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Wetland monitoring by remote sensing techniques: A case study of Işıklı Lake

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Abstract

Lakes are considered to be among the most important ecosystems in the world due to their natural functions and economic values. The importance of lakes comes from being one of the main reservoirs of biological diversity and an important source of fresh water in addition to their use in irrigating agricultural lands. The fisheries and aquaculture sectors are a source of income for millions of people, especially for low-income families, and contribute directly and indirectly to their food security. Today, lakes face irreparable damage due to global warming, on one hand, the population increases, and food and growing production needs on the other hand. Therefore, studying the effects of these factors on lakes has been of great importance to decision-makers in local governments. The main purpose of this study is to observe the land cover change of Işıklı Lake and its surroundings with Sentinel-2 images. In this paper, we study the changes in Işıklı Lake over seven years using medium-resolution Sentinel-2 images. Işıklı Lake is of great importance not only because of its economic value but also because it is an ecological and natural resource. However, the lake faces many challenges due to climatic and human activities, especially in the last decade. But since exchange between land cover classes are slow and time-consuming, the resulting damage may go unnoticed. Therefore, long historical data such as aerial photographs or satellite images of the area are fundamental to monitor the changes that occur and preventing further change. Atmospheric correction was first applied to Sentinel-2 images. Then, each image was classified using the Maximum Likelihood technique. Finally, by comparing each classified images, changes on the basis of class were determined. It has been observed that there is a serious decrease in the lake area.

1. Introduction

Wetlands are among the most important ecosystems in the world. They are an essential source of biodiversity, as they provide habitats for a wide range of plant and animal species. Wetlands have been called the kidneys of the Earth as they sequester pollutants generated in urban areas [1]. However, about 50% of wetlands have disappeared since the beginning of the 20th century [2]. Wetlands play an essential role in cleaning water, replenishing groundwater, protecting the shorelines, and reducing droughts and floods [3]. For these reasons, scientists are paying increasing attention to wetlands.

Climate change, rapid urbanization, and increasing demands of the industry worldwide are the most common causes of wetlands degradation [4]. The most critical problems preventing wetland management are directly related to the socio-economic structure and the agricultural and commercial activities of the local populations living around these resources [5]. Therefore wetland studies are very important for protecting wetlands and minimizing the effects of climate change.

The Ramsar Convention distinguishes between 42 types of wetlands; these types can be grouped into three main classes: artificial wetlands, inland wetlands, and coastal wetlands [6]. The first article of the Ramsar Convention defines wetlands as areas where water is the controlling factor in the environment (such as fens, marshes, peatlands, or water), whether these areas are natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish or salt [7]. The scope of the Convention has been systematically expanded through time to include all aspects of wetland conservation and responsible use [8]. The main goal of the Convention is the conservation of wetlands worldwide through international cooperation. Turkey signed the Ramsar Convention on December 30, 1993, and became an official party by publishing the agreement in the Official Gazette on May 17, 1994 [5]. In The Ramsar Convention, wetland standards were considered of international importance. According to these standards, wetlands are defined as Class A and Class B. Class A wetlands are defined as “wetlands of international importance that host rare or unique species of flora and fauna,” while Class B wetlands are defined as “wetlands of international importance” [5]. According to these definitions, Işıklı Lake has been classified as class A. Remote sensing is considered the primary source of spatial information about Earth's surface cover and composition [9]. Various sensors capture objective information about the world and provide valuable historical data that can be used by scientists interested in tracking changes over time [10]. Scientists need to analyze remotely sensed data over a specific period to determine the long-term impact of factors such as urbanization, population growth, and climate change on wetlands. But the process of acquiring and analyzing time series of multispectral images may be challenging because the images used in the study had to be recorded under similar environmental conditions, such as acquisition time, sun angle and spectral bands. Otherwise, it causes changes in both the time and spectral content of the recorded images. One approach to solving this problem is by reducing the spectral information to a single index and the multispectral images to a single index region for each time period [11]. Thus, the problem is simplified to the time-series analysis of one variable for each pixel in the image.

Monitoring wetland distribution and dynamics is very important for decision-making in land management and nature conservation. Since wetlands are often difficult to access and traditional survey techniques are time-consuming and expensive, remote sensing techniques using satellite images covering large geographical areas at specific time periods provide the most appropriate tools for comprehensively investigating Land Use Land Cover (LULC) change over time [12]. This study focuses on analyzing the LULC change around Işıklı Lake between the years 2015 and 2022. For this purpose, two Sentinel-2 satellite images were acquired annually between 2015–2022 and converted into LULC maps using a Maximum Likelihood classification approach. Then, a post-classification change detection approach was applied to determine the seasonal loss of the lake area, the aquatic vegetation that covers it, and the LULC changes in the lake's surrounding areas.

