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Investigation of spatial change in Lake Surface with Google Earth Engine: Example of Marmara Lake

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Abstract

It is essential to monitor the changes in wetlands on the earth's surface to understand the impact of global climate changes and human activities on water resources. Remote Sensing (RS) techniques are beneficial in monitoring and mapping the dynamics of changes in wetlands. Although RS techniques seem practical in monitoring water surfaces, traditional RS methods require a high amount of workforce, software, hardware, and especially data storage needs. For this purpose, in this study, the change in water surface area of Marmara Lake, located within the borders of Manisa Province, between 2013-2022, was investigated with Google Earth Engine (GEE). The change in the water surface area was analyzed for four different seasons using Landsat-8 (OLI) images. The Normalized Difference Water Index (NDWI) was used in the study. The study is divided into four different classes according to the land use conditions of the region: vegetation, water surface, bare lands, and agricultural lands. Support Vector Machines (SVM), a machine learning algorithm, were used for classification. According to the analyzes made, it has been determined that a wetland of 3,975.78 ha has dried up in the lake surface area in the last eight years. This calculated area corresponds to an area of 75.04%, according to the average of all areas.

1. Introduction

Water is undoubtedly the most valuable resource for living things and an essential ecosystem component. Climatic changes and human activities are significant for managing water resources for sustainable socio-economic development [1]. At the same time, wetlands are a valuable natural resource for groundwater recharge and flood control [2]. However, the reduction and destabilization of wetlands pose a significant threat to biodiversity conservation and the ecological environment [3]. Therefore, the mapping and recording of wetlands play an essential role in the planning, protecting, and managing of wetlands [4]. In general, wetlands are part of the topography. They are considered one of the crucial ecosystems consisting of water, vegetation, soil, and microorganism systems and play an essential role in protecting the aquatic ecosystem [5].

Extraction of water bodies plays a vital role in wetland management, assessing water cover status, and detecting and monitoring surface water exchange [6]. Furthermore, thanks to satellite data, remote sensing (RS) techniques assist in monitoring temporal changes in water bodies and establishing decision-making policies [7]. RS is highly preferred, so it is cost-effective, fast, reliable, reproducible, challenging to access for larger areas, and an effective technique [8].

Landsat images are advantageous to other satellite platforms in temporal tracking water surfaces, thanks to an archive of approximately 40 years and free access [9]. Furthermore, monitoring water surfaces is convenient with various machine learning algorithms and specially developed water extraction indexes on satellite images [10]. For example, the Normalized Difference Water Index (NDWI) uses the green and infrared bands to distinguish between water, soil, and terrestrial vegetation [11]. The modified NDWI (MNDWI) was proposed by using Short-Wave-Infrared (SWIR) band instead of the Near-Infrared (NIR) band, which used NDWI due to vegetation cover soil characteristics, and the effect on built-up areas in the detection of water surfaces. Soil, vegetation, and resident classes have lower negative values because they reflect more of the SWIR band than the green band. Various methods have been proposed for the detection of water surfaces. These can be threshold determination over a calculated index [12-14], or different classification algorithms are used. These; Random Forest (RF), Support Vector Machines (SVM), and Maximum Likelihood Classification (MLC) are frequently preferred methods [15-20].

Satellite data analysis reaching thousands of gigabytes is laborious and time-consuming for long time-series data [21]. In addition, the availability of suitable software and storage space appear as additional costs for data processing. Google Earth Engine (GEE), which works in the cloud platform and has been highly preferred in RS studies in recent years, provides access to all archives of Landsat data [22]. The Google firm developed GEE to map human settlements over large areas, study past changes, and continually update current estimates [23]. Thanks to its application program interface (API), GEE provides the opportunity to develop with JavaScript and Python languages and access and apply data at a petabyte-scale [24].

Today, climatic changes cause severe effects on the ecosystem, especially water resources. Climatic changes such as global warming cause severe effects on lakes, which are freshwater sources. Depleting water resources, especially in developing countries such as Türkiye, causes severe pressures on the country's economy and policy [18]. Marmara Lake, located within the borders of Manisa Province in the Aegean region, is among the lakes of great importance, especially regarding agricultural irrigation and fishing activities.

