipitation relationship. The distributed lag DL model developed showed that monthly precipitation data with a delay of 1 month were effective on vegetation growth. The researchers also noted that the effect of water deficit on plant growth will be longer when higher lag rows occur. The negative amplitude of NDVIA persisted for a longer period Figure 1a when negative amplitude of the rainfall anomaly increased in the study area Figure 1b. In addition, the temporal behavior dynamics of NDVI are highly sensitive to soil moisture in areas with an annual precipitation of 500 mm or less (Nicholson and Farrar, 1994). The moderate correlation between NVIDIA and rainfall anomaly can be associated with the long-term average precipitation 462 mm of Şanlıurfa province, which is below this threshold value stated by Nicholson and Farrar (1994). Similarly, Richard and Poccard (1998) reported a higher NDVI-rainfall correlation in South Africa with average annual precipitation of 900 mm compared to regions with 300 mm.

4. Conclusion

Drought is one of the negative consequences of climate change, and is directly related to crop production; therefore, agricultural drought was discussed in the present study. The possibilities of using big remote sensing data obtained from different sources with developing information technologies were evaluated with Google Earth Engine for drought monitoring. Long-term agricultural drought in the Şanlıurfa province, which has an important place in agricultural production for Turkey, was assessed using 17-year of big remote sensing data. The results are in line with the research findings using similar data and conventional methods. The effect of severe drought between 2007 and 2009, that negatively affected agricultural production in the Fertile Crescent, was clearly monitored using NDVIA and precipitation anomaly. Vegetation and rainfall have a delayed relationship; however, a statistically positive moderate correlation was obtained between the anomaly assessments and the data obtained. This result reveals that drought can be monitored by anomaly calculations, especially in regions where annual precipitation is less than the precipitation threshold required for the temporal response of the NDVI. The results of current study for Şanlıurfa province of Turkey revealed that the integration of remote sensing and information technologies offers unique opportunities to rapid and efficient monitoring of changes in vegetation resulting from climatic and anthropogenic effects. In this context, artificial intelligence models should be developed to more reliably estimate changes in productivity due to the occurrence of climate anomalies. In addition, the models used for low vegetation covers dominated in semi-arid and arid climates should also be developed for the regions with higher NDVI values and precipitation dynamics.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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