2. Study area

Işıklı Lake is located in the upper basin of the Büyük Menderes River in Denizli Province at the coordinates of 38°14′N 29°54′E (Figure 1). The average elevation of the lake is 818 meters, and its surface area is 73 km^2, and its deepest point is 7 meters. However, since the lake is used for irrigation in terrestrial agriculture in the summer, its depth varies up to 3 meters annually. With the beginning of irrigation in May, the water level in the lake drops significantly, and a large part of its surface is covered with aquatic plants. In July, August, and September, aquatic vegetation covers approximately 60-70% of the lake's surface [13]. Originally a natural lake, it was converted into a dam in 1968 by DSI (Turkiye General Directorate of State Hydraulic Works) to protect the surrounding settlements and agricultural areas from flood risks [14]. Today, the lake is used as a reservoir to store water for irrigation in the surrounding plains. There are several reed islets in the middle of the lake. On the western and eastern shores of the lake, there are large poplars and agricultural fields, and in the south, there is a broad plain where grain is cultivated [14].

3. Method

In this study, the Maximum Likelihood technique was preferred as the classification technique. The most important reason for this preference is the theoretical basis of the method. The Maximum Likelihood method is based on strong theoretical foundations and has been proven to be an effective technique for a wide range of classification problems. Producer accuracy and user accuracy metrics were preferred for evaluation. Two multispectral satellite images were used to assess the change in LULC over seven years. Moreover, The Maximum Likelihood method is a well-understood and widely used statistical technique, with a long history of application in a variety of fields. Sentinel-2 images for 2015 and 2022 were downloaded from the USGS Earth Explorer website. Images taken at the same time of year are used to reduce possible errors in detecting changes due to the sun angle, atmospheric conditions, and changing phenology. The Dark Object Subtraction atmospheric correction has been carried out to remove surface reflectance values' effects from images and distinguish certain LULC types with spectral signatures. Although atmospheric correction is not a prerequisite in change detection analyses, more accurate results are expected when atmospherically-corrected images are used [15].