In this study, the temporal analysis of the change of Marmara Lake was examined using Landsat images on the GEE platform. Considering the characteristic land use of the region, the study area, which is divided into four different classes, is classified by the SVM machine learning algorithm. In addition, NDWI has been added to the classification as a new band because it differentiates it from other details by increasing the reflection values on the water surface. This study determined quantitative and qualitative temporal and spatial changes on the water surface between 2013-2022. It has been revealed that monitoring the changes in the water body of Marmara Lake, which is of great importance, especially for the region, is relatively easy with RS techniques. In addition, thanks to the code developed on the GEE platform, the Marmara Lake change will be realized dynamically and instantly in the coming years. In addition to providing a robust data analysis for decision-makers, this study also creates a database for climate change monitoring, agricultural activities, lake water use, and fishing and hunting activities in the region.

2. Material and Method

2.1. Study Area

The Marmara Lake, which was analyzed within the scope of the study, is within the borders of the Salihli and Gölmarmara districts of Manisa province, located in the Aegean Region. The lake is an alluvial barrier lake within the depression area due to the breaking of faults in the north, west, and southeast directions within the Gediz graben. Marmara Lake, which is approximately 10-11 km in the east-west direction and approximately 3-5 km in the north-south direction, is spread over approximately 56 km^2. The lake's depth varies between 3-5 m according to the water surface area, and it is at an average height of 79 m from the sea [25]. Lake water irrigates agricultural lands around the Ahmetli district within the Lower Gediz Irrigation Project [26]. The study area is shown in Figure 1.

2.2. Data

This study used Landsat-8 (OLI) satellite images of the 2013-2022 time series (Collection 1 Tier 1 calibrated Top of Atmosphere, TOA) to monitor the water surface area change in Marmara Lake. The Landsat-8 satellite has a temporal resolution of 16 days from an altitude of about 705 km. The images obtained from the OLI sensor of this satellite have an area of 180 km and a 12-bit radiometric resolution. The sensor records geometrically corrected images in the VIS, NIR, and SWIR spectral regions for nine spectral bands with a spatial resolution of 30 m and panchromatic bands with a resolution of 15 m. Satellite images were analyzed seasonally, and images with less than 15% cloud coverage were generally selected. The band information of the satellite image used in this study is given in Table 1.

