AUTOMATIC EXTRACTION OF SURFACE DYNAMICS USING GOOGLE EARTH ENGINE FOR UNDERSTANDING DROUGHT PHENOMENON

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KEY WORDS: Drought monitoring, Ecological disasters, Remote sensing, Sustainable environment, Google Earth Engine.

ABSTRACT:

Atmospheric drought due to meteorological events occurring out of seasonal norms, and consequent droughts in agriculture and wetlands cause great damage to the ecological balance. The initial effects of this situation appear on a local scale, while the aftereffects, which last for years, appear on a global scale. Monitoring and detecting drought with remote sensing technologies can contribute to the management of water resources and forest areas and enable many measures to be taken to reduce the effects of drought. Within the scope of this study, a system that automatically performs the extraction of different drought parameters depending on years has been developed. Işıklı Lake was selected as the study area and the change of water areas over the years has been extracted from satellite images. With the system developed on the Google Earth Engine platform, different parameters were analyzed over a 13-year period and their consistency was tested. As a result, it is seen that the water areas in the lake decreased by 30% between 2010 and 2022. Likewise, the systematic decrease in the parameters, especially in 2015 and afterward, indicates the drought in the region. With the proposed automatic system, it is thought that early precautions can be taken for drought scenarios that may occur in larger-scale regions.

1. INTRODUCTION

Drought has been a global disaster in recent years and has greatly affected our country (Şen, 2022). Active monitoring of drought is a leading series of studies for the measures that can be taken and helps to identify different phenomena that cause drought. Drought is a dynamic caused by a lack of precipitation and the resulting hydrological imbalance that naturally occurs in the landscape (Pachauri et al., 2021). Drought also has negative impacts on agriculture, the economy, the ecosystem, and society (Abbasian et al., 2021). Prolonged droughts lead to disasters such as death, famine, or mass migration in some countries (Godfray et al., 2010). Turkey has been a geography where global climate change has been felt intensely in recent years and cyclical events such as decreasing water resources, drought, and flood disasters have been experienced frequently (Turan, 2018). Drought first shows its effect in the agricultural sector and then starts to affect other sectors negatively, so early diagnosis and intervention can have a slowing effect on the negative consequences of drought (Kapluhan, 2013).

Analyses with ground samples are often used to determine the severity of drought, especially for specific crops and different vegetation types (Kiarash et al., 2018; Venuprasad et al., 2007). The concept of remote sensing is the observation and analysis of an object without any physical contact. With the increase in spatial resolution in images with the developing satellite technology, the sensitivity of spatial analysis, especially with remote sensing method, has also increased.

Different parameters and indices have been used so far to detect drought (Alahacoon, 2022). One of the most used is land surface temperature (LST), which is directly related to drought in the region. LST value obtained with the thermal band of optical satellite imagery allows instantaneous measurement of the surface temperature in the region at certain periods in time (Zhao et al., 2021). Soil moisture is high during periods of heavy precipitation, but otherwise it is low (Sehler et al., 2019). Soil moisture in the field provides information about regional characteristics and is a parameter for measuring drought severity (Nicolai-Shaw et al., 2017). Cammalleri and Vogt (2015) monitored drought in the region by using LST and soil moisture values together and showed the correlation between them.

Normalized difference vegetation index (NDVI) is a powerful analysis tool used to predict the past, current development and future state of vegetation (Xing et al., 2020). It has also been shown in previous studies that it can be used to distinguish between different plant species in the landscape (Pesaresi et al., 2020; da Silva et al., 2017). The Enhanced Vegetation Index (EVI), on the other hand, provides complementary information on the spatial and temporal changes of vegetation cover while minimizing some of the noise present in NDVI (Pettorelli et al., 2005). Finally, Palmer Drought Severity Index (PDSI) and precipitation data were analysed for the region and their changes over the years were analyzed and correlated with other parameters and area changes. The contributions of the study to the literature are as follows:

1- Drought analysis in different regions quickly and dynamically with the help of the system developed on the Google Earth Engine platform,

2- The relation of different drought parameters with the change in water areas and analyzing these data with annual averages.

1.1 Study area and data set

Işıklı Lake in Denizli province of Turkey was selected as the study area. Işıklı Lake is a closed basin lake that expands and shrinks during the year and the deepest point is 8 meters. Işıklı Lake is frequently used for irrigation for agricultural purposes especially after May (Sülük et al., 2013). Figure 1. shows the study area.

