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Determination of surface area change with remote sensing: The case of Salt Lake

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Abstract

Nowadays, with the advancement of technologies and development of applications, the use of Remote Sensing (RS) techniques is becoming widespread. Thanks to RS, applications such as determination of land surface areas, change analysis, protection of water resources, mapping and sustainable management have begun to be realized. RS and Geographic Information Systems (GIS) provide great advantages and convenience especially in monitoring the temporal changes in the surface areas of water/lake resources. The temporal change of the surface area of a selected water source is observed over months and years. Lakes are important water resources located in terrestrial areas. In this study, it is aimed to determine the surface area change of Salt Lake in the last decade (2014-2023) using RS technique. The determined study area was obtained from Landsat 8 OLI_TIRS satellite images, especially in the summer months (7th and 8th months). Iterative Self-Organized Data Analysis Technique (ISODATA) was preferred as the method for unsupervised classification. Due to the low cloudiness, the images were generally obtained in August. From these images, vegetation/water area was analyzed using NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index) and drought and wetlands in the region were monitored. According to the NDVI results, the highest value was determined as 0.73 in 2022 and the lowest value was determined as 0.59 in 2017. For the NDWI index in 2022, these values were calculated as 0.66 and -0.98, respectively. The average surface area of the Salt Lake in the last decade was found to be 999,464 km^2 and the changes between the years were compared with each other.

1. Introduction

Water is one of the most important natural resources for all living and non-living beings. There are many different areas which water is needed, such as the combined use of humans and living ecosystems, economic development, energy production and national security. Due to its water feature, it is also a very effective element on the inanimate natural environment. Water also has an effect on spontaneous natural events such as the formation of soil by physical disintegration of rocks, the soil becoming fertile by dissolving the substances in it, photosynthesis in green leaves, and the transportation of necessary building blocks in plant species. In the first quarter of the twenty-first century, many countries, especially in arid and semi-arid regions, face serious water problems. The main factors creating the water crisis are population growth, financing problems, global warming, climate change, development of industry and technology. In addition, irresponsible pollution of drinking water resources causes irreversible problems. As Türkiye population exceeds 80 million, it is of great importance to meet the need for quality drinking water and to use water resources more effectively and efficiently in order to meet the intensive water needs of the rapidly developing industry in recent years. This naturally means that there will be a universal crisis. The rapid increase in the number and population of cities in Türkiye makes it difficult to meet water needs. For this reason, most of the water needs of rapidly developing and growing cities are met by purifying them from streams, dams and lakes, as well as spring and ground water. The need for quality water for all these uses can only be met with correct soil and water management. Water management; it is the development and use of water resources in a planned and programmed manner. Sustainable water resources management is a problem that can be solved by calculating the ecological distribution of water in nature and calculating the common denominator of all nations, global policies and practices. The main goal in sustainable water resources management is to determine the sustainable potential, taking into account the needs of today and the future, without causing permanent damage to the resource (Aksungur et al., 2008; Ciftci et al., 2003; Ozsoy, 2009; Karaman & Gokalp, 2010; Meric, 2004; Ozkan et al., 2013;

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Akin & Akin, 2007; Akuzum et al., 2010; Dorak et al., 2019). Lakes are large, stagnant bodies of water that accumulate in hollow areas on land and are not connected to the sea. While lakes constitute 87% of the fresh water on earth, the area they cover on land is 2%. It is fed by surface waters, rainfall, streams and springs. Water levels of lakes vary depending on nutrition. There may be changes in water levels due to level differences depending on the nutrition of the lake and the climatic conditions in the basin. In addition to ecological balance, lakes also contribute to people for purposes such as irrigation of agricultural areas, provision of drinking and utility water, transportation, electricity production, aquaculture, fishing, salt and soda production, hunting and tourism. Recent negative impacts on our lakes include climate change, global warming, excessive human consumption and incorrect water use, and dumping of factory wastes and garbage into the lakes. For this reason, monitoring the changes occurring in lakes and taking precautions for this is of great importance in the protection and management of water resources. Thanks to RS and GIS supported software, provides time and cost advantages to users in determining the surface area changes of lakes, which are an important resource of the earth between years. Methods such as NDVI and NDWI, which are widely used, produce concrete information in the interpretation of wetlands; imaging, mapping, processing and spatial analysis of surface areas. In this way, Türkiye natural resources are monitored more closely and solutions and suggestions are offered for problems such as drought (Bagdatli et al., 2014; Susam et al., 2006).