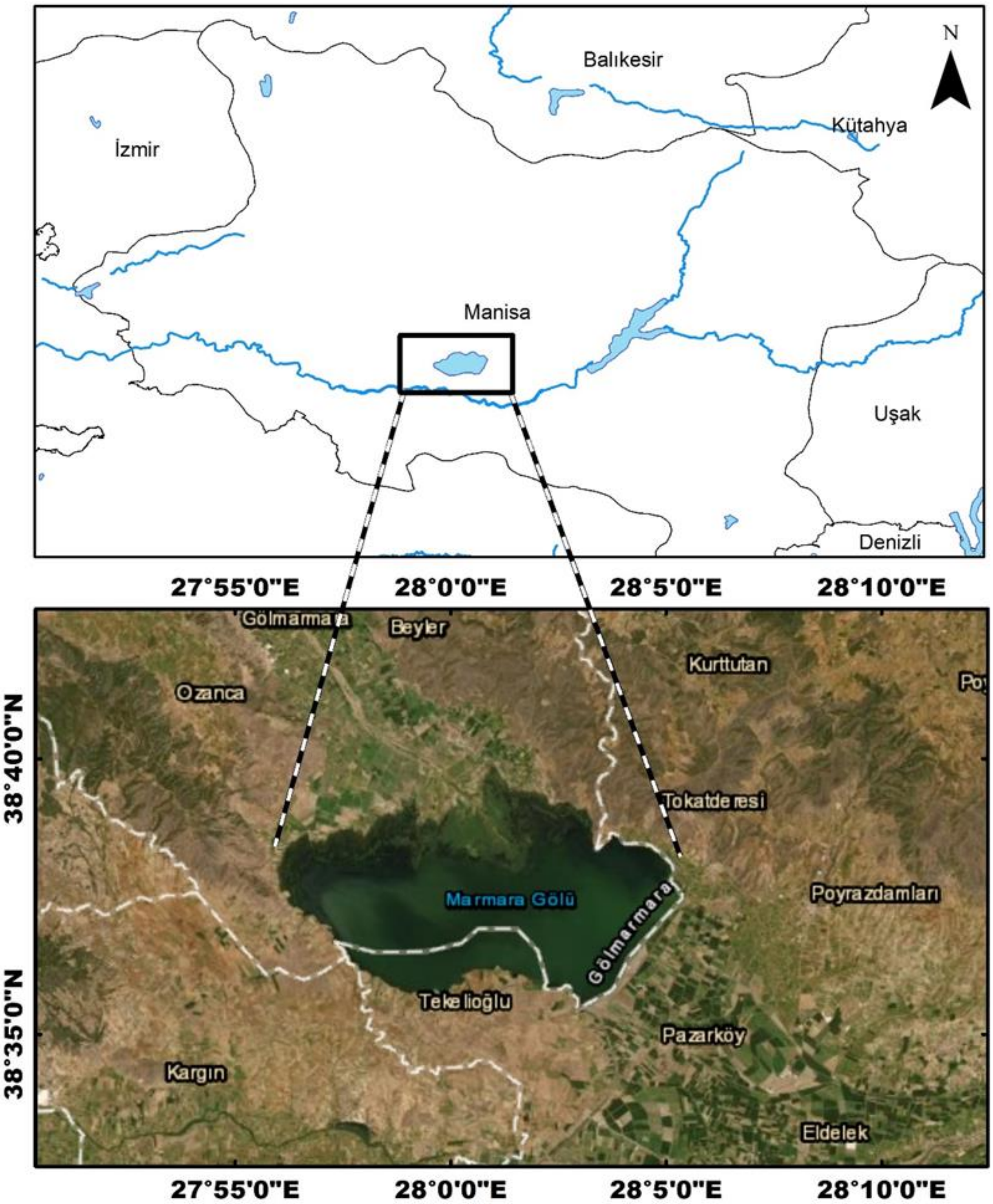

Figure 1. Study area

Table. 1 The spectral bands and resolutions of optical Landsat 8 datasets used in this study

Spectral Range	Wavelength Range (µm)	Resolution (m)
Blue (B2)	0.45-0.51	30
Green (B3)	0.53-0.59	30
Red (B4)	0.64-0.67	30
NIR (B5)	0.85-0.88	30
SWIR 1 (B6)	1.57-1.65	30

2.3. Method

First, NDWI was calculated using Lansat -8 (OLI) satellite images to monitor the temporal changes on Marmara Lake's water surface. In the second step, the classification process was done with the SVM algorithm. In the third step, an accuracy assessment was performed for each classified image. Then, all classification maps were converted to raster vectors, and lake surface areas were calculated. The flowchart is given in Figure 2.

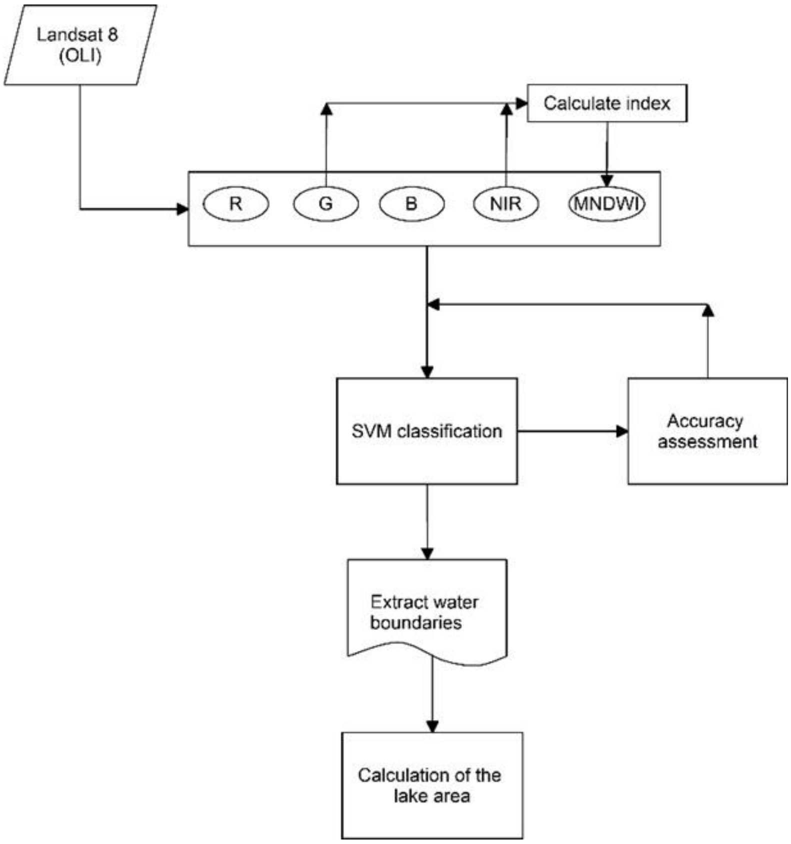

Figure 2. Classification flowchart

2.3.1. Normalized difference water index

In Lansat -8 (OLI) satellite images, the NDWI is the normalized difference between the green band (band 3) and the near-infrared band (band 5). This index distinguishes water surfaces from other details on remotely sensed images. NDWI is widely used in the extraction of water bodies. The NDWI index is calculated by Equation 1.