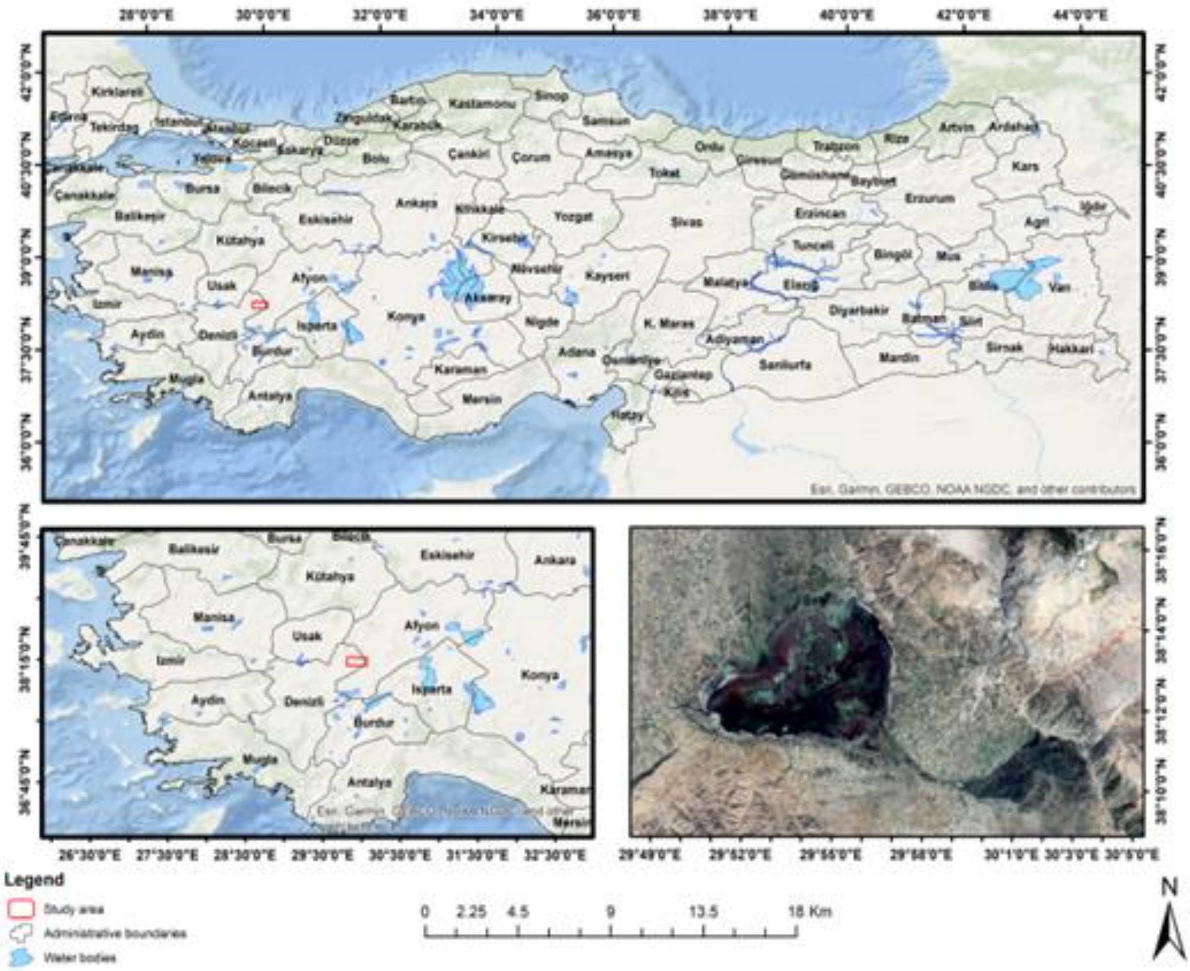

Figure 1. Study Area

4. Results

Supervised classification of Sentinel-2 images was performed using the built-in Maximum Likelihood Algorithm in ENVI Software (Figure 2). This approach is one of the techniques that can produce the most statistically consistent results in evaluating remotely sensed images [16]. The procedure is based on the Bayesian probability theorem, representing the marginal distributions of data and their internal correlations under the assumption of multivariate normality in N-dimensional Euclidean space [17]. This study used eight bands as input for the image classification process. Then, the post-classification comparison change detection approach was applied. This approach involves a pixel-by-pixel comparison of two different images [18]. With this technique, a matrix of change trends can be produced, providing quantitative and qualitative information about each LULC type's gain, loss, and stability.

This information helps us to draw a comprehensive picture of spatiotemporal changes in LULC. In Figure 3, the changes by classes are given graphically. The results of the accuracy values are shown in Table 1 and Table 2 (Bold values indicate correctly classified verification pixels, PA refers to procedure accuracy, and UA refers to user accuracy.). Overall accuracy for 2015 and 2022 was computed as 92.33% and 94.8%, respectively. The Kappa indices for the 2015 and 2022 maps are determined as 0.90 and 0.93, respectively. These results meet the minimum standard of 85% accuracy prescribed by the USGS classification scheme. User accuracy for individual classes ranges from 90% to 95.71% in 2015 and from 93.06% to 98.38% in 2022. The results indicate that the lake lost 40% of its surface area in just seven years, which is considered a short period compared to this amount of change. Consequently, the proportion of aquatic vegetation also decreased by 49%. At the same time, there was a decrease in the area of agricultural land by 24 percent and forest lands by 40%. In contrast, there was an increase in dry agricultural land, pasture lands, and built-up areas by 44%, 19%, and 4%, respectively. These findings indicate that the change process is proceeding at a rapid pace and may lead to irreparable damage to the lake if the local government and decision-makers do not take serious steps to address the problem. Class-based changes in the study area are proportionally in Table 3; are spatially presented in Table 4. Also Change Map is given in Figure 4.