When studies on the unsupervised classification method are examined within the scope of the literature; Jomaa et al. (2003), used three Landsat-TM satellite images from June 1987, 1994 and 1998 to detect land changes in the Hermel and Dahr El Baidar region in Lebanon. They applied an unsupervised classification method to make it easier to separate different and unchanged pixels. In 1998, it was determined that the land for agriculture in the Hermel region was more than 70 hectares, and in the Dahr El Baidar region there was 165 hectares. Weih Jr. & Enderle (2005), made land cover classification for 5 research basins in Garland and Saline counties of Arkansas with the help of LANDSAT 7 Enhanced Thematic Mapper Plus (ETM+) satellite images. While the satellite images were based on 146 training areas with supervised classification and applied using the maximum likelihood algorithm, with unsupervised classification the Iterative Self-Organizing Data Analysis Techniques (ISODATA) algorithm was applied to classify these images into 300 spectral classes. As a result of supervised and unsupervised classification methods, the overall accuracy was obtained as 74.85% and 40.94%, respectively. They stated that in the dense pine afforestation class, which constitutes 10.69% of the total area of the basins with an area of 1,216.69 ha, there is a more accurate classification result in the unsupervised classification (64.29%) compared to the supervised classification (43.86%). Ragettli et al. (2018), applied an unsupervised classification method to determine the development of irrigated areas in the Central Asian Chu and Talas River Basins, located between Kyrgyzstan and Kazakhstan, from 2000 to 2017 years. Within the scope of the study, they achieved 23% growth in irrigation areas between 2000 and 2017, and 77-96% accuracy as a result of supervised classification. Sonde et al. (2020), obtained satellite data with 0.6 m and 0.5 m resolution by QuickBird and World view-2 satellite in detecting urban sprawl in Uran Taluka of Raigad district in Jawaharlal Nehru Port Trust (JNPT) district. They applied the unsupervised classification method, which is an easier and faster method than supervised classification, to determine the change in the land. Within the scope of the study, they stated that there was a decrease of 6.585% and 4.81% in urban area and vegetation areas, respectively, from 2006 to 2010, and an increase of 0.25% in urban area from 2010 to 2014. Agarwal & Twary (2023), investigated the changes in land use and land cover in Sanganer and Sitapura of Jaipur City. They applied the Landsat 5 MSS satellite image from 2000-2009 (10 years). In the study, the construction rate increased from 18.64% to 33.57%, the open area increased from 39.80% to 43.14%, and the water mass increased from 0.48% to 1.10%, however it was observed that vegetation cover decreased from 19.29% to 10.11%. They revealed that agricultural lands decreased from 29 to 10.11% and from 21.77% to 12.05%. Pradhan et al. (2023), examined the temporal changes of the Bangalore region of India from 1989 to 2022. They applied supervised and unsupervised classification methods. As a result of the classification, they found that there was a decrease in vegetation and water levels and an increase in urban area structures. Afshinfar et al. (2023), they examined the water basin changes of Iran Tar and Hoyer lakes between 2013-2022 years (10 years) using Landsat 8 satellite images. From the results obtained, they found that the amount of the water basin increased from 2013 to 2017, while both lakes decreased in 2018, there was no change in 2020, and both lakes decreased from 2020 to 2022. Yang (2023), used Landsat 8 satellite imagery to study land change of the Tibetan Plateau in Lhasa, China. Unsupervised classification (ISO data) has been applied to the satellite image. As a result of the study, it was observed that the built-up area and heat island density increased in the city of Lhasa in the period between 2014 and 2021 years. Oztas et al. (2023), examined the surface area changes of Burdur Lake in the Lakes region between 1984 and 2021. They applied the unsupervised classification (ISODATA) method to Landsat 4-5 and 8 satellite images over a 36-year period (1985-2021). From the results obtained, they obtained that the surface area of Burdur Lake decreased from 205.96 km^2 to 122.39 km^2 and this value decreased by 40.6%. Chasia et al. (2023), examined land cover changes in the East African Sio-Malaba-Malakisi River Basin. They applied the unsupervised classification (ISODATA) technique to Landsat 4-5 and 8 satellite images between 1986 and 2017. As a result of the classification, they concluded that while the cultivated areas increased by 30%, there was a decrease of approximately 12% in forest areas. Zafar et al. (2024), In this study, the performance of CART (Classification and Regression Tree), RF (Random Forest) and SVM (Support Vector Machine) for LULC estimation is compared by processing RS data in Google

Earth Engine (GEE). In total, four classes of LULC (Water Bodies, Vegetation, Urban Area and Wasteland) for Lahore city are obtained using satellite images from Landsat-7, Landsat-8 and Landsat-9 for the years 2008, 2015 and 2022 respectively. From the results, RF showed the best performance with the maximum overall accuracy of 95.2% and the highest Kappa coefficient value of 0.87. SVM showed the maximum accuracy of 89.8% with the highest Kappa value of 0.84 and CART showed the maximum overall accuracy of 89.7% with the highest Kappa value of 0.79. The results obtained from this study may be helpful to the decision makers, planners and RS experts in selecting a suitable machine learning algorithm for LULC classification in an unplanned urbanized city like Lahore. Garajeh et al. (2024), in this study, a data-driven approach using the product called JRC-Global surface water mapping layers V1.4 on Google Earth Engine (GEE) was used to map and monitor the impacts of climate change on surface water resources. Key climate variables affecting water bodies including air temperature (AT), true evapotranspiration (ETa), and total precipitation were analyzed between 2000 and 2021 using temperature-vegetation index (TVX) and Moderate Resolution Imaging Spectrometer (MODIS) products. The findings showed a clear link between global warming and the shrinkage of surface water resources in the LUB. The results showed that the increase in AT corresponded to a decrease in water surface area, highlighting the significant influence of AT and ETa in controlling the water surface in the LUB (partial rho of −0.65 and −0.68, respectively). In contrast, no significant relationship was found between precipitation and water surface area (partial rho + 0.25). The results of the study show that about 40% of the water bodies in LUB have remained permanent, especially in the last four decades. This revealed that about 30% of the permanent water resources have disappeared, turning into seasonal water bodies, accounting for about 13% of the total. They commented that this study provides comprehensive information to monitor changes in surface water resources and assess the impact of climate change on water resources. Farhan et al. (2024), In this study, four LULC classes namely urban area, vegetation cover, wasteland and water bodies were obtained by Landsat data and Support Vector Machine (SVM) in GEE. The findings showed that the built-up area increased by 975.6 km2 (196.5%) from 1992 to 2002, while vegetation cover decreased by 579.15 km2 (30.4%). In addition, normalized difference built-up index (NDBI) and normalized difference vegetation index (NDVI) were taken to measure the relationship with LST. Negative and positive correlation were obtained among NDVI, NDBI and LST, respectively. Urban heat island ratio index (UHIRI) was also mapped and showed an increasing trend during this research. They stated that these results are an important factor for the division of development and planning in order to secure the permanent utilization of land resources for future urbanization growth.