$$\text{NDWI}=\frac{Green-NIR}{Green+NIR} \tag{1}$$

where NIR represents the near-infrared band, and green represents the green band. Water generally takes high NDWI values. NDWI values range from -1 to +1. Values close to +1 and +1 represent water, while values of 0 and below indicate the absence of water [27].

3. Results

In the study, satellite images of different time series (2013-2022) were processed on the GEE platform, and the change in the water surface area of Marmara Lake was examined. The satellite images monitored annual water surface changes with the NDWI index and SVM algorithm used to extract the water surface. When seasonal changes are examined, the average water surface area in 2013 was calculated as 5,297.95 ha. The same area was determined as 1,322.18 ha on average as of January 2022. The lake water surface area detected a decrease of 3,975.78 ha in the mentioned period. This area corresponds to approximately 75% of the surface area calculated in 2013. In other words, most of the Marmara Lake dried up in the specified period. Since the water levels in the spring seasons will be more realistic, this situation is shown in Fig. 3 with the maps of the spring seasons of 2013 and 2021.

Additionally, when seasonal inspections of the lake's water area were conducted, it was determined that the lake reached its maximum size in the spring of 2014 and completely dried up in the fall of 2021. The change in the lake water surface is shown in Figure 3. In Figure 4, the seasonal water surface and average area change graph show that the water surface area continued to average around 5,000 ha between 2013 and 2016, but the average water surface tended to decrease in the following years.

