



ISSN: 0067-2904

Using Remote Sensing Techniques to Monitor the Changes in AL-Habbaniya Lake, West of Iraq

Noor Z. Kouder, Yasser Chasib Bakheet, Rafah R. Ismail*, Dhiaa Mahdi

Department of Astronomy and Space, College of Science, University of Baghdad, Baghdad, Iraq

Received: 13/4/2025

Accepted: 29/1/2026

Published: 30/10/2026

Abstract

Lakes and other water bodies change over time and are influenced by natural and anthropogenic processes during the hydrological cycle. One method for monitoring those factors is remote sensing, which collects digital information about objects or regions remotely and is useful for a wide range of tasks. It is a powerful reminder that data is focused on changes in the Earth's surface, rather than being opposed to the traditional methods. Al-Habbaniya Lake, a vital reservoir west of Baghdad, mainly serves three functions: flood control, supplying ecosystem services, and irrigation. Recently, the lake's surface area has significantly fallen due to drought, slow water flow in the Euphrates River, and delayed maintenance, influencing its agricultural, recreational, and natural functions. The focal point of this study is to monitor changes in Al-Habbaniya Lake in western Iraq using remote sensing techniques over approximately 34 years, 1988, 2002, and 2022, using Landsat satellite images. The methods employed are atmospheric correction, image masking, maximum-likelihood supervised classification, and identification of land cover change using ENVI 5.3. The strengths of this study are: (i) multi-temporal analysis through the use of Landsat images, (ii) atmospheric correction, which reduces the uncertainty of the data due to atmospheric effects, (iii) binary masking, which maximizes the accuracy of the lake area, and (iv) maximum likelihood classification, which maximizes the analysis of the pixels. Results showed that the water category decreased from 362.94 km² (95.02%) in 1988 to the lowest point in 2002 at 103.03 km² (26.97%), and then rose to 189.20 km² (49.53%) in 2022. The soil class rose from 0.58 km² (0.15%) in 1988 to 201.63 km² (52.79%) in 2002, then decreased from 2002 to 2022 to 98.48 km² (25.78%). In the case of vegetation, the area grew from 18.45 km² (4.83%) in 1988 to 77.31 km² (20.24%) in 2002, and finally expanded to 94.30 km² (24.69%) in 2022. Results of the change detection showed that in 1988-2002, 48.71% of the study area was changing from water to land. Conversely, 2002-2022 showed some recovery in ecology, with 11.51% of the study area recovering to water, from bare soil. Generally, the work showed that between 1988 and 2002, water loss was enormous, and only partially recovered in the following decades, providing valuable information for water management of a critical ecosystem.

Keywords: Al-Habbaniya, Remote Sensing, Landsat, Masking, Classification, Change detection.

*Email: rafah.ismail@sc.uobaghdad.edu.i



استخدام تقنيات الاستشعار عن بعد في رصد التغيرات في بحيرة الحبانية غرب العراق

نور زبير خضر, ياسر جاسب بخيت, رفاه رشيد اسماعيل*, ضياء كمال مهدي

قسم الفلك والفضاء, كلية العلوم, جامعة بغداد, بغداد, العراق

الخلاصة

تتغير المسطحات المائية والبحيرات بمرور الوقت خلال الدورة الهيدرولوجية، وذلك من خلال عمليات طبيعية وبشرية. يُعد الاستشعار عن بُعد أداة فعالة لتتبع هذه التغيرات، إذ يوفر بيانات شاملة وفي الوقت المناسب حول التغيرات في سطح الأرض مقارنة بالطرق التقليدية. تُعد بحيرة الحبانية، وهي خزان حيوي يقع غرب بغداد، مسؤولة بشكل رئيسي عن ثلاثة أغراض: إدارة السيطرة على الفيضانات، والري، وتوفير خدمات النظم البيئية. في الآونة الأخيرة، انخفضت مساحة سطح البحيرة بشكل ملحوظ نتيجة للجفاف، وانخفاض مدخلات نهر الفرات، وتأجيل الصيانة، مما أثر على وظائفها الزراعية والترفيهية والبيئية. تركز هذه الدراسة على مراقبة ورصد التغيرات في بحيرة الحبانية في غرب العراق من خلال تطبيق تقنيات الاستشعار عن بعد على مدى فترة زمنية تبلغ حوالي 34 عامًا، باستخدام صور الأقمار الصناعية Landsat، وتحديدًا صور الأقمار الصناعية لعام 1988 و2002 و2022. الطرق المطبقة في الدراسة تشمل التصحيح الجوي، وإخفاء الصور، والتصنيف المراقب باستخدام طريقة الاحتمالية القصوى، وكشف التغير بالغطاء الأرضي من خلال برنامج ENVI 5.3. تكمن نقاط قوة هذه الدراسة في: (1) التحليل متعدد الأزمنة باستخدام صور القمر الاصطناعي لاندسات، (2) التصحيح الجوي، مما يُقلل من عدم اليقين في البيانات المرتبطة بالتأثيرات الجوية، (3) الإخفاء الثنائي، مما يجعل مساحة البحيرة أكثر دقة، و(4) تصنيف الاحتمالية القصوى لتحليل دقيق للبيكسلات الصورية. أظهرت النتائج أن صنف المياه انخفض بشكل ملحوظ من 362.94 كيلومتر مربع (95.02%) عام 1988 إلى أدنى نقطة في عام 2002 عند 103.03 كيلومتر مربع (26.97%)، وارتفعت إلى 189.20 كيلومتر مربع (49.53%) في عام 2022. زاد صنف التربة من 0.58 كيلومتر مربع (0.15%) في عام 1988 إلى 201.63 كيلومتر مربع (52.79%) في عام 2002، ثم انخفضت من عام 2002 إلى عام 2022 إلى 98.48 كيلومتر مربع (25.78%). بالنسبة لفئة الغطاء النباتي، فقد زادت من 18.45 كيلومترًا مربعًا (4.83%) عام 1988 إلى 77.31 كيلومترًا مربعًا (20.24%) عام 2002، ثم زادت إلى 94.30 كيلومترًا مربعًا (24.69%) عام 2022. أشرت نتائج كشف التغيرات إلى أن 48.71% من مساحة الدراسة تحولت من الماء إلى اليابسة خلال الفترة 1988-2002، بينما شهدت الفترة 2002-2022 بعض التعافي البيئي، مما يشير إلى أن 11.51% من مساحة الدراسة تحولت من تربة جرداء إلى ماء. وبشكل عام، أظهرت الدراسة فقدانًا كبيرًا للمياه خلال الفترة 1988-2002، ثم تعافيًا جزئيًا في العقود الأخيرة، مما يوفر معلومات مهمة لإدارة موارد المياه مستقبلاً في هذا النظام البيئي الهام.

1. Introduction

Remote sensing, along with its applications, is an essential tool for surveying and understanding surface changes on Earth, particularly in areas where natural and human forces influence the environment [1]. Earth processes, such as the dispersion of molecules in the atmosphere and the absorption of such radiation, can result in large errors in remote sensing data up to 10% [2]. Satellite imaging plays an important role in supplying accurate geographical information [3], [4].

The reliability and availability of remote sensing data have made them one of the most important sources of data on Earth's surface, captured by the various satellite platforms [5], [6]. One of the fundamental capabilities of remote sensing and Earth observation is image classification, which is used for land cover mapping, environmental monitoring, and disaster management, among others [7]. The classification process, in a nutshell, involves grouping

satellite images or areas into pre-established land cover classes. This will enable the derivation of critical information on the changing nature of the Earth, which can be applied to evidence-based decision-making across various industries worldwide [8], [9]. The use of masks makes filtering pixels easier, thereby minimizing the risk of false classification and resulting in more accurate overall analysis [10].