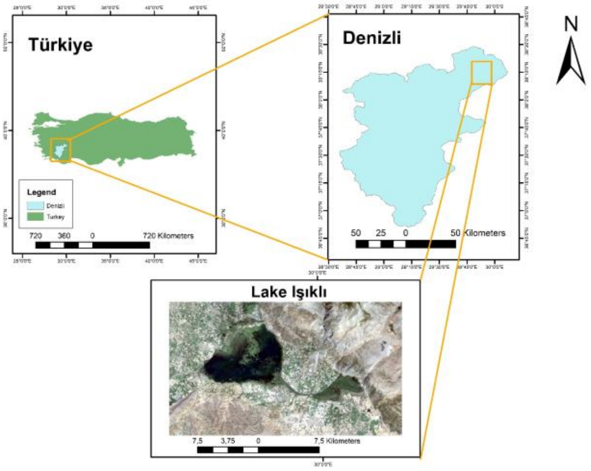

Figure 1. Study area

The satellite images used in the study are different for each parameter. Landsat 4-5 and Landsat-8 satellite images were used for the detection of water areas in the lake. The dates of the satellite images used are 2010, 2013, 2016, 2019 and 2022 respectively. Since Landsat-8 was not yet available in 2010, Landsat 4-5 satellite images were used only for 2010. The satellite images used for the detection of water areas in the lake are given in Figure 2. Table 1 and Table 2 show the bands and wavelength ranges of Landsat 4-5 and Landsat 8 satellites in the electromagnetic spectrum, respectively.

Figure 2. Satellite images used in the study

Landsat 4-5	Wavelength (micrometer)	Spatial resolution (m)
Band 1 – Blue	0.45-0.52	30
Band 2 – Green	0.52-0.60	30
Band 3 – Red	0.63-0.69	30
Band 4 – Near Infrared	0.76-0.90	30
Band 5 - SWIR 1	1.55-1.75	30
Band 6 – Thermal	10.40-12.50	120
Band 7 – SWIR 2	2.08-2.35	30

Table 1. Landsat 4-5 satellite specifications

Landsat 8	Wavelength (micrometer)	Spatial resolution (m)
Band 1 – Coastal Aerosol	0.43-0.45	30
Band 2 – Blue	0.45-0.51	30
Band 3 – Green	0.53-0.59	30
Band 4 – Red	0.64-0.67	30
Band 5 – Near Infrared	0.85-0.88	30
Band 6 – SWIR 1	1.57-1.65	30
Band 7 - SWIR 2	2.11-2.29	30
Band 8 – Panchromatic	0.50-0.68	15
Band 9 – Cirrus	1.36-1.38	30
Band 10 – TIRS 1	10.6-11.19	100
Band 11 – TIRS 2	11.50-12.51	100

Table 2. Landsat 8 satellite specifications

The satellite images obtained within the scope of the study were obtained in August of each year. Thus, it was ensured that the analyses were carried out in the same period as the annual period.
Land surface temperatures were obtained from MODIS satellite. The advantage of MODIS satellite compared to other thermal band satellites is that it can take temperature values from the same region every 8 days, so its temporal resolution is sufficient for the analysis. Another reason for choosing MODIS satellite for the determination of land surface temperatures is that Landsat 8, which has a thermal band and provides higher spatial resolution, was launched into orbit in 2013, so data could not be obtained for 2010, 2011 and 2012. Soil moisture was obtained from the SMOS and SMAP satellites provided by NASA in partnership with the United States Department of Agriculture. The SMOS satellite is the first satellite to explicitly provide soil moisture data (Kerr et al., 2010). Since satellites provide data every 3 days, their temporal resolution is high and they have an important place for applications that require field monitoring (O'Neill et al., 2010). Landsat satellite images were also used to calculate NDVI and EVI values. Average NDVI and EVI values in the study area between 2010 and 2022 were calculated annually and used in the analysis. PDSI values were obtained from the TerraClimate dataset derived from the MODIS satellite (Abatzoglou et al., 2018). MODIS satellite, which has a high temporal resolution, allowed the study region to be examined in short intervals with frequent transitions and PDSI values were calculated.

2. METHODOLOGY

Normalized Difference Water Index (NDWI) was used to determine the change of water areas in Işıklı Lake. After determining the change of water areas in terms of area and percentage, the 13-year period in the region was analysed for 6 different drought parameters with the system developed on the GEE platform. The correlations of the different results obtained were analysed.