In this study, was examined the surface area change of Salt Lake between 2014 and 2023 years. Later, VOSviewer software and Scopus database were used to examine past studies on Salt Lake, the saltiest water resource in Türkiye and the Eastern Mediterranean. VOSviewer is important, free software that offers convenience to researchers to discover evolutions, relationships and new concepts in the literature. VOSviewer uses elements in networks consisting of scientific publications, journals, researchers, research institutions, countries, keywords and/or terms; It creates relationship networks through co-authorship, co-occurrence, citation, bibliographic coupling or cogitation links. In addition to providing visualization, mapping and multidimensional analysis, it also enables in-depth analysis of bibliometric data sets (Arslan, 2022; Dirik et al., 2023; Ongun, 2023). Studies on Salt Lake were evaluated in more detail thanks to the VOSviewer software (Figure 1).

When Figure 1 is examined, it can be seen that the subjects examined are climate change, remote sensing, chemistry, biodiversity, water quality, Eurasian continental area, environmental monitoring/observation, groundwater, genetics and microbiology and calibration processes. It was determined that these studies were mostly carried out in Türkiye with nearly 140 studies, followed by France, United Kingdom, USA, Germany and Malaysia.

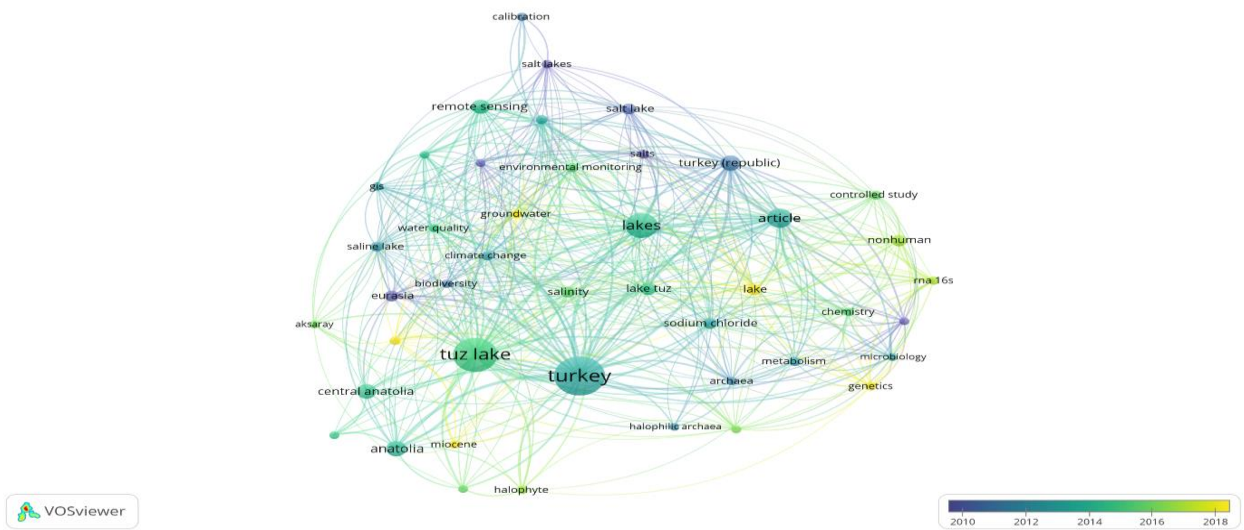
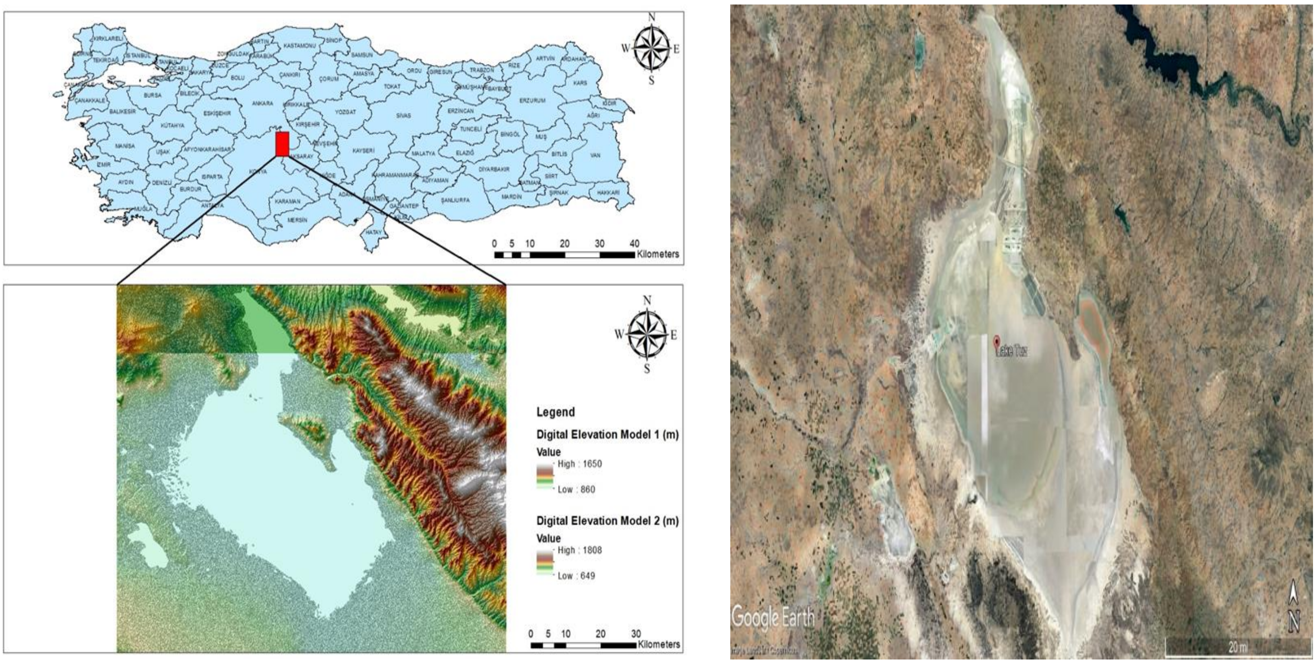


Figure 1. Salt Lake relationship image

2. Materials and Methods

Salt Lake, which has an area of approximately 166 thousand 500 hectares (1665 km^2) today (Uygun & Sen, 1978), is located within the borders of Ankara, Konya and Aksaray provinces of the Central Anatolia Region, and is a closed basin extending in the northwest-southeast direction (Figure 2a). The current satellite image obtained with the help of Google Earth Pro software is presented in Figure 2b. Salt Lake is surrounded by the 1288 m high Pasa Mountain in the north, the fault zone between Sereflikochisar and Aksaray in the east, the Cihanbeyli Plateau in the west, the Bozdag massif in the southwest and the Obruk plateau in the south. In Türkiye, due to the increase in altitude from west to east, the degree of continentality increases and temperatures reach very low values during the winter months.