The most significant water body relevant to the present study is Al-Habbaniya Lake, a highly vital water body in the center of Iraq, southeast of Al-Ramadi City. The lake plays a vital role in managing water resources and stability of the ecosystem in the area [11], [12]. The changes in water cover over the years, driven by both environmental and anthropogenic factors, have necessitated a detailed study to trace its condition and establish the impact of the changes. The research uses Landsat satellite data from Landsat-5 TM, Landsat-7 ETM+, and Landsat-8 OLI, collected in 1988, 2002, and 2022. The paper will generate trustworthy images of chromatic classifications and estimate water-cover variation at Al-Habbaniya Lake at the specified time using improved atmospheric correction methods, image-masking software, and supervised classification techniques. The primary objective of the research is to assess variation in water body size over time within the lake and to derive data on processes at a larger scale within the environment and human endeavors that affect the region. The study outcomes will support sustainable management of water resources and decision-making that will help conserve this highly valuable ecosystem. Numerous scholars have conducted studies on the changes in the different large Lakes of Iraq using remote sensing and different methods. M. The instruments to be used in monitoring Al-Habbaniya Lake had been the Image ratioing instruments, including the Normalized Difference Vegetation Index (NDVI), Water Index, and Salinity Index, and the outcomes revealed that during the period between 1990 and 2001, the vegetation area had increased, and the water and salinity soil area had decreased [13]. M.M. Hason et al. used GIS and satellite images to assess the surface area of Haditha Dam Lake between 1985 and 2019, where the average surface area decreased by a quarter between 2001-2016 than in 1988-2000, with 148 to 427 km² [14]. M.A. Al-Obaidi and Y.K. AL-Timimi used Landsat images from 2000 to 2020 and applied the Normalized Difference Water Index (NDWI) and unsupervised classification to examine the Mosul Lake. Their results showed that the water areas ranged from 225 to 320 km², with an average increase of 25.46 and a decrease of 19.79 [15]. A. Ghanbari et al. (2021), based on Sentinel-2 images and SVM classification, compared Najaf Sea changes in 2017-2024 to reveal the minimum area of 213.11 km² in 2017, the maximum area of 302.16 km² in 2020, and minor improvements until 2024 [16]. M. R. Mahmood et al. used Sentinel-2 and Landsat data to analyze changes in the surface water of Haditha, Therthar, and Razzazah lakes using SVM. They identified Razzazah and Therthar as being 2.5 and 28.6 at the time of the study, respectively, and Razzazah as 67 percent, with significant geomorphological changes in the northern and eastern areas of the lake [17].

2. Atmospheric Correction

The mixture of gaseous particles, aerosols, and water vapors that comprises the atmosphere may interfere with the signal reaching the sensor in several ways. Therefore, atmospheric correction would be required to remove these distortions from the photos and enable the retrieval of the target's pure ground radiance [18]. Without atmospheric correction, a remotely sensed image's value at a given pixel location does not accurately reflect the ground-leaving radiance at that location. Changes in the solar radiation reflected by the Earth's surface, as reflected by satellite sensors, result from the interaction of solar radiation with the atmosphere [19]. Atmospheric correction aims to determine the true surface reflectance values by eliminating the effects of atmospheric impacts on satellite images. An efficient atmospheric correction is needed to remove these distortions and make the images

comparable using the retrieved true reflectance values. This is because multitemporal images are frequently acquired by different sensors on different dates under variable atmospheric conditions, solar illumination, and viewing angles [20]. The advantage of utilizing reflectance is that it can normalize for varying solar illumination geometry caused by the time interval between data collections and compensate for varying atmospheric solar irradiance values resulting from spectral band differences [21]: The following equations demonstrate how these corrections are calculated [18] [19] [20].

2.1. Converting the Digital Numbers to TOA radiance is expressed as:

$$L_{\lambda} = ML \times Q_{cal} + AL \quad (1)$$

Where L_{λ} = Top of Atmosphere spectral radiance; ML = Band-specific multiplicative scaling factor; Q_{cal} = the quantized calibrated pixel value; AL = Band-specific additive rescaling factor.

2.2. Conversion of TOA radiance to TOA reflectance is expressed as:

$$\rho_{\lambda} = (\pi * L_{\lambda} * d^2) / (ESUN_{\lambda} * \sin(\theta)) \quad (2)$$

Where ρ_{λ} = TOA planetary reflectance; L_{λ} = Radiance in $W/(m^2 * sr * \mu m)$; d = Earth-sun distance; $ESUN_{\lambda}$ = Solar irradiance in $W/(m^2 * \mu m)$; θ = Sun elevation in degrees.

3. Masking Image Technique

Image masking is the process of partially concealing and partially displaying an image. This method is often used to remove specific portions of the image. Masked pixels will appear as transparent in the final image and will be excluded from any subsequent image processing (referred to as a masked image). An image with certain pixel intensities set to zero and others to non-zero is referred to as a mask image. When the pixel intensity value in the mask image is zero, the pixel intensity of the resulting masked picture will be set to the background value (normally zero) Use Masks can be constructed using various inputs such as Areas of Interest (ROIs), shapefiles, binary raster, or tools like the Build Raster Mask in ENVI v. 5.3. A binary image called a mask is made up of the values (0) and (1) [10], [22].

4. Maximum Likelihood Classifier Method

The most popular decision rule for supervised classification is the maximum likelihood technique, which bases its conclusions on the likelihood that a pixel belongs to a certain class. The class with the highest probability is assigned to each pixel. When this classifier classifies an unknown pixel, it statistically examines the variance and covariance of the category [23]. The mean vector and the covariance matrix, however, may completely characterize the distribution of a category response pattern, provided that the category training data are normally distributed. The statistical likelihood that a given pixel value belongs to a specific land cover category can be calculated using these parameters, and the probability density function for each category can be generated accordingly. The chance of a pixel value falling into each category is calculated using the probability density functions to categorize an unidentified pixel. If the analyst chooses the probability values, the pixel would be classified as either unknown or the category with the highest likelihood [24]. The maximum likelihood classifier method requires the probability density function [23] [24]:

$$P(x|\omega_i) = (1/((2\pi)^{(n/2)} \times |\Sigma_i|^{(1/2)})) \times \exp(-1/2 \times (x-\mu_i)^T \times \Sigma_i^{-1} \times (x-\mu_i)) \quad (3)$$

Where x = pixel values in all bands; μ_i = Mean vector for class ω_i ; Σ_i = Covariance matrix for ω_i ; $|\Sigma_i|$ = Determinant of covariance matrix; n = Number of bands

The decision rule for pixel classification is:

$$P(\omega_i|x) = (P(\omega_i) \times p(x|\omega_i)) / \sum (P(\omega_j) \times p(x|\omega_j)) \quad (4)$$

Where $P(\omega_i|x)$ = Posterior probability of class ω_i given pixel x ; $P(\omega_i)$ = Prior probability of ω_i ; $p(x|\omega_i)$ = Likelihood of observing pixel x given class ω_i

5. Change Detection

Change detection is the method of spotting variations in an object's or phenomenon's condition through repeated observation. This method is typically used to account for changes to the Earth's surface at least twice. The speed and precision of change detection on Earth's surface can help us comprehend the connections and interactions between natural and human activities and can guide effective resource management. To examine the temporal impacts of the item or phenomena in change detection applications, multi-temporal datasets must be used [25], [26]. Comparing aerial photos or satellite images of the region obtained at various dates is a common method of change detection. Analyses of land use change, monitoring of shifting cultivation, evaluation of deforestation, seasonal variations in pasture production, damage evaluation, crop stress detection, monitoring of disasters, snow-melt measurements, day/night thermal characteristics analysis, and other environmental changes are only a few instances of the various uses for change detection [27], [28].

6. Study Area Description

Al-Habbaniya Lake is situated in Anbar Governorate, approximately 60 km west of Baghdad, with an elevation range of 35-90 m. Between 39°18'03 N and 34°23'12 E. Al-Habbaniya Lake has a 9-13 m depth, 35km length, 25 km maximum width, and $3.26 \times 10^9 \text{ m}^3$ storage capacity [29], [30]. The Euphrates River is the principal source of water for the lake. Al-Habbaniya depression is connected to the Euphrates River by an inlet channel, and it has two outlet channels: one returns to the Euphrates, and the other flows to the Al-Razzazh depression. Water from the lake is used mainly for multiple purposes (agricultural irrigation, drinking water, and animal activities) [29]. Figure 1 shows the location of the research region.