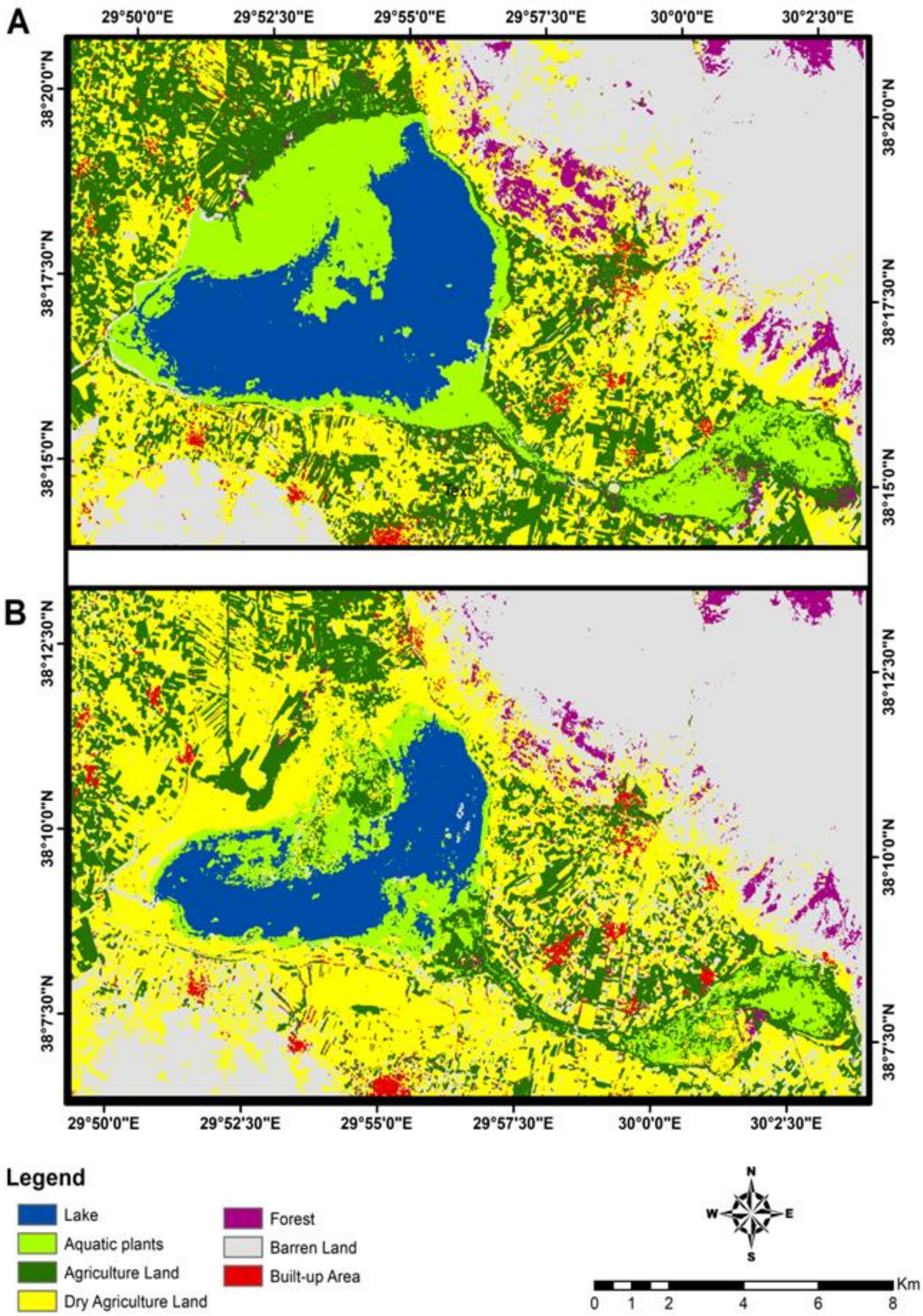

Figure 2. Classification results. (A) 2015 LULC map and (B) 2022 LULC map

Table 1. Error matrix for the year 2015 dated imagery

	Lake	Aquatic plants	Agriculture Land	Dry Agriculture Land	Forest	Barren Land	Built-up Area	Total	PA	UA
Lake	48	2	0	0	0	0	0	50	92.31	96
Aquatic plants	4	67	4	1	0	0	0	76	93.06	88.16
Agriculture Land	0	3	63	0	1	0	0	67	90	94.03
Dry Agriculture Land	0	0	0	64	0	3	4	71	90.14	90.14
Forest	0	0	3	0	28	0	0	31	93.33	90.32
Barren Land	0	0	0	3	1	67	0	71	95.71	94.37
Built-up Area	0	0	0	3	0	0	48	51	92.31	94.12
Total	52	72	70	71	30	70	52	417		
Overall Accuracy	92.33%									
Kappa Coefficient	0.9096									

Table 2. Error matrix for the year 2022 dated imagery

	Lake	Aquatic plants	Agriculture Land	Dry Agriculture Land	Forest	Barren Land	Built-up Area	Total	PA	UA
Lake	67	1	0	0	0	0	0	68	95.71	98.53
Aquatic plants	2	56	1	0	0	0	0	59	93.33	94.92
Agriculture Land	0	3	59	0	0	0	0	62	95.16	95.16
Dry Agriculture Land	0	0	0	67	1	1	2	71	93.06	94.37
Forest	1	0	0	3	61	2	2	69	98.39	88.41
Barren Land	0	0	0	2	0	50	0	52	94.34	96.15
Built-up Area	0	0	2	0	0	0	60	62	93.75	96.77
Total	70	60	62	72	62	53	64	443		
Overall Accuracy	94.8%									
Kappa Coefficient	0.9393									