Central Anatolia Region has a continental climate with hot and dry summers and cold and snowy winters. For this reason, Salt Lake receives the most rainfall in spring and the least rainfall in summer. It reaches a surface area of 1642 km^2 in the spring months when rainfall and water are abundant (MEUCC, 2024). Salt Lake is one of the places with the least rainfall in the south of Southeastern Anatolia after the Igdır/Malatya Plain in Türkiye (320 mm). Average precipitation is around 400 mm. A real drought is experienced in the Salt Lake and its Basin, especially in August (summer months), when the temperature increases, due to the lack of precipitation and the increase in the evaporation rate. Salt Lake and its surroundings, which have a geologically tectonic structure are a "Class A" wetland according to Ramsar criteria (Susam et al., 2006; Julianto, 2021; MEUCC, 2024; Minaz & Kubilay, 2021; Hosgoren, 1994; Tas & Akpinar, 2021; Yurteri & Kurtttas, 2021; Cuce et al., 2023; Cengiz, 2005; Isildar & Ercoskun, 2021; Akin, 2019; Koday, 1999; Oguz, 2017).



(a) (b)

Figure 2. (a) Salt Lake location map ve (b) Satellite image of Salt Lake

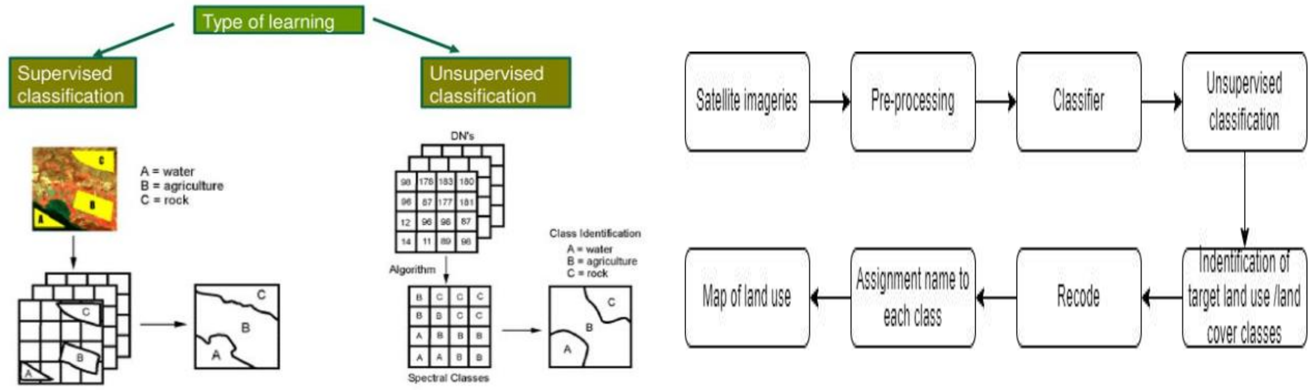
In this study were used two different types of materials. The first of these is the data created by Landsat 8 OLI_TIRS images. The other type of material is ArcGIS software, which performs analysis and image processing. The Landsat 8 OLI_TIRS images used were obtained from the Earthexplorer website (Earthexplorer, 2024).
The materials used in the study are as follows:

- Landsat 8 OLI_TIRS
- ArcGIS/ArcMap 10.8 Software

Since it provides more accurate results than unsupervised classification methods, images were classified using the Iterative Self-Organized Data Analysis Technique (ISODATA) method in ArcGIS/ArcMap environment, which is one of the GIS software, and the surface area changes of Salt Lake in the last decade (2014-2023) were determined. The resolution of the images obtained is 30 meters. The main reason for choosing unsupervised classification in the study is that it is more useful than supervised classification, does not require any prior knowledge about the studied area, is easier, faster, more accurate and allows objects to be analyzed systematically. In addition, NDVI and NDWI values were obtained in the study in order to monitor the healthy/unhealthy vegetation density, drought, water and terrestrial surface of Salt Lake in the last ten years.

2.1. Unsupervised Classification

Unsupervised classification is a method of automatically grouping or classifying each pixel in the image on the software using various algorithms based entirely on clustering, without any operator support. Although it is not possible to obtain precise and clear information about the data classes obtained as a result of this classification method, information such as how many different classes there are in the study area or the sizes of these classes can be obtained. An example of supervised and unsupervised classification is shown in Figure 3a. The classes that will emerge as a result of unsupervised classification are spectral classes. It can help researchers determine the spectral numbers of separable classes in the study area determined before the study. Although it is not known in advance what these spectral classes are, the natural characteristics of the classes can be determined later by comparing topographic maps of that region, high-resolution satellite images, aerial photographs and existing auxiliary information (Ozcalik, 2020; Aliyazicioglu, 2019; Caf, 2019; Sanli, 2017; Matci, 2019; Ekercin, 2007; ESA, 2009). The unsupervised classification workflow diagram is given in Figure 3b.