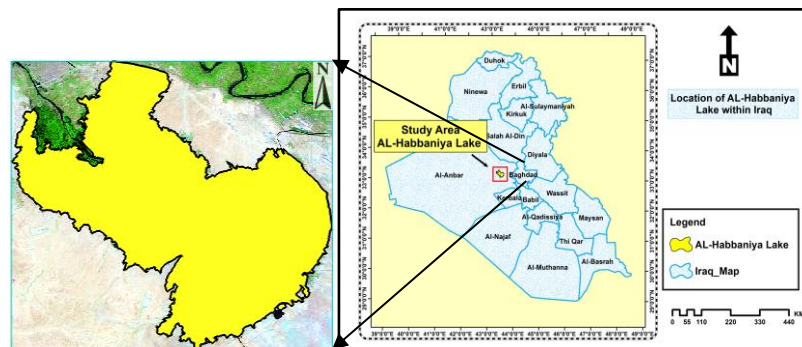


Figure 1: The location of the study area (AL-Habbaniya Lake) within Iraq

7. Methodology

The block diagram of the methodology is shown in Figure 2. Details for each step can be illustrated in the following sections.

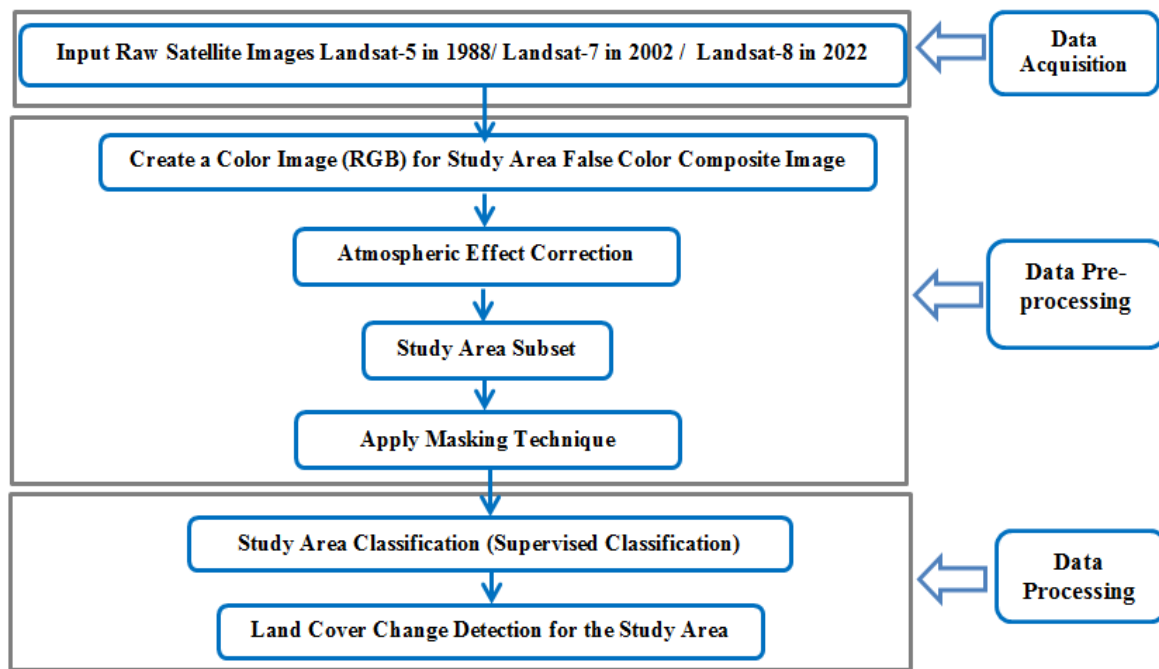


Figure 2: Flow chart of the methodology

7.1 Remote Sensing Data

The Landsat imagery, including the TM image of Landsat-5, the ETM+ image of Landsat-7, and the OLI image of Landsat-8, were chosen for this study (Table 1). The available data comprise three image scenes (Path=169, Row=37) from Landsat-8 (July 2, 2022), Landsat-7 (July 27, 2002), and Landsat-5 (July 12, 1988), obtained from the United States Geological Survey (USGS) database. The images were selected during the summer season and at close dates (close period) to eliminate the effects of Earth's atmosphere. All Landsat images used were geo-referenced with a spatial resolution of 30 m. The acquired images are all free of cloud coverage. Specifications of the Landsat imagery are shown in Table 1.

Table 1: Specification of the (TM), (ETM+), and (OLI) multispectral images used in this work (USGS Earth Explorer Archive)

ID	Satellite & Sensor	Path/ Row	Name of Bands	Spectral Resolution in (μm)	Spatial Resolution in (m)	Acquisition Date
1	Landsat-5 Thematic Mapper (TM)	169 /37	Band 1: (Blue) Visible Band 2: (Green) Visible Band 3: (Red) Visible Band 4: (Near) Infrared Band 5: (SW1) Infrared Band 7: (SW2) Infrared	(0.45 - 0.52) (0.52 - 0.60) (0.63 - 0.69) (0.77 - 0.90) (1.55 - 1.75) (2.09 - 2.35)	30	12 -7 - 1988
2	Landsat-7 Enhanced Thematic Mapper Plus (ETM+)	169 /37	Band 1: (Blue) Visible Band 2: (Green) Visible Band 3: (Red) Visible Band 4: (Near) Infrared Band 5: (SW1) Infrared Band 7: (SW2) Infrared	(0.45 - 0.52) (0.52 - 0.60) (0.63 - 0.69) (0.77 - 0.90) (1.55 - 1.75) (2.08 - 2.35)	30	27-7 - 2002
3	Landsat-8 Operational Land Imager (OLI)	169 /37	Band 2: (Blue) Visible Band 3: (Green) Visible Band 4: (Red) Visible Band 5: (Near) Infrared Band 6: (SW1) Infrared Band 7: (SW2) Infrared	(0.45 - 0.51) (0.53 - 0.59) (0.64 - 0.67) (0.85 - 0.88) (1.57 - 1.65) (2.11 - 2.29)	30	2 -7 - 2022

7.2 Data Pre-processing

7.2.1 Result of Atmospheric Correction

False color composites of the study area for 1988, 2002, and 2022 were created by merging the shortwave infrared, near-infrared, and blue bands. Figures 3a, 4a, and 5a show these composites. Atmospheric correction was applied to each image (1988, 2002, and 2022) to prepare the images for further processing. Figures 3b, 4b, and 5b show the corrected images. This step was performed using the QUAC-Atmospheric Correction Module of the ENVI Toolbox.

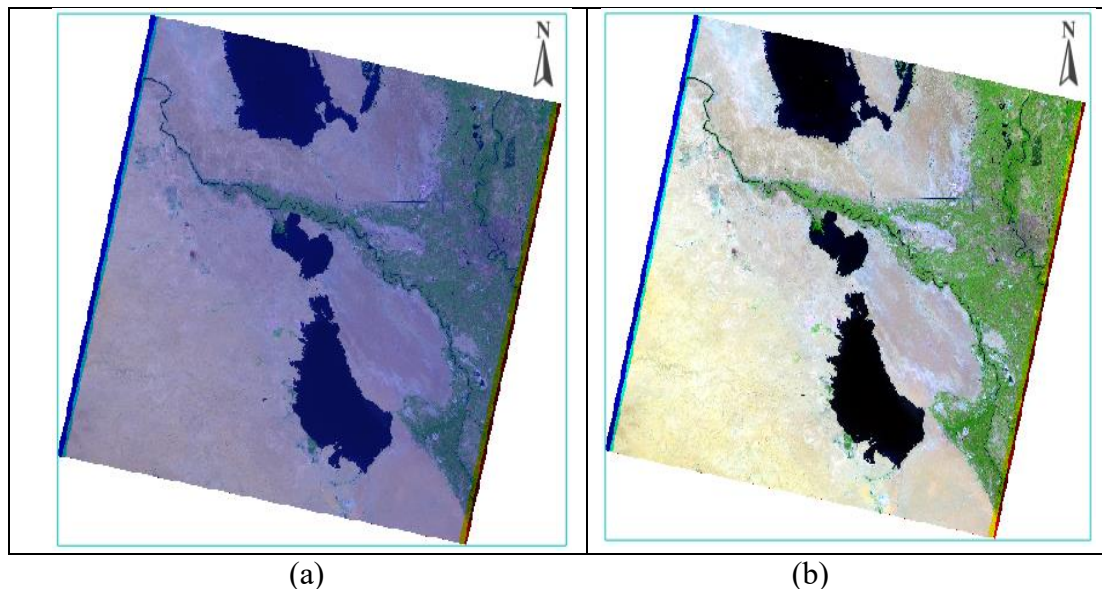


Figure 3: False color composite image (Band 7, Band 4, and Band 1) for Landsat-5 satellite image (12/7/1988): (a) Before applying atmospheric correction, (b) After applying atmospheric correction