2.1 Normalized Difference Water Index (NDWI)

NDWI was first developed by McFeeters in 1996 to identify water bodies. McFeeters (1996) found that NDWI utilizes reflected green light in the near infrared and visible region while eliminating terrestrial features and vegetation. NDWI is one of the most suitable methods for remote sensing of water surfaces (Aksoy et al., 2019). This is because NDWI obtained from remote sensing data is very sensitive to changes in hydrological conditions (Talukdar and Pal, 2019). The NDWI formula is as follows (Eq. 1):

$$NDWI = \frac{(GREEN)-(NIR)}{(GREEN)+(NIR)} \quad (1)$$

2.2 Normalized Difference Vegetation Index (NDVI)

Drought can be directly associated with NDVI data. In NDVI values ranging between +1 and -1, vegetation cover decreases as you move towards negative values. The NDVI formula is as follows (Eq. 2):

$$NDVI = \frac{(NIR)-(RED)}{(NIR)+(RED)} \quad (2)$$

2.3 Enhanced Vegetation Index (EVI)

In areas with high vegetation diversity, NDVI may not provide enough information, so the more advanced vegetation index EVI is used. The EVI formula is given below (Eq. 3):

$$EVI = G * \frac{NIR - RED}{(L + NIR + C1 * RED - C2 * BLUE)} \quad (3)$$

If the EVI value is between 0.2 and 0.08, it is assumed that there is drought, while if it is greater than 0.2, it is assumed that there is healthy vegetation. In the study, Landsat satellite images were used to find NDWI, NDVI and EVI values.
Land surface temperature was obtained with the MODIS data set over the GEE platform. The high temporal resolution of the MODIS satellite enables it to be used frequently, especially for long-term analysis in a region. Soil moisture values were also obtained from SMOS and SMAP data. PDSI is one of the first indices to successfully measure the severity of drought in different climates (Palmer, 1965). In PDSI values ranging from -4 to +4, a value of -4 is a sign of extreme drought, while a value of +4 represents an extremely moist land structure (Huang et al., 2011). When calculating PDSI, not only soil and water content but also other parameters such as temperature and precipitation are calculated.

3. RESULTS

The image of water areas and other areas extracted with NDWI from satellite images between 2010 and 2022 is given in Figure 3. Table 3 shows the water areas in the lake.

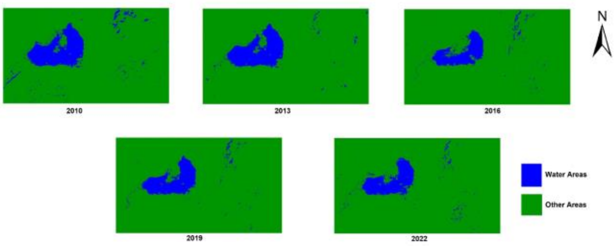

Figure 3. Işıklı Lake water and other areas by years

Year	Water areas (ha)
2010	4626,99
2013	4141,53
2016	2836,71
2019	3361,59
2022	3237,39

Table 3. Water areas by years

Figure 3 visually shows that the water area in the main water body where the lake is located has decreased over the years. In the Table 3, it is seen that the highest water area was obtained in 2010 with approximately 4600 hectares, while the lowest water area was obtained in 2016 with approximately 2800 hectares. When the percentage changes are analyzed, it is seen that the water area in the lake decreased by approximately 38% in 2016 compared to 2010. Although the water level increased slightly in the following 3-year period, it was observed that it started to decrease again in 2022. The change in total water area between 2010, the first year analyzed, and 2022, the last year, was found to be 30%.
Table 4. and Table 5. shows the annual averages of land surface temperature, soil moisture, NDVI, EVI, PDSI and precipitation in the study region obtained by the GEE platform to analyze the drought data between 2010 and 2022, respectively.