(a) (b)

Figure 3. (a) Unsupervised classification (ESA, 2009) (b) Unsupervised classification workflow diagram

2.2. ISODATA Technique

ISODATA (Iterative Self-Organizing DATA) is a more commonly used technique in unsupervised classification method. This method is a type of minimum distance clustering. In order for classification to occur, how many clusters are wanted to be created in the image, how many iterations are needed and the threshold value must be given. The image is classified according to minimum distance classification. A new median value is calculated for the clusters. The image is reclassified with the new median values obtained. This process is repeated for the given number of iterations. After each iteration, how many pixels remain in a cluster is calculated as a percentage. In this method, a lower limit can be determined on the number of pixels of the clusters to be created, and an upper limit can be determined depending on a certain standard deviation value. Accordingly, as a result of clustering, the number of classes may be less or more than desired. In addition, not only the number of iterations but also the rate of change between iterations can be used to finalize the process. The rate of change is the fraction of the number of pixels in the image whose cluster values change with the new iteration (Oztas et al., 2023; Basar, 2008; Dogan, 2019).

2.3. Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) is primarily preferred in calculating the "greenness" or leaf area of plants, chlorophyll concentration in leaves, plant productivity, vegetation area or water accumulation in an area, vegetation characteristics and index measurements. It is the most widely used vegetation index. The vegetation index is based on the observation that different surfaces reflect different types of light. Photosynthetically active vegetation absorbs most red light and reflects much near infrared light. Dead or dry vegetation reflects more red light and less infrared light. NDVI analysis can be performed through various GIS and RS programs. The quality of the satellite images used for this analysis (cloud ratio, resolution, etc.) is important for the robustness and accuracy of the analysis. Vegetation index/greenness level can be determined by taking the (NIR, Near-infrared (band 5)) and RED (band 4) ratio from Landsat 8 OLI_TIRS satellite image. This formula is probably the most common among vegetation rate indices. NDVI is calculated on a pixel-by-pixel basis as the normalized difference between the NIR and Red spectrum of an image. In Equation 1 describes the relationship between these algorithms (Soesanto et al., 2022; Firmansyah et al., 2022; Arifin et al., 2022; Prasati, 2010; Julianto, 2021).

$$\mathrm{NDVI} = \frac{NIR-RED}{NIR+RED} \quad (1)$$

2.4. Normalized Difference Water Index (NDWI)

The NDWI is used in the analysis of water areas from the reflectance values of the green and near infrared bands of remote sensing images. NDWI detects the presence of water bodies by ignoring the presence of soil and vegetation thanks to the near infrared and visible green light. The NDWI is between -1 and +1. In this context, values greater than zero indicate water bodies, while values less than zero or zero indicate areas without water. High NDWI values correspond to high water content and high vegetation rate. Low NDWI values correspond to low water content and low vegetation rate. NDWI can be determined by taking the ratio of (GREEN, (band 3)) and (NIR, Near infrared (band 5)) from Landsat 8 OLI_TIRS satellite images. Equation 2 describes the relationship between these algorithms. The values of water bodies are greater than 0,5. Since vegetation cover has much smaller values, vegetation can be more easily distinguished from water bodies. Generally, values between 0,2 and 1 represent water bodies (Gao, 1996; Ozvan et al., 2023; McFeeters, 1996; EOS, 2024; Yeler, 2023; Kaplan, 2020; Pettorelli et al., 2005; Reis et al., 2016; Ak & Erdogan, 2022). NDWI values are shown in the following ranges:

- 0,2 – 1 – Water surface
- 0,0 – 0,2 – Flooding, humidity
- -0,3 – 0,0 – Moderate drought, non-aqueous surfaces
- -1 – -0,3 – Drought, non-aqueous surfaces

$$\text{NDWI} = \frac{GREEN-NIR}{GREEN+NIR} \quad (2)$$

4. Results and Discussion

In this study, Landsat 8 OLI_TIRS satellite images on the United States Geological Survey (USGS) website were used to detect areal changes in the lake surface area of Salt Lake in the last decade (2014-2023 years). Information about Landsat 8 OLI_TIRS satellite images used in the last decade is shown in Table 1. The spatial resolution of the Landsat 8 OLI_TIRS satellite image is 30*30 meters for each year. The spectral properties of the bands are shown in Table 2. There are two main reasons for selecting satellite image data, especially in the summer months (7th and 8th months). The first of these is the low cloud cover rate, and the second is the determination of the average water surface area difference between the summer and spring months (1642 km^2).

Table 1. Information about Landsat 8 OLI_TIRS satellite images

Image Data Date	Path/Row	Spatial Resolution (m)
August 13, 2014	177/33	30*30
August 16, 2015	177/33	30*30
August 18, 2016	177/33	30*30
July 4, 2017	177/33	30*30
August 24, 2018	177/33	30*30
August 27, 2019	177/33	30*30
August 29, 2020	177/33	30*30
August 16, 2021	177/33	30*30
August 19, 2022	177/33	30*30
August 22, 2023	177/33	30*30

Table 2. Landsat 8 OLI_TIRS spectral bands (Oguz, 2017)

Band Number	Wavelength (μm)	Spatial Resolution (m)
Band 1 Coastal/Aerosol	0.435 - 0.451	30
Band 2 Blue	0.452 - 0.512	30
Band 3 Green	0.533 - 0.590	30
Band 4 Red	0.636 - 0.673	30
Band 5 (Near-InfraRed, NIR)	0.851 - 0.879	30
Band 6 (Short-Wave InfraRed, SWIR-1)	1.566 - 1.651	30
Band 7 (Short-Wave InfraRed, SWIR-2)	2.107 - 2.294	30
Band 8 (Panchromatic, Pan)	0.503 - 0.676	15
Band 9 Cirrus	1.363 - 1.384	30
Band 10 (Thermal-InfraRed, TIR-1)	10.60 - 11.19	100
Band 11 (Thermal-InfraRed, TIR-2)	11.50 - 12.51	100

A total of 36 Landsat 8 OLI_TIRS satellite images were used in this study to examine the change in the surface area of Salt Lake. Satellite images were provided to cover the entire lake. The resulting surface areas are listed in Table 3.