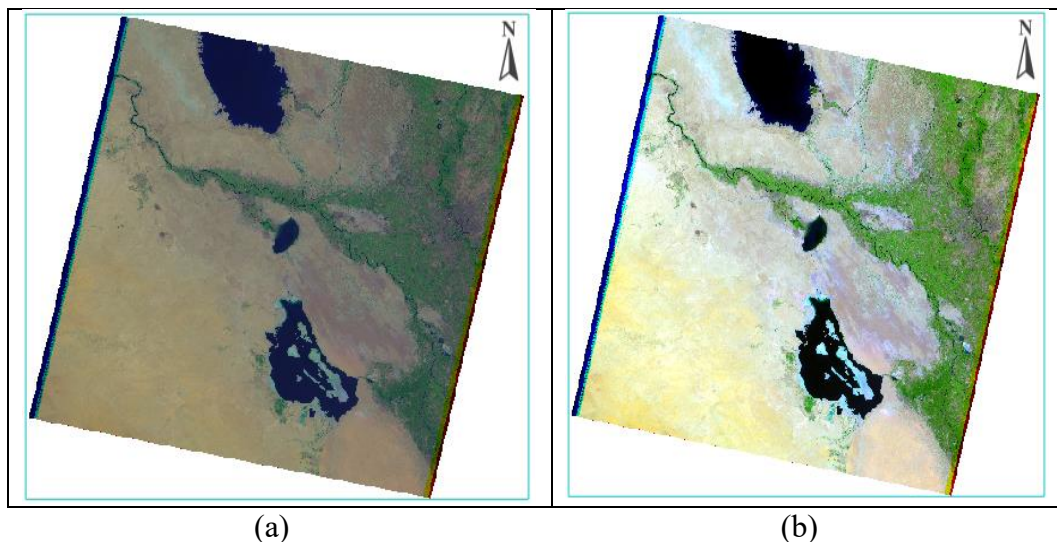


Figure 4: False color composite image (Band 7, Band 4, and Band 1) for Landsat-7 satellite image (27/7/2002): (a) Before applying atmospheric correction, (b) After applying atmospheric correction

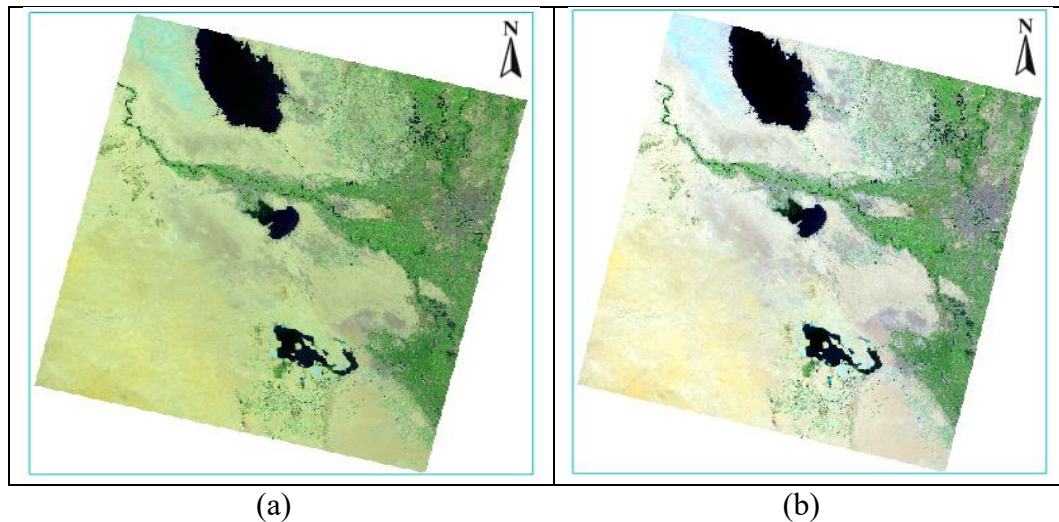


Figure 5: False color composite image (Band 7, Band 5, and Band 2) for Landsat-8 satellite image (2/7/2022): (a) Before applying atmospheric correction, (b) After applying atmospheric correction

7.2.2 Result of Study Area Subset

The results of subsetting the study area from the atmospheric correction process are illustrated in Figures 6, 7, and 8. The study area (Al-Habbaniya Lake) was subset using the Regions of Interest Module (Subset Data from ROIS Tool) of the ENVI Toolbox Software.

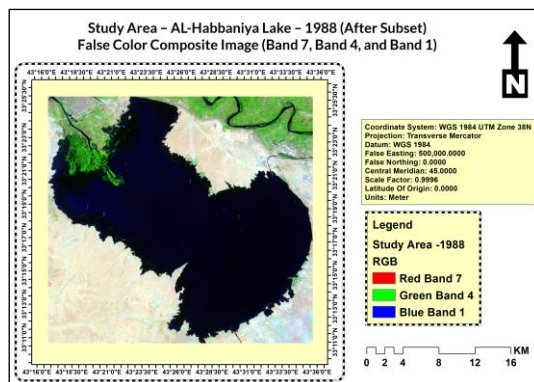


Figure 6: The study area subset for Landsat-5 satellite image on (12/7/1988) – (Bands: 7,

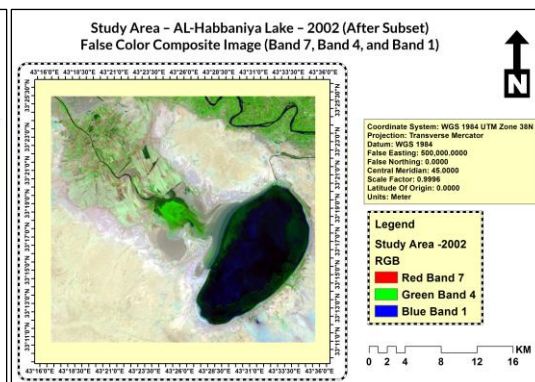


Figure 7: The study area subset for Landsat- 7 satellite image on (27/7/2002) – (Bands: 7, 4,

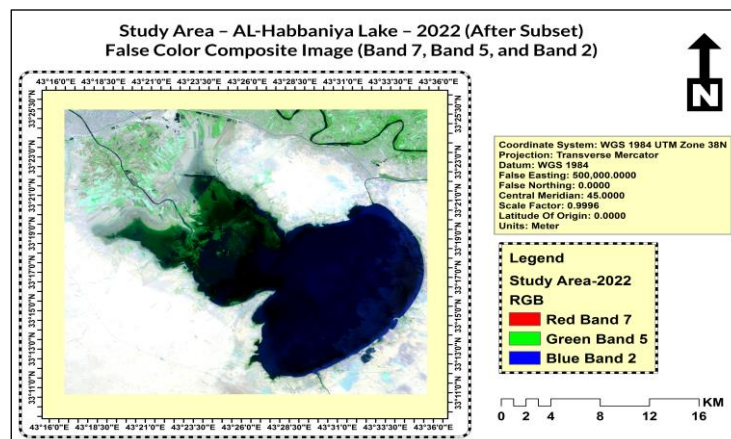


Figure 8: The study area subset for Landsat- 8 satellite image on (2/7/2022) – (Bands: 7, 5, and 2)

7.2.3 Masking Technique Result

Masking is superior to other techniques because it reduces computational load, improves accuracy by removing spectral noise outside the area of interest, uses less memory, and ensures statistical integrity for supervised classification algorithms. The theory is based on binary logic, where pixels are represented as either 0 (masked/excluded) or 1 (unmasked/included). The masking algorithm has five steps: (1) create a binary mask by converting vector boundaries to raster format matching the satellite image resolution, (2) ensure geometric registration with the same spatial resolution and projection, (3) apply (masked image = original image $\times$ mask) where masked pixels become null values and unmasked pixels keep their spectral values, (4) apply masks to all spectral bands at once, (5) check boundary alignment and validate masked areas are excluded, so the classification and change detection techniques can applied only to lake pixels and not to surrounding land areas. Figure 9 represents the mask image (binary image) used to hide and exclude areas outside the lake body. This image consists of two colors: black and white. The black areas have a value of zero and will be masked in the subsequent steps. No further techniques will be applied to them as they are outside the lake's body. The white areas have a value of one and represent the lake body under study. These areas will undergo further processing techniques.