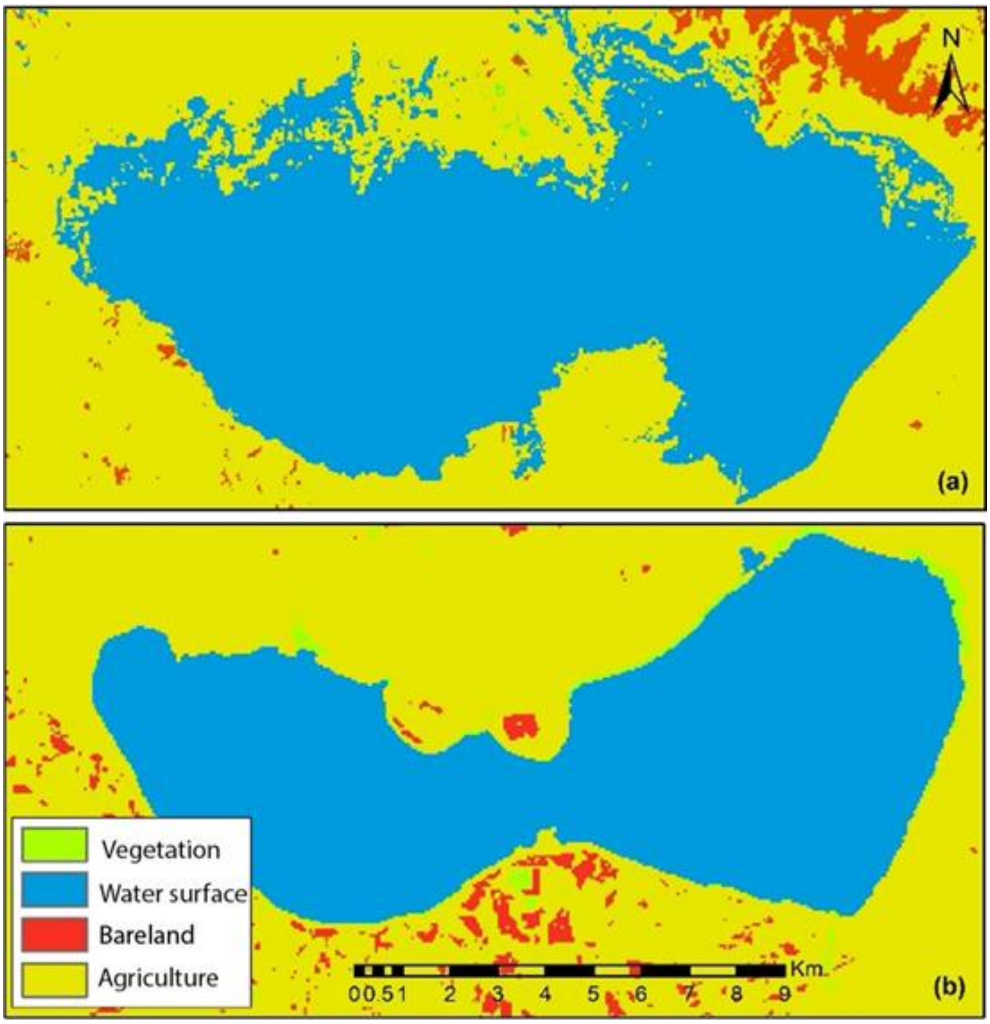

Figure 3.2013 (a)-2021(b) spring land change

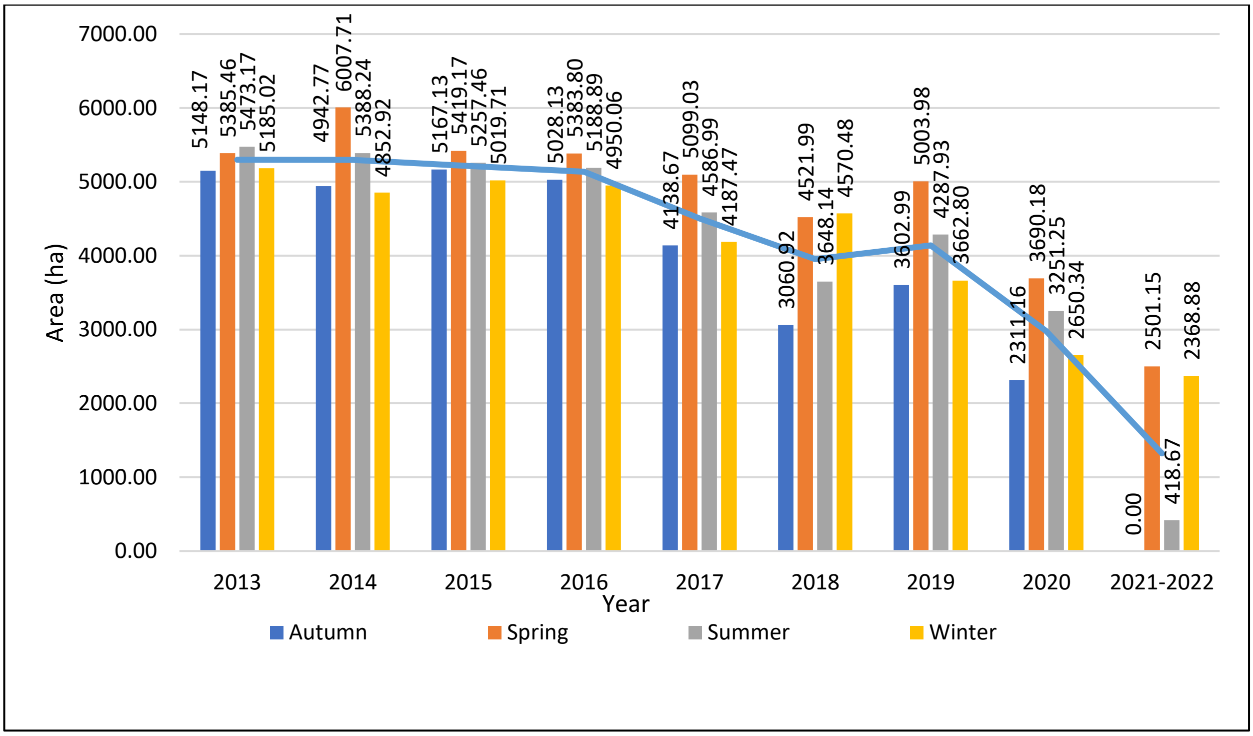

Figure 4. Seasonal change of water surface areas

RS techniques are widely preferred today in the determination of water surfaces. Like this study, Hossen et al. [28] investigated the changes in the surface area of Lake Manzala in Egypt with RS techniques. They applied supervised and unsupervised classification techniques in their study. They also used NDWI to extract the water surface. Their study found that the water surface decreased by 46% between 1984 and 2015. Today, quite common water extraction indexes such as NDWI, MNDWI, and AWEI are used to extract water surfaces. The selection of these indices varies according to the characteristics of the water (dirty water, shallow or deep water, etc.) or environmental effects (urban area, shaded area, open area, etc.). Although the NDWI index was used in this study, MNDWI was used in our research, which gives better results, especially in shallow waters. Yang et al. [29] used MNDWI and AWEI indexes to extract water in urban areas in their study. In this study, it is noteworthy that MNDWI and AWEI were used to separate water from other details, especially in urban areas. The shadow effect on water in urban areas is greater than in open areas. Due to this effect, MNDWI index is more sensitive to spectral differences on water. Chen et al. [30] took into account the seasonal changes of the lake water in their study, as in our study. For this purpose, they estimated the lake water level from satellite altimetry data. Worden and Beurs [31] evaluated their performance using different water extraction indices on Landsat 8 images to detect water surfaces in the Caucasus. In their study, they determined that MNDWI performed better than others. They determined the water surfaces with 93% accuracy. This classification accuracy showed high accuracy, similar to our study.

3.1. Accuracy assessment

The classification accuracy of this study was tested by an error matrix. User's accuracy (UA), producer's accuracy (PA), overall accuracy (OA), and kappa ($\boldsymbol{\kappa}$) were calculated in the created error matrix. For this purpose, random polygons were defined for each class on the GEE platform, and the pixels within these polygons were accounted for classification accuracy. Classification accuracy values are given in Table 2.

Table.2 Classification accuracies

	Autumn				Spring				Summer				Winter			
	UA	PA	OA	κ	UA	PA	OA	κ	UA	PA	OA	κ	UA	PA	OA	κ
2013	100.	100.00	89.6	0.75	90.8	93.7	90.0	0.78	87.2	100.	93.7	0.86	81.	100.0	91.0	0.79
2014	100.	100.00	96.8	0.93	79.4	99.8	90.8	0.81	90.0	100.	94.4	0.88	84.	100.0	92.3	0.81