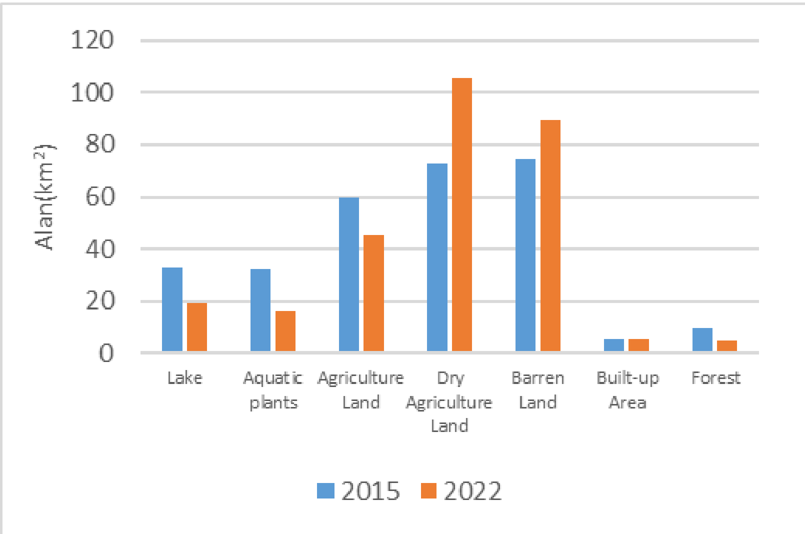

Figure 3. The area of each LULC type in 2015 and 2022

Table 3. LULC matrix (in percentage) showing the change in LULC classes between 2015 and 2022

	Lake	Aquatic plants	Agriculture Land	Dry Agriculture Land	Barren Land	Forest	Built-up Area	Row Total	Class Total
Lake	59.317	0.108	0	0	0.001	0.018	0	100	100
Aquatic plants	27.381	19.459	1.291	0.022	0.08	0.488	0.002	100	100
Agriculture Land	0.859	30.831	37.245	14.54	1.419	6.227	10.829	100	100
Dry Agriculture Land	10.163	45.3	52.266	62.268	9.218	21.29	40.391	100	100
Barren Land	2.271	2.853	6.436	20.27	88.539	26.847	10.627	100	100
Built-up Area	0.009	0.186	2.089	2.69	0.122	0.119	38.118	100	100
Forest	0	1.263	0.673	0.21	0.621	45.011	0.033	100	100
Class Total	100	100	100	100	100	100	100	0	0
Class Changes	40.683	80.541	62.755	37.732	11.461	54.989	61.882	0	0
Image Difference	-40.57	-49.857	-24.157	44.902	19.735	-40.212	3.979	0	0

Table 4. LULC matrix (in km^2) showing the change in LULC classes between 2015 and 2022

	Lake	Aquatic plants	Agriculture Land	Dry Agriculture Land	Barren Land	Forest	Built-up Area	Row Total	Class Total
Lake	19.45	0.03	0	0	0	0	0	19.49	19.49
Aquatic plants	8.98	6.26	0.77	0.02	0.06	0.05	0	16.13	16.13
Agriculture Land	0.28	9.92	22.18	10.57	1.06	0.6	0.55	45.16	45.16
Dry Agriculture Land	3.33	14.57	31.12	45.25	6.9	2.05	2.06	105.29	105.29
Barren Land	0.74	0.92	3.83	14.73	66.29	2.59	0.54	89.65	89.65
Built-up Area	0	0.06	1.24	1.95	0.09	0.01	1.95	5.31	5.31
Forest	0	0.41	0.4	0.15	0.46	4.34	0	5.77	5.77
Class Total	32.79	32.17	59.54	72.66	74.87	9.65	5.11	0	0
Class Changes	13.34	25.91	37.37	27.42	8.58	5.31	3.16	0	0
Image Difference	-13.3	-16.04	-14.38	32.63	14.78	-3.88	0.2	0	0

5. Conclusion

This study investigated the LULC change around Işıklı Lake by comparing the land cover maps obtained from two Sentinel-2 images taken in 2015 and 2022. The applied remote sensing techniques have proven to be very useful in producing regular land cover maps with a low cost and reasonable effort. The study results reveal that a large part of the water body of the Işıklı Lake is lost due to over-irrigation, reduced annual precipitation, and rising annual temperatures. Between 2015 and 2022 (considered a short period for this change), the lake lost 13.3 km^2 or 40% of its area. This lake is very important for the region as it is the main reservoir of biodiversity and an important source of freshwater and irrigation. But considering the significant decrease in the lake's water, it could suffer irreparable damage in the upcoming years. Therefore, we recommend the local government and those responsible for water management in Turkey take serious steps to protect this lake.