Results of applying the masking technique to the study area for the years 1988, 2002, and 2022 are shown in Figures 10-12, respectively. The masking technique for the study area was executed using the Masking Module - Apply Mask & Build Mask Tools in the ENVI Toolbox Software.

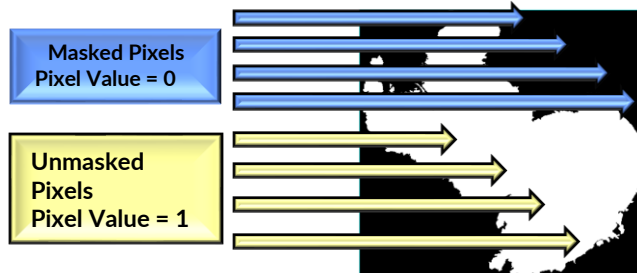


Figure -9: The Mask Image (Binary Image)

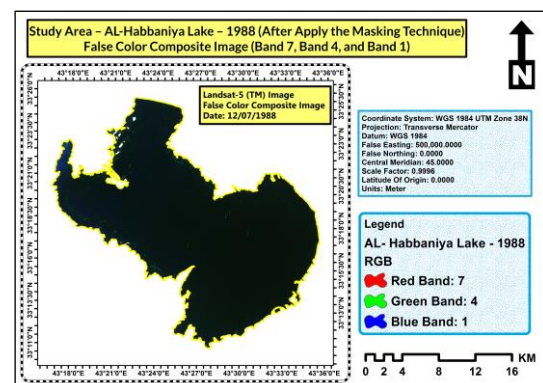


Figure -10: The masking technique for the Landsat-5 satellite image on 12/7/1988

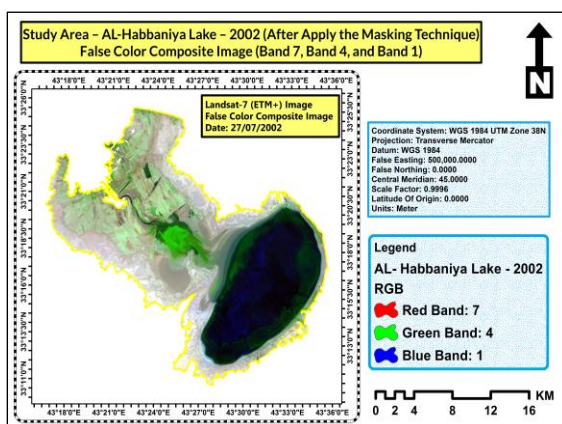


Figure 11: The masking technique for Landsat-7 satellite image on 27/7/2002

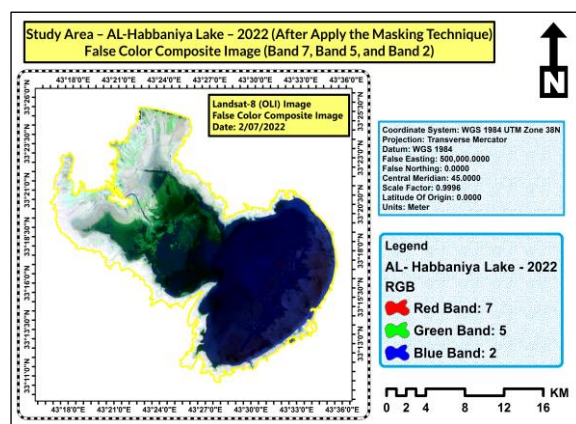


Figure 12: The masking technique for the Landsat-8 satellite image on 2/7/2022

8.1 Result of Study Area Classification

Supervised classification involves creating distinct spectral signatures for each land cover class. These signatures were created in this study using images from 1988, 2002, and 2022, along with representative training samples for the Water (W), Vegetation (V), and Soil (S) classes within Al-Habbaniya Lake. The mean and standard deviation of the reflectance corresponding to each land-cover class in all spectral bands were then computed. The summary statistics of these spectral signatures are demonstrated in Tables 2, 3, and 4 using the Landsat-5 TM (1988), Landsat-7 ETM+ (2002), and Landsat-8 OLI (2022) images. These statistics show the separability of classes in spectral space and were used to provide a quantitative basis for ML decision algorithms. The algorithm based on these signatures estimated the probability that each pixel belonged to one of a set of previously defined classes and assigned that class according to the maximum-likelihood principle.

Table 2: Spectral signature statistics (Mean & StdDev) for selected classes from Landsat-5 (1988)

Band Name	Water class		Vegetation class		Soil class	
	Mean	StdDev	Mean	StdDev	Mean	StdDev
Blue	0.120129	0.005035	0.117877	0.011152	0.150575	0.028897
Green	0.100984	0.009011	0.112856	0.018030	0.162148	0.042750
Red	0.057417	0.004626	0.090501	0.025624	0.164051	0.062532
NIR	0.035563	0.002398	0.098984	0.034835	0.151119	0.094306
SWIR 1	0.014492	0.001952	0.034724	0.014177	0.138789	0.120708
SWIR 2	0.010661	0.002397	0.021242	0.006895	0.113923	0.101022

Table 3: Spectral signature statistics (Mean & StdDev) for selected classes from Landsat-7 (2002)

Band Name	Water class		Vegetation class		Soil class	
	Mean	StdDev	Mean	StdDev	Mean	StdDev
Blue	0.133428	0.010850	0.127723	0.019454	0.219737	0.023390
Green	0.129712	0.017117	0.125501	0.031158	0.259153	0.035730
Red	0.101800	0.016234	0.120533	0.050898	0.321660	0.049807
NIR	0.064512	0.013915	0.225909	0.094352	0.346797	0.053972
SWIR 1	0.039913	0.012806	0.124084	0.093871	0.394793	0.065913
SWIR 2	0.030806	0.008837	0.068623	0.058918	0.327057	0.055818

Table 4: Spectral signature statistics (Mean & StdDev) for selected classes from Landsat-8 (2022)

Band Name	Water class		Vegetation class		Soil class	
	Mean	StdDev	Mean	StdDev	Mean	StdDev
Blue	0.903753	0.043344	0.897449	0.143186	0.137024	0.091809
Green	0.103252	0.035824	0.103072	0.193955	0.167286	0.144240
Red	0.797488	0.057125	0.103189	0.289465	0.195241	0.205153
NIR	0.741631	0.052112	0.127516	0.450378	0.219844	0.211969
SWIR 1	0.800252	0.037036	0.102644	0.461445	0.239016	0.235997
SWIR 2	0.801900	0.030206	0.938426	0.312404	0.214557	0.248649

The supervised classification produced three separate color-coded maps (produced using Geographic Information Systems (GIS) software) for Al-Habbaniya Lake, all of which show significant land cover changes over the 34 years (Figures 13, 14, and 15). In this research, a classification algorithm was implemented for the study area using the Classification

Workflow Module - Supervised Classification - Maximum Likelihood Classification Tool in the ENVI Toolbox. The details of these classified maps will be presented in the following sections:

Classification Results for 1988: The classified image of 1988 presents Al-Habbaniya Lake at its peak water extent, with a predominantly blue-colored water body covering approximately 95% of the study area. The lake appeared like a continuous, wide water surface with only minimal fragmentation. Vegetation, represented in green, occupied a few peripheral areas, mainly along the lakeshore, and accounted for less than 5% of the total area. Soil/bare land, which would have been shown in brown/red, was almost absent, accounting for just 0.15% of the total study area, indicating that the lake was at or very near full operational capacity.

Classification Results for 2002: The 2002 classification shows a terrific remodelling of the lake's landscape. The water (blue) has shrunk tremendously to isolated areas and spread across the study area, which only comprises 26.97% of the total area, a reduction of 68.05% compared to 1988. The most drastic shift is an extremely huge expanse of soil/bare land (brown/red), which grew by 0.15% to 52.79% of the area. Vegetation (green) exhibited remarkable growth to 20.24% which probably was an area with emergent vegetation ground cover growing into the newly exposed lakebed.