Year	Average Land Surface Temperature (Celsius)	Average Land Soil Moisture (mm)
2010	23,3240	10,6244
2011	21,0108	8,5929
2012	22,0412	11,7241
2013	22,4353	11,2471
2014	22,7441	11,2227
2015	21,7654	10,6055
2016	23,7182	9,0517
2017	22,2779	10,3815
2018	21,9464	12,3509
2019	23,1536	10,5232
2020	23,6890	9,9830
2021	23,8964	8,1482
2022	23,3274	9,8020

Table 4. Average values of the LST and soil moisture parameters used for drought detection around Işıklı Lake between 2010-2022

Year	NDVI	EVI	PDSI	Precipitation (mm)
2010	0,2416	0,2338	0,7008	1,7913
2011	0,2340	0,2560	0,7074	1,5058
2012	0,2041	0,2396	0,7942	1,6979
2013	0,2301	0,2310	0,5852	1,3961
2014	0,2410	0,2681	0,4071	1,5231
2015	0,2407	0,2758	0,8875	1,5413
2016	0,2368	0,2578	0,1516	1,2618
2017	0,2438	0,2469	0,2932	1,4008
2018	0,2801	0,2868	0,3911	1,7836
2019	0,2327	0,2647	0,4272	1,3616
2020	0,2373	0,2616	0,2241	1,2141
2021	0,2117	0,2568	0,1297	1,3582
2022	0,2343	0,2490	0,3540	1,2934

Table 5. Average values of the NDVI, EVI, PDSI and precipitation parameters used for drought detection around Işıklı Lake between 2010-2022

It was observed that the highest values in average land surface temperatures were generally obtained in 2016 and onwards. Only in 2018, a lower surface temperature was obtained compared to other values. The highest average temperature value was obtained in 2021 with 23.8964. Looking at the average soil moisture values, it was observed that the lowest soil moisture value was obtained in 2021 with 8.1482. Considering the annual average NDVI and EVI values, the lowest NDVI value was obtained in 2012 with 0.2041. The second lowest NDVI value was obtained in 2021 with 0.2117. In EVI values, the lowest value was 0.2310 in 2013. Looking at the PDSI values, it was observed that there was a very sharp percentage decrease, especially in 2016 and the lowest PDSI values were obtained in this period. Finally, when the precipitation data falling in the study area were analyzed, it was observed that there was precipitation above the average only in 2018 in the last 7 years compared to the average in the 13-year period. The lowest precipitation amount was obtained in 2020 with 1.2141, while the highest precipitation amount was obtained in 2010 with 1.7913.

Separate graphs were created to analyze the parameters more clearly among themselves. Figure 4 shows the averages of LST and soil moisture data over the years.

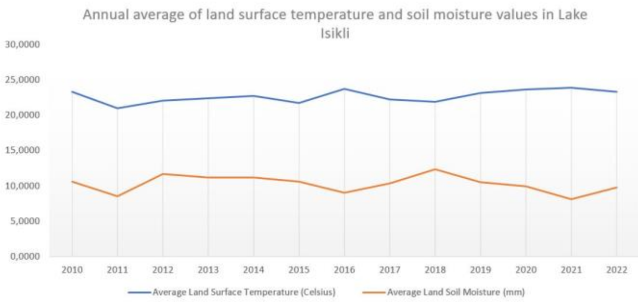

Figure 4. Annual average LST and Soil moisture values

Figure 4 shows that LST and soil moisture values generally follow a certain pattern.

Figure 5. shows the graph of annual average NDVI and EVI values.

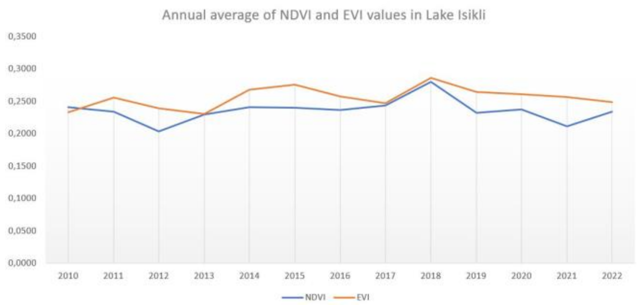

Figure 5. Annual average NDVI and EVI values

In Figure 5. it is observed that NDVI values have more sudden changes while EVI values follow a smoother trend.

Figure 6. shows the graph of annual average values of PDSI and precipitation data.