Table 3. Surface area changes of Salt Lake

Years	Satellite	Surface Area (km^2)
August 13, 2014	Landsat 8 OLI_TIRS	997.977
August 16, 2015	Landsat 8 OLI_TIRS	923.737
August 18, 2016	Landsat 8 OLI_TIRS	975.580
July 4, 2017	Landsat 8 OLI_TIRS	1049.642
August 24, 2018	Landsat 8 OLI_TIRS	974.737
August 27, 2019	Landsat 8 OLI_TIRS	1000.045
August 29, 2020	Landsat 8 OLI_TIRS	966.104
August 16, 2021	Landsat 8 OLI_TIRS	1005.094
August 19, 2022	Landsat 8 OLI_TIRS	1039.551
August 22, 2023	Landsat 8 OLI_TIRS	1062.172

When Table 3 is examined, the surface area of Salt Lake decreased from 997,977 km^2 in 2014 to 923,737 km^2 in 2015, from 1049,642 km^2 in 2017 to 974,737 km^2 in 2018 and from 1000,045 km^2 in 2019 to 966,104 km^2 in 2020. The lake surface area change graph according to years is shown in Figure 6. A trend line has been added for the summer month on a seasonal basis based on the last decade. The trend line equation is $y=7.9437x-15035$ and the R^2 value is calculated as 0,32. The r value (Pearson Correlation Coefficient (Relationship Coefficient)) which is square root of the R^2 value, takes values between -1 and +1. In this section, Pearson Correlation Coefficient (r) was calculated as 0,57.

Figure 4 shows the NDVI results calculated by using the Landsat 8 OLI_TIRS satellite image. The values obtained as a result of NDVI analysis vary between -1 and +1. In places where the vegetation is healthy and dense, the index value approaches +1, while in places where the vegetation is abundant, unhealthy and weak, the index value approaches -1. NDVI values were calculated with the help of the formula given in Equation 1. When the NDVI values in Figure 4 are examined, it is seen that there is drought in the region due to very little and unhealthy green vegetation. The maximum and minimum values are 0.83 in 2022 and 2023 years and -0.65 in 2016 and

2017 years, respectively. In Table 4 shows the average NDVI values of the last decade. When Figure 5a is examined, it is determined that the highest and lowest values are 0.73 in 2022 and 0.59 in 2017 years, respectively. NDVI values are same (0,67) in 2016, 2018 and 2020 years. It was determined that in 2022, the vegetation cover (0.73) was denser and healthier than in other years and the drought level was less.

In Figure 5, the lake surface area is clearly observed in the NDWI for the 2014-2023 years applied to the satellite image. In this index, water areas outside the lake area and light-colored terrestrial surfaces are included in the water masses. According to the results obtained, the highest and lowest values in the NDWI were seen in 2022 year and these values were 0,66 and -0,98, respectively. In Figure 5b, shows that NDWI values are close to each other between 2014 and 2020 years, with an average value of 0,33. The lowest and highest values in the NDWI were found to be 0,28 and 0,82 in 2017 and 2022 years, respectively. As a result of this, positive NDWI values belong to the lake surface area, while zero and negative NDWI values mean that the water area is shallower.