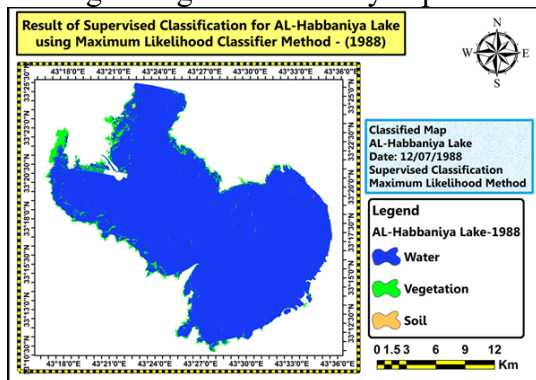


Figure 13: The maximum likelihood classifier method for AL-Habbaniya Lake on (12/07/1988)

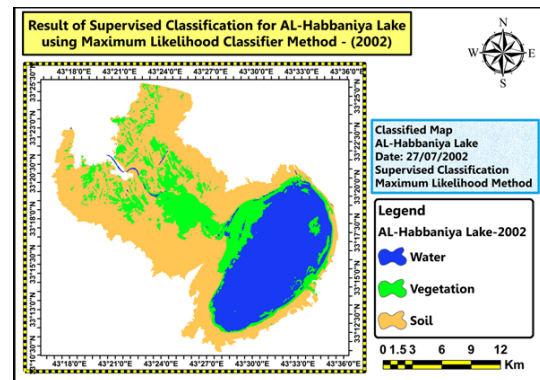


Figure 14: The maximum likelihood classifier method for AL-Habbaniya Lake on (27/07/2002)

Classification Results for 2022: It shows a partial recovery; nonetheless, water coverage (blue) went up to 49.53% of the total area, representing 22.56% recovery from the 2002 minimum. However, it is 45.49% lower than the 1988 baseline. Vegetation (green) continued to grow, yet it occupied 24.69% of the maximum coverage as compared to the other two periods. Soil/bare land (brown/red) was reduced significantly to 25.78% meaning that previously exposed land was re-flooded.

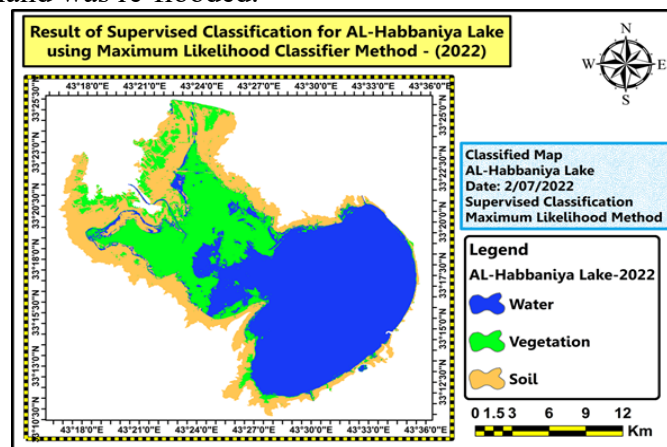


Figure 15: The maximum likelihood classifier method for AL-Habbaniya Lake on 2/07/2022)

Table 5 presents the supervised classification of the study area in detail, including results for area (km²) and percentage of water, vegetation, and soil classes in 1988, 2002, and 2022. Table 5 provides basic information on land cover on the whole distribution throughout the study period. According to the classification statistics in Table 5, there was a drastic change in land cover at Al-Habbaniya Lake between 1988 and 2022. The water cover famously dropped from 362.94 km² (95.02%) in 1988 to 103.03 km² (26.97%) in 2002 with a loss of 68.05%, and equals 18.57 km²/year, and then gradually regained 189.20 km² (49.53%) in 2022 at the rate of 4.31 km²/year; it remains at 45.49% below the baseline set in 1988. The vegetation area steadily increased from 18.45 km² (4.83%) in 1988 to 94.30 km² (24.69%) in 2022. It increased by 411.10%. Notably, the period from 1988 to 2002 experienced a faster increase (4.20 km²/year) compared to the period from 2002 to 2022 (0.85 km²/year). Soil/bare land exhibited the greatest fluctuations, rising from 0.58 km² (0.15%) in 1988 to 201.63 km² (52.79%) in 2002 at a rate of 14.36 km²/year and then subsiding to 98.48 km² (25.78%) in 2022 at a rate of -5.16 km²/year; their value remains above the 1988 baseline by a measure of 16,920.69%, thus indicating extreme ecosystem transformation during the period of study.

Table 5: Supervised classification for Al-Habbaniya Lake - based on the maximum likelihood method for the years (1988 – 2002 – 2022)

Class	Land Cover Types	Color	Class Area (Km ²)			Area Percentage (%)		
			Landsat-5 (1988)	Landsat-7 (2002)	Landsat-8 (2022)	Landsat-5 (1988)	Landsat-7 (2002)	Landsat-8 (2022)
1	Water Body		362.9448	103.0302	189.1998	95.017424	26.972874	49.531713
2	Vegetation		18.4536	77.3145	94.2957	4.831075	20.240611	24.686218
3	Soil		0.5787	201.6324	98.4816	0.151501	52.786515	25.782069
Total			381.9771	381.9771	381.9771	100%	100%	100%

Figure 16 Comparison of land cover classes in the study area based on the percentage of each class's area over three different time periods.

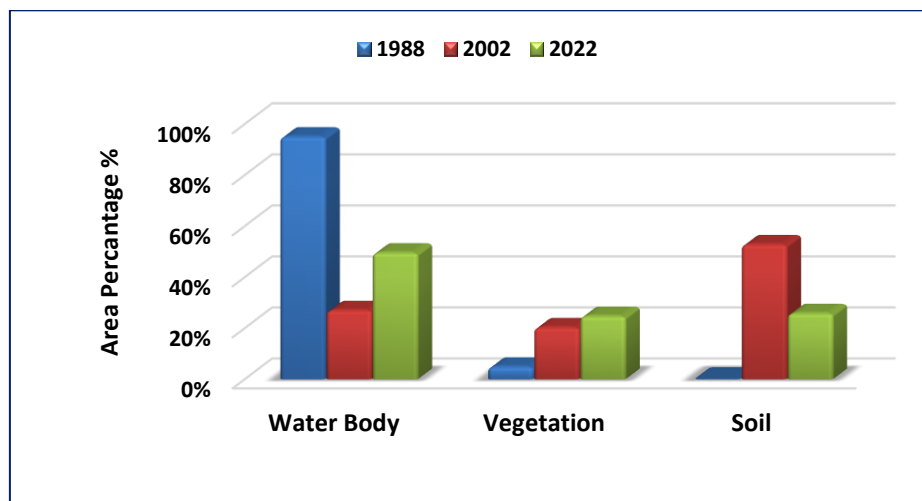


Figure 16: Comparisons of land cover types in the study area based on the percentage of class area over three different time periods (1988, 2002, and 2022)

8.2 Change Detection Result

The results of land cover change detection over different time periods (1988–2002, 1988–2022, and 2002–2022) are presented in Tables 6, 7, 8, 9, 10, and 11. In this study, the change detection technique for AL-Habbaniya Lake was performed using (Change Detection Module - Thematic Change Workflow & Change Detection Difference Map Tools) of the ENVI Toolbox Software. According to the land cover change detection analysis, the results indicate considerable environmental dynamics taking place in Al-Habbaniya Lake over the 34-year study period. The most significant change occurred between the years 1988 and 2002, where over an area of 259.91 km², water coverage decreased at an annual rate of 18.57 km², as presented in Table 6, while the area of soil increased by a total of 201.05 km² at a rate of 14.36 km²/year and vegetation increased by 58.86 km² at 4.20 km²/year (Table 6). An analysis from 1988 to 2022 reveals a water loss of 173.75 km² at an average rate of 5.11 km² per year, with soil and vegetation areas increasing by 97.90 km² and 75.84 km², respectively (Table 7). During the period from 2002 to 2022, partial recuperation manifested itself in the fact that water coverage increased by 86.17 km² at a rate of 4.31 km²/year and vegetation expanded by 16.98 km² at a rate of 0.85 km²/year while the surface area of soil decreased by 103.15 km² at a rate of 5.16 km²/year (Table 8). Change detection matrices indicate that this represents a water-to-soil conversion for the entire 1988-2002 period, accounting for 48.71% of the total area (Table 9, Figure 17), and at a level of 23.85% as part of water-to-vegetation transitions within the period 1988-2022 (Table 10, Figure 18). The recovery period (2002-2022) registered significant soil-to-water (11.51%) and soil-to-vegetation conversions (17.14%) (Table 11, Figure 19), denoting the response of the lake to variable water supply from the Euphrates River and climatic conditions, thus marking a vulnerability in this critical water resource to environmental and anthropogenic pressures.