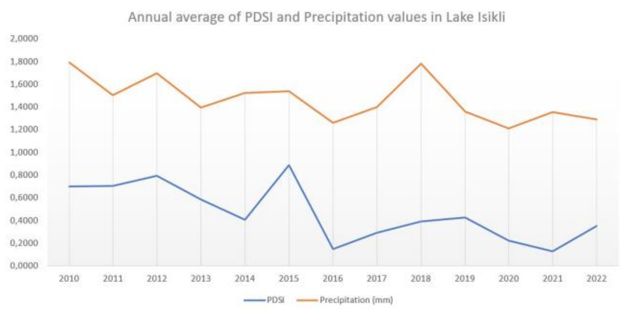

Figure 6. Annual average PDSI and Precipitation values

When the annual trends in Figure 6. are analyzed, it is observed that both parameters have been decreasing over the years and their patterns are generally compatible with each other.

Finally, the graph of the water areas in Işıklı Lake is given in Figure 7.

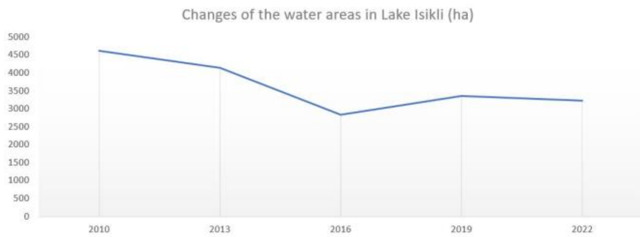

Figure 7. Water areas in Işıklı Lake by years

Figure 7. shows that there has been a decrease of approximately 30% in water area over the 13-year period.

3.1 Discussion

In this study, the water areas in Işıklı Lake from 2010 to 2022 and different drought parameters in the region were analyzed with the help of GEE. First, the lake's water areas were extracted using NDWI values, and their changes over the years were determined. Then, LST, soil moisture, NDVI, EVI, PDSI, and precipitation data were analyzed over a period of 13 years and correlated with the change of water areas in the lake. In addition, the parameters were compared among themselves and their effects on each other were also shown.

According to the change of water areas in Işıklı Lake, there has been a systematic decrease since 2010. The fact that the lake is a closed basin and is constantly used for agricultural irrigation is an important factor in decreasing water areas. Again, the fact that the precipitation in the region has been much lower than the average in recent years causes the lake not to be sufficiently fed and therefore to have losses in water areas.

When the 13-year period LST values were analyzed, it was observed that most of the values after 2016 were above the 13-year average. This indicates that excessive temperature increase will lead to accelerated evaporation in the lake and will cause a decrease in soil moisture, which is another parameter. It was also determined that LST data obtained from thermal bands will be used to identify water areas, although their spatial resolution is lower.

When soil moisture, another parameter, was analyzed, low values were obtained especially in the last 3 years. These values indicate that the soil cannot hold enough water, and therefore, drying soil may cause drought. It is shown in the graphs that LST is directly effective in the change of soil moisture. Apart from this, different factors such as excessive use of pesticides, especially in agricultural regions, also cause low soil moisture.

NDVI and EVI, which are the indices used to analyze vegetation more accurately, follow a consistent trend with each other. Especially when the images taken in the same months of different years are analyzed, the decreases in NDVI values over the years indicate that the health of the vegetation in the region has deteriorated.

In the PDSI values, serious decreases were observed in percentage terms in the years after 2016. Considering the PDSI, drought values between 0.49 and -0.99 indicate regular conditions. Looking at the change in the region, very low levels of PDSI values have been obtained after 2016. These values hint that a dangerous drought process will begin for the region in the coming years.

Finally, when the amount of precipitation in the region is analyzed, it is seen that the total precipitation in the last 7 years, except 2018, has been below the average. Especially in closed lakes such as Işıklı Lake, which is not fed from different sources, the decrease in precipitation poses a great danger to the sustainability of the lake.

4. CONCLUSIONS

This study demonstrates that reductions in water levels and consequent changes can be correlated with soil moisture, land surface temperature, NDVI, EVI, PDSI, and precipitation parameters. In addition, the system developed in the study provides great convenience for GEE to continuously monitor a dynamic disaster such as drought. The developed system will enable rapid analysis in a different study region, thus creating a chance to actively intervene. In order to protect lakes, which are of great ecological importance, by taking precautions and to prevent possible causes of drought, some action plans should be implemented. In this way, steps will be taken to solve the "water" problem, which will be one of the biggest problems of our time.

ACKNOWLEDGEMENTS

We would like to thank Prof. Dr. Filiz Sunar and Prof. Dr. Orhan Altan for providing the opportunity to present this study at the 39th International Symposium on Remote Sensing of Environment (ISRSE-39).

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