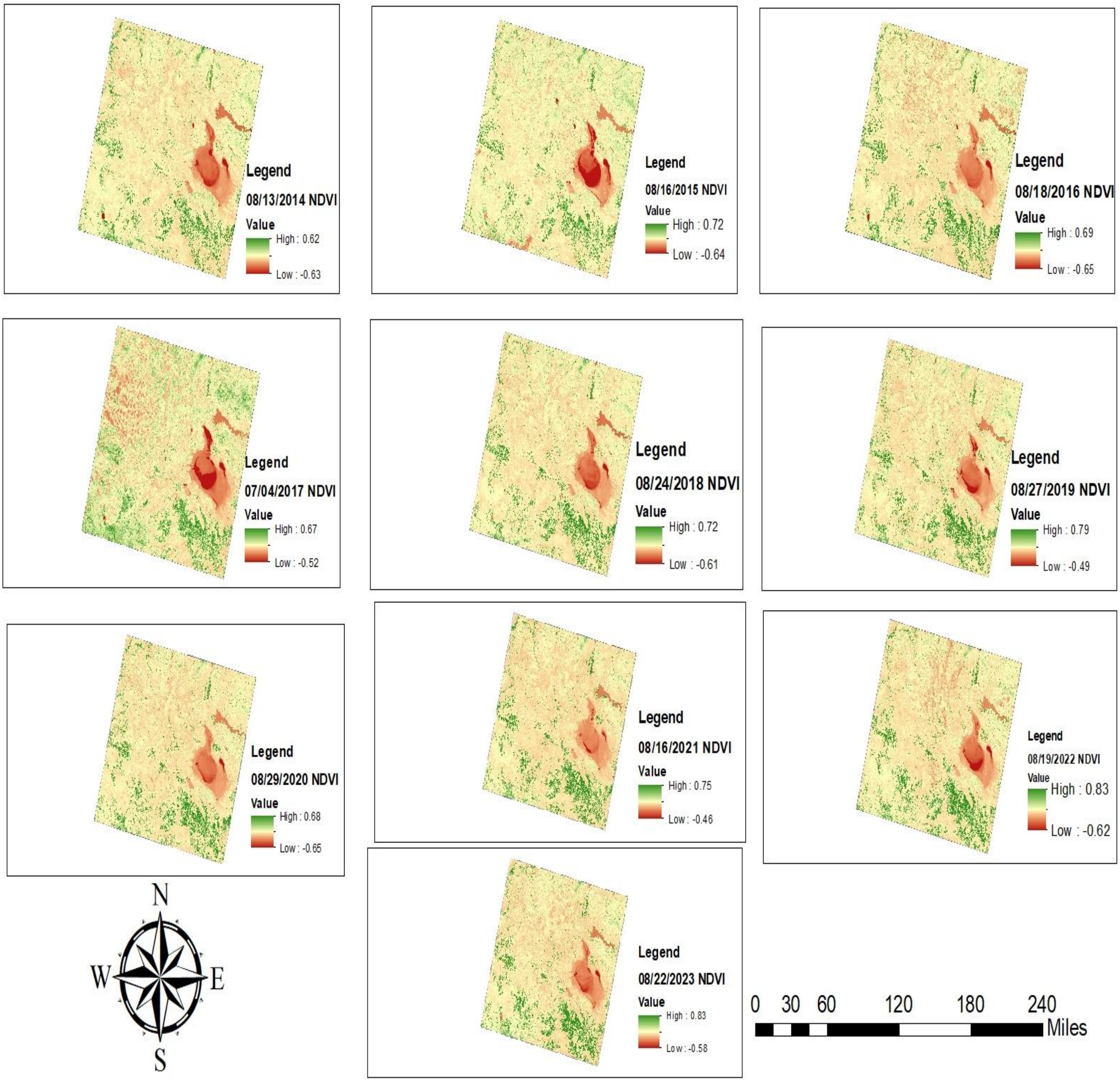
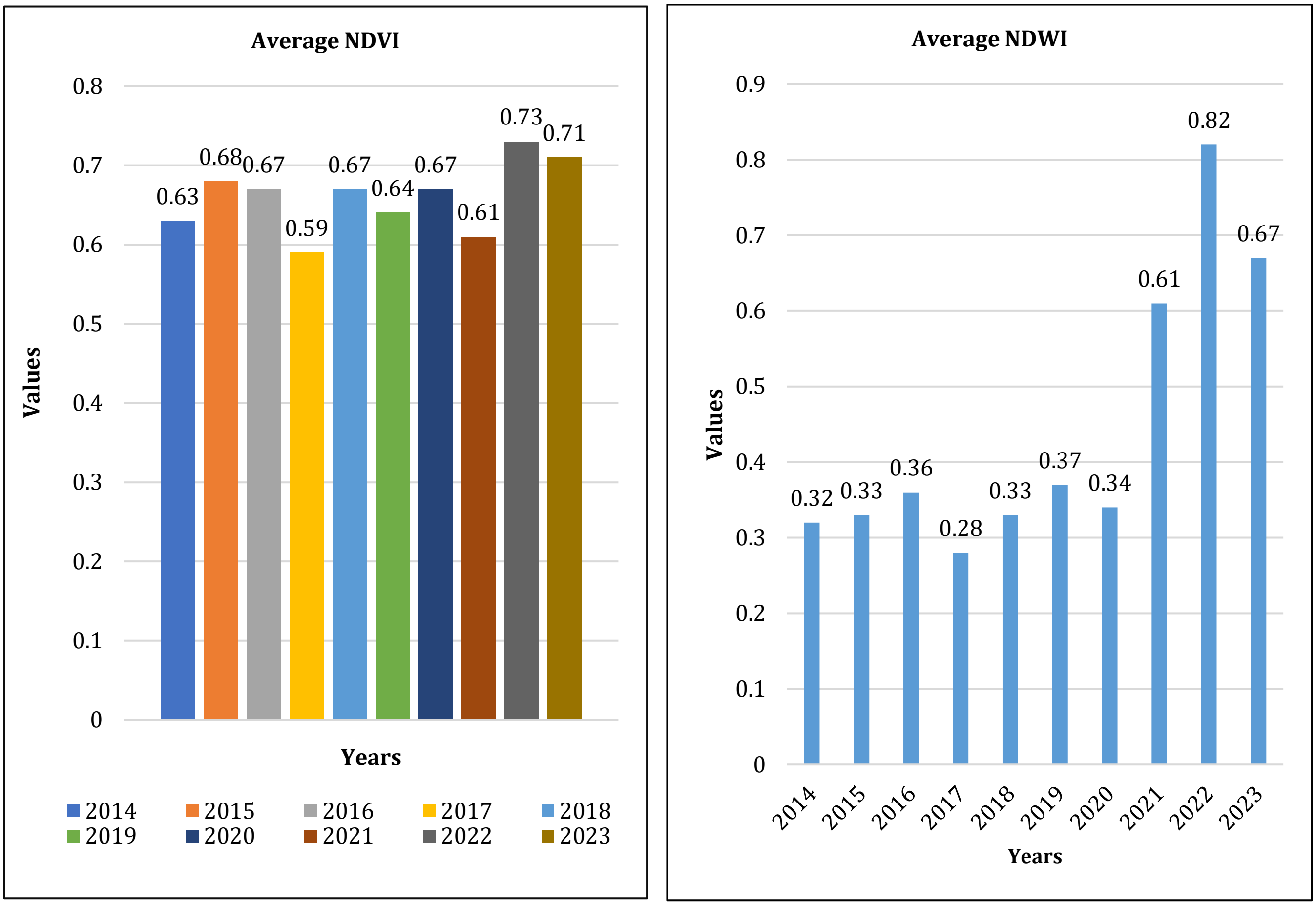


Figure 4. Landsat 8 OLI_TIRS satellite images NDVI results



(a) (b)