Figures 17-19 show change detection maps of land cover for the study area (produced using GIS software) for the years 1988 to 2002, from 1988 to 2022, and from 2002 to 2022, respectively. These maps serve an important purpose by showing specific areas of transformation and the types of changes, for instance, from water to soil or water to vegetation. Figure 17 shows that there was a large amount of significant water conversions between 1988 and 2002 to soils and vegetated lands along the lake margin and in shallow areas of the lake, as visual validation of the information in Table 6. Figure 18 shows the period 1988-2022 with cumulative long-term changes, emphasizing long-term areas of water losses with similar terrestrial gains, as explained in Table 7. Figure 19 for the period 2002-2022 shows areas of water recovery (soil/vegetation to water), in particular in the middle part of the lake, whereas vegetation shifts did not differ in other areas, demonstrating the dynamics of change (Table 8). These maps were valuable for providing a spatial background for the quantitative analysis and for deeper insight into the location and patterns of land cover change.

Table 6: Change detection data of the study area for the period (1988-2002)

Class	Land Cover Types	Color	Class Area (km ²)		Class Area Change (km ²)	Rate (km ² /year)
			Landsat-5 (1988)	Landsat-7 (2002)		
1	Water Body		362.9448	103.0302	- 259.9146	18.56532
2	Vegetation		18.4536	77.3145	58.8609	4.20435
3	Soil		0.5787	201.6324	201.0537	14.36097
	Total		381.9771	381.9771		

Table 7: Change detection data of the study area for the period (1988-2022)

Class	Land Cover Types	Color	Class Area (km ²)		Class Area Change (km ²)	Rate (km ² /year)
			Landsat-5 (1988)	Landsat-8 (2022)		
1	Water Body		362.9448	189.1998	-173.745	5.11014
2	Vegetation		18.4536	94.2957	75.8421	2.23065
3	Soil		0.5787	98.4816	97.9029	2.87949
	Total		381.9771	381.9771		

Table 8: Change detection data of the study area for the period (2002-2022)

Class	Land Cover Types	Color	Class Area (km ²)		Class Area Change (km ²)	Rate (km ² /year)
			Landsat-7 (2002)	Landsat-8 (2022)		
1	Water Body		103.0302	189.1998	86.1696	4.30848
2	Vegetation		77.3145	94.2957	16.9812	0.84906
3	Soil		201.6324	98.4816	-103.1508	5.15754
	Total		381.9771	381.9771		

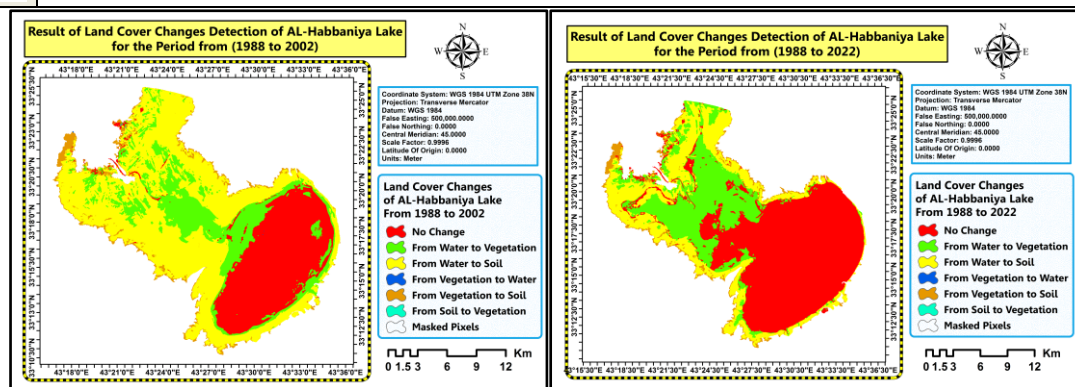
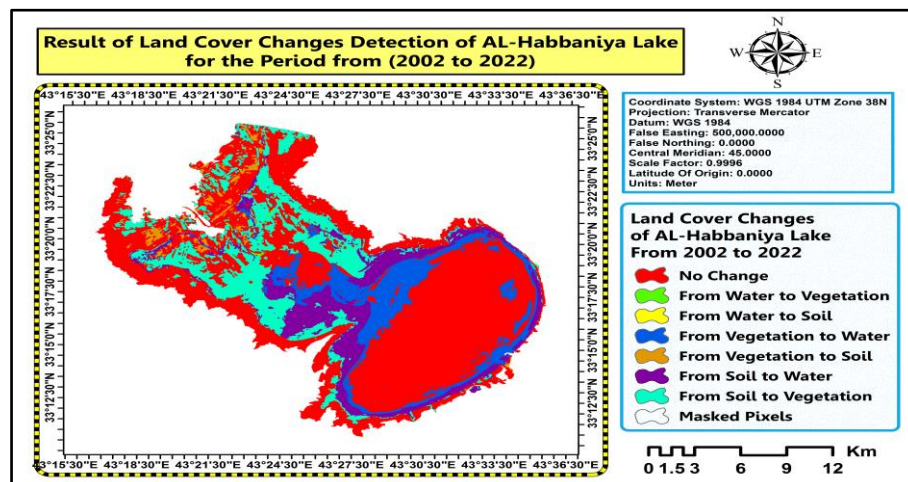
**Figure 17:** Result of land cover changes detection of AL-Habbaniya Lake for the period from 1988 to 2002.**Figure 18:** Result of land cover changes detection of AL-Habbaniya Lake for the period from 1988 to 2022.**Figure 19:** Result of land cover changes detection of AL-Habbaniya Lake for the period from 2002 to 2022.

Table 9: Land cover change detection of Al-Habbaniya Lake for the period from 1988 to 2002.

Classes	Type of Change	Color	Area (km ²)	Percent (%)	Direction of Change	
					Increasing	Decreasing
1	No Change		104.6475	27.396276	Neither an increase nor a decrease (Stability in the Water Area)	
2	Water to Vegetation		75.5757	19.785401	Increase (Vegetation Area)	Decrease (Water Area)
3	Water to Soil		186.0786	48.714596	Increase (Soil Area)	Decrease (Water Area)
4	Vegetation to Water		0.036	0.009425	Increase (Water Area)	Decrease (Vegetation Area)
5	Vegetation to Soil		15.5952	4.082758	Increase (Soil Area)	Decrease (Vegetation Area)
6	Soil to Vegetation		0.0441	0.011545	Increase (Vegetation Area)	Decrease (Soil Area)
7	Masked Pixels		-	-	-	-
Total			381.9771	100%		

Table 10 : Land cover change detection data of Al-Habbaniya Lake for the period from 1988 to 2022

Classes	Type of Change	Color	Area (km ²)	Percent (%)	Direction of Change	
					Increasing	Decreasing
1	No Change		191.7108	50.189082	Neither an increase nor a decrease (Stability in the Water Area)	
2	Water to Vegetation		91.0998	23.849545	Increase (Vegetation Area)	Decrease (Water Area)
3	Water to Soil		85.5603	22.399327	Increase (Soil Area)	Decrease (Water Area)
4	Vegetation to Water		0.0162	0.004241	Increase (Water Area)	Decrease (Vegetation Area)
5	Vegetation to Soil		13.5693	3.552386	Increase (Soil Area)	Decrease (Vegetation Area)
6	Soil to Vegetation		0.0207	0.005419	Increase (Vegetation Area)	Decrease (Soil Area)
7	Masked Pixels		-	-	-	-
Total			381.9771	100%		

Table 11: Land cover change detection of Al-Habbaniya Lake for the period from 2002 to 2022.