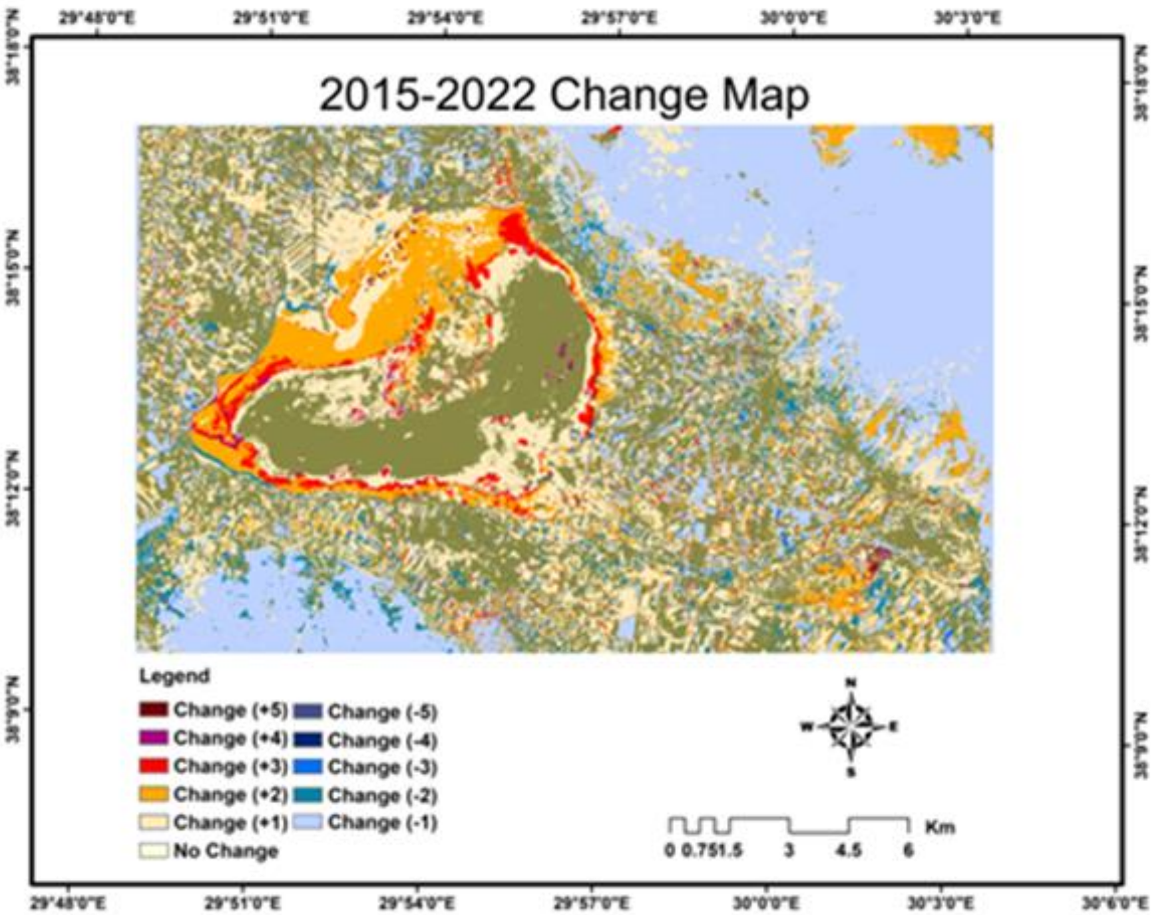

Figure 4. 2015-2022 Change map.

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Author contributions

Abdullah Fadhil Tawfeeq: Conceptualization, Methodology, Software, Writing-Reviewing **Ümit Haluk Atasever:** Validation, Investigation, Writing-Reviewing and Editing

Conflicts of interest

The authors declare no conflicts of interest.

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