Figure 5. (a) Average NDVI values (b) Average NDWI values

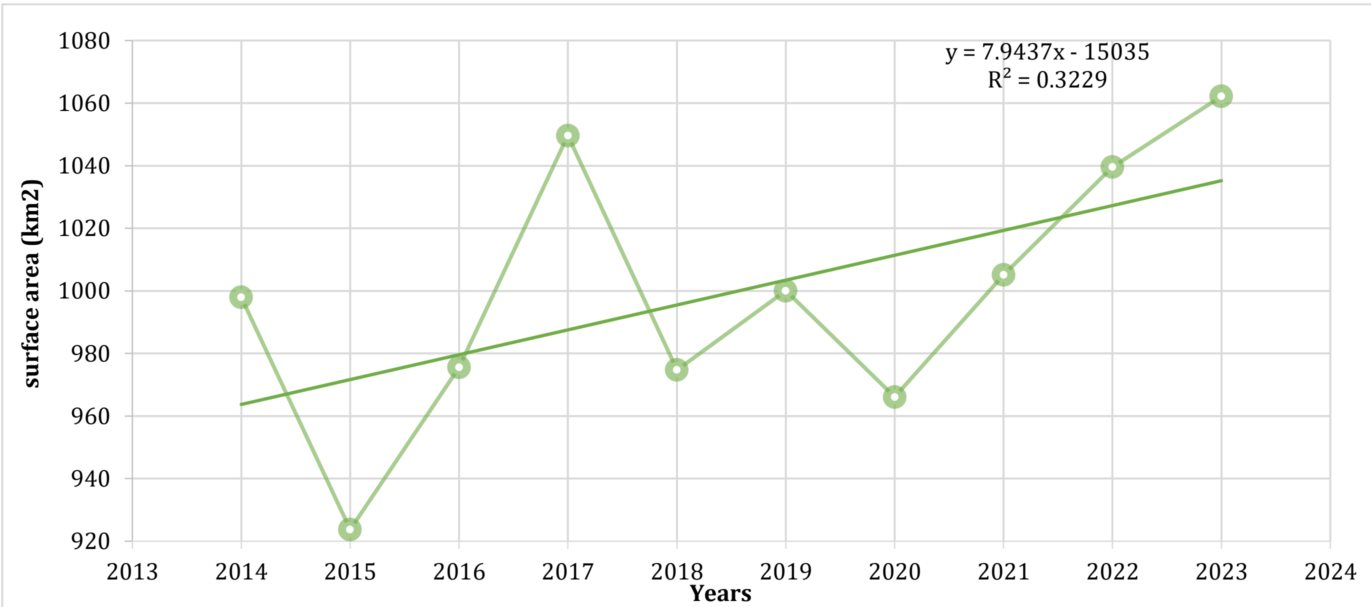


Figure 6. Graph of Salt Lake Surface Area Change

Figure 6 demonstrate that Salt Lake has an average surface area of 999,464 km^2 in the last decade (2014-2023 years) during the summer months (7th and 8th months) when drought is evident. There appear to be fluctuations between years. It was determined that the highest water surface area was 1062,172 km^2 in 2023, and the lowest value was 923,737 km^2 in 2015. Similar values were obtained in 2016 and 2018 years. In addition, it is seen that the water surface area difference between 2015-2017 years is greater than the difference between 2020-2023 years. While the surface area of Salt Lake reaches 1642 km^2 in the spring months (4th and 5th months) (Ozvan et al., 2023), there is a surface area difference of approximately 642,536 km^2 according to spring months of summer months between 2014 and 2023 years. This clearly show that there is by 39.13%. decrease in water level during the summer months. There is a gradual increase in the water level of the lake surface area from 2020 to 2023. The main reasons for this, are increase in water levels in the last four years (2020-2023 years) due to the high rainfall in the spring months of the Central Anatolia Region (natural factor) and people's awareness. It was also observed that there was by 6.43% increase in water surface area from 2014 to 2023. Authorities and the public need to take precautions to protect Salt Lake. These measures include combating climate change, the importance and protection of biological diversity, education and awareness, sustainable use, protection of water resources, saving and efficient use of water.

5. Conclusion and Recommendations

In recent years, the use of Geographic Information Systems (GIS) and Remote Sensing (RS) technologies has been rapidly increasing in order to detect and monitor changes in lake surface areas. These technologies offer significant advantages in large-scale studies, providing faster and more accurate data collection while saving time, cost, and effort. Detecting changes in surface area of lakes is especially important for the conservation of ecosystems like Salt Lake. Moreover, these technologies play an effective role in the sustainable management of water resources, biodiversity conservation, and combating climate change. However, it has been observed that an effective process has not yet been developed in Türkiye to prevent surface area and volume losses in lakes. Therefore, identifying the natural and anthropogenic factors that lead to changes in lake surface area is of great importance. In the case of Salt Lake, RS and GIS analyses can assist in monitoring these changes and help in the formulation of environmental management strategies. Actively using these technologies for the sustainable management of lakes and wetlands is a critical step for water resources management, biodiversity conservation, and environmental monitoring. Additionally, the use of these technologies can support the development of innovative strategies for the protection of lake ecosystems, ensuring the conservation of water resources and biodiversity. In this context, long-term monitoring of important ecosystems such as Salt Lake will allow for the effective implementation of environmental protection measures. This proposal highlights how RS and GIS technologies can be effectively used to detect changes in lake surface area, using Salt Lake as a case study, and emphasizes the need for the development of strategies for the conservation and sustainable management of lakes. Furthermore, these technologies play a key role in environmental management and biodiversity conservation.

In this study aimed to determine the change in the surface area of Salt Lake in the last decade (2014-2023). In addition, vegetation and water area analysis were performed via RS and GIS by using Landsat 8 OLI_TIRS satellite images with the help of NDVI and NDWI of this region. From the NDVI and NDWI values, it was determined that the vegetation around the Salt Lake was unhealthy/very low density and was a lake surface area. Therefore, there is a drought situation in the region. It was observed that in 2022 year, while vegetation (0.73) was denser and healthier compared to other years, and the drought level was less. United States Geological Survey (USGS)'s Landsat 8 OLI_TIRS satellite images between 2014 and 2023 years and the unsupervised classification (ISODATA) method in ArcGIS 10.8 software were used. According to data covering the last decade period, it was determined that there was a decrease in the water surface area of approximately 642,536 km^2 in Salt Lake according to spring months of summer months. This corresponds to a rate of 39.13%. There are generally fluctuations in water surface area change. It was observed that there was an increase in water level between 2020-2023 years and 2015-2017 years, and drought occurred in the decreased periods.

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There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

Research and publication ethics were complied with in the study.

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