2015	100.	100.00	95.6	0.90	94.4	100.	95.7	0.91	86.4	100.	96.8	0.93	82.	100.0	91.9	0.81
2016	41.0	100.00	86.4	0.71	98.7	100.	93.4	0.87	93.1	100.	96.8	0.93	83.	100.0	93.2	0.84
2017	86.0	100.00	94.7	0.87	100.	100.	95.5	0.91	94.9	100.	94.4	0.87	88.	100.0	92.5	0.81
2018	100.	100.00	91.8	0.79	100,	100.	93.9	0.88	100.	100.	95.7	0.90	81.	100.0	92.4	0.82
2019	99.8	20.19	92.3	0.82	100,	100.	89.0	0.78	100.	100.	93.5	0.85	91.	100.0	91.3	0.79
2020	100.	100.00	94.3	0.85	90.0	100.	93.5	0.84	100.	100.	95.2	0.86	100	100.0	92.0	0.80
2021-	0.00	0.00	91.8	0.71	100.	100.	94.7	0.87	100.	100.	97.0	0.92	99.	100.0	96.2	0.89

Table 2 shows the accuracy values for UA and PA water surfaces. The OA and $\boldsymbol{\kappa}$ values represent the accuracy assessment of the complete classification. UA and PA values for water surfaces were above 85% in almost all years. Likewise, it was seen that the OA value was classified with an accuracy of nearly 90% over the seasons of all years. Classification accuracy could not be calculated due to water withdrawal in the lake in the 2021 autumn season. According to the classification accuracies calculated in this study, it can be easily said that this classification is successful.

4. Conclusion

In the study, the water surface area changes of Marmara Lake, located within the borders of Manisa province, were examined with GEE, a cloud-based RS platform. The change in the lake's water surface area between 2013-2022 is shown in Fig. 4, and a 75.04% decrease in the water surface area has been detected. In addition, while the amount of agricultural land around the lake was 13,369.39 ha in 2013, this area was determined as 15,100.79 ha in 2021. In other words, the agricultural area around the lake has increased by 12.95%. As shown in Fig. 3, this area was used for agricultural purposes after the water withdrawal from the lake.

As a result, the increased agricultural lands around the lake, unconscious resource use, drought, and evaporation due to global climate change have caused significant lake water surface area changes. Marmara Lake, one of the critical water resources of the Aegean Region, has an important place in terms of biodiversity. To protect such resources, more conscious and sustainable land management plans should be prepared, and it is recommended that these areas be protected.

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Author contributions

Ramazan Gungor: Conceptualization, Methodology, Software **Osman Salih Yilmaz:** Data curation, Writing-Original draft preparation, Software, Validation. **Fusun Balik Sanli and Ali Murat Ates:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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