Class	Type of Change	Color	Area (km ²)	Percent (%)	Direction of Change	
					Increasing	Decreasing
1	No Change		223.0128	58.383814	Neither an increase nor a decrease (Stability in the Water Area)	
2	Water to Vegetation		0.4158	0.108855	Increase (Vegetation Area)	Decrease (Water Area)
3	Water to Soil		0.045	0.011781	Increase (Soil Area)	Decrease (Water Area)
4	Vegetation to Water		42.1956	11.046631	Increase (Water Area)	Decrease (Vegetation Area)
5	Vegetation to Soil		6.8535	1.794218	Increase (Soil Area)	Decrease (Vegetation Area)
6	Soil to Vegetation		43.9686	11.510795	Increase (Water Area)	Decrease (Soil Area)
7	Masked Pixels		65.4858	17.143907	-	-
Total			381.9771	100%		

9. Conclusions and Future Work

The current study enables the calculation of land cover changes in the study region (AL-Habbaniya Lake) over 34 years, based on output findings that demonstrate land cover change detection results. Increases in soil and vegetation classes represented the most significant change for the period from 1988 to 2002, while the change was represented by a decrease in the water class, with the water class of AL-Habbaniya Lake decreasing by 18.56532% (259.9146 km²) in 2002 compared to 1988, the Soil class increasing by 14.36097% (201.0537 km²), and the vegetation class increasing by 4.20435% (58.8609 km²). Similarly, the most significant change for the period from 1988 to 2022 was represented by increases in soil and vegetation classes while the water class decreased, with the water class decreasing by 5.11014% (173.745 km²) in 2022 compared to 1988, the soil class increasing by 2.87949% (97.9029 km²), and the vegetation class increasing by 2.23065% (75.8421 km²). Increases in Water and vegetation classes represented the most significant change for the period from 2002 to 2022, while the soil class decreased, with the water class increasing by 4.30848% (86.1696 km²) in 2022 compared to 2002, the soil class decreasing by 5.15754% (103.1508 km²), and the vegetation class increasing by 0.84906% (16.9812 km²).

The results indicate that the study area is experiencing apparent decline in surface water due to lack of rainwater, lack of seasonal torrents, declining groundwater levels, ongoing processes of evaporation with rising atmospheric temperatures and climate change, and insufficient water levels in the Euphrates River (one of the lake's most significant water sources) caused by insufficient water reaching the Euphrates River from neighboring countries. All of these factors have caused the water level to drop, the water surface area to shrink, and soil salinity to increase, posing a serious threat to the lake.

There has been a non-linear annual change in al-Habbaniya Lake. The years between 1988 and 2002 were extremely ecologically stressed and degraded; meanwhile, the period from 2002 to the present appears to show some recovery, allowing further ecological change. The year 2002 was important because it registered the maximum exposure to soil and the lowest water level, indicating a season of acute environmental stress. Subsequent recovery may indicate that certain driving forces change, such as rainfall patterns or water management policies. However, the increase in vegetation, even though water has been recovered, implies that new ecological societies are developing that are robust to water-level changes. Climatic statistics (such as evaporation rates, rainfall, and temperature) can be studied in the future alongside human-induced alterations (such as population increase, irrigation methods, and dam construction) related to these developments to give a more in-depth causal account.

Acknowledgements

The authors would like to sincerely thank the United States Geological Survey (USGS) for providing access to Landsat satellite data that made this research possible.

References

- [1] A. K. Resen, "Remote Sensing- Based Assessment of Climatic Decades in Baghdad City Using Statistical Trend Analysis and Variance Testing (ANOVA)," *Iraqi Journal of Physics*, vol. 23, no. 2, p. 35–44, 2025. <http://doi.org/10.30723/ijp.v23i2.1430>
- [2] M. V. K. Sivakumar, P. S. Roy, K. Harmsen, and S. K. Saha, Satellite remote sensing and GIS applications in agricultural meteorology, 2003. [Online]. Available: <http://www.bishensinghbooks.com>
- [3] N. Manohar, M. A. Pranav, S. Aksha & T. K. Mytravarun, "Classification of Satellite Images," in *In International Conference on Information and Communication Technology for Intelligent*

- Systems, Singapore, 2020. http://doi.org/10.1007/978-981-15-7078-0_70
- [4] R. R. Ismail, S. H., Halos, and B. Q. Al-Abudi, "Detection of the most frequent sources of dust storms in Iraq during 2020–2023 using space tools," *Kuwait Journal of Science*, vol. 52, no. 1, p. 100328., 2025. <https://doi.org/10.1016/j.kjs.2024.100328>
- [5] N. Hameed and T. A. Naji, "A Novel Approach for Synthesizing the Pan-chromatic Band to (10 m) of Landsat 9 Based on Sentinel-2 Data to Improve Classification Performance," *Iraqi Journal of Science*, vol. 66, no. 5, p. 2153–2174, 2025. <http://doi.org/10.24996/ijis.2025.66.5.30>
- [6] • P. C. Pandey, N. Koutsias, G. P. Petropoulos, P.K. Srivastava, and E. Ben Dor, "Land use/land cover in view of earth observation: Data sources, input dimensions, and classifiers—A review of the state of the art," *Geocarto International*, vol. 36, no. 9, pp. 957-988, 2021. <https://doi.org/10.1080/10106049.2019.1629647>
- [7] K. Pathak, A. Jain, "Satellite Image Classification using Deep Learning," *International Research Journal of Modernization in Engineering Technology and Science*, vol. 5, no. 4, pp. 1458-1467, 2023. <http://doi.org/10.56726/IRJMETS35775>
- [8] E. H. E. Yasin and C. Kornel, "Evaluating satellite image classification: exploring methods and techniques," in *Geographic Information Systems - Data Science Approach*, 2024. <http://doi.org/10.5772/intechopen.1003196>
- [9] • S. M. R. Alam, and M. S. Hossain, "A rule-based classification method for mapping saltmarsh land-cover in south-eastern Bangladesh from Landsat-8 OLI," *Canadian Journal of Remote Sensing*, vol. 47, no. 3, pp. 356-380, 2021. <https://doi.org/10.1080/07038992.2020.1789852>
- [10] E. Stoyanova, S. Katsarska-Filipova, "Mask importance in burned area mapping based on remote sensing, GIS and open-source products," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 48, pp. 1013-1020, 2023. <http://doi.org/10.5194/isprs-archives-XLVIII-1-W2-2023-1013-2023>
- [11] W. S. Razzak, A. Al-tae, and A. A. AL-Fanharawi, "Determination of some Heavy Metals Bioaccumulation in Water, Sediments, and Phragmites australis and Ceratophyllum demersum Plant in Euphrates River in Al-Samawa City/Iraq," Doctoral dissertation, M.Sc Thesis, College of Science, University of Al-Muthanna, Iraq, 104 p, 2021.
- [12] T. A. Wahhab, and F. M. Hassan, "Primary Productivity of Iraqi lakes: A Review," *In IOP Conference Series: Earth and Environmental Science*, vol. 1088, no. 1, p. 012006, 2022. <http://doi.org/10.1088/1755-1315/1088/1/012006>
- [13] M. Ahmed and A. Al-Khafaji, "Assessment Environmental Changes in Al-Habbaniya Lake and Surrounding Areas in the Central Part of Iraq," *Journal of Natural Sciences Research*, vol. 3, no. 4, 2013. [Online]. Available: www.iiste.org
- [14] M. M. Hason, M. R. Abbas, B. B. Ahmad, and T. R. Abbas, "Monitoring of Water Surface Change of Haditha Dam's Lake Using Satellite Data Technique," *Hason, M. M., Abbas, M. R., Ahmad, B. B., & Abbas, T. R. (2020, November). IOP Conference Series: Materials Science and Engineering*, vol. 928, no. 2, p. 022018, 2020. <http://doi.org/10.1088/1757-899X/928/2/022018>
- [15] M. A. Al-Obaidi and Y. K. AL-Timimi, "Change Detection In Mosul Dam Lake, North of Iraq Using Remote Sensing and GIS Techniques," *Iraqi Journal of Agricultural Sciences*, vol. 53, no. 1, p. 38–47, 2022. <http://doi.org/10.36103/ijas.v53i1.1506>
- [16] A. Ghanbari, and H. J. Jumaah, "Monitoring surface water area changes of Najaf Sea in Iraq using RS and GIS for sustainable development," *Adv. Eng. Days*, vol. 9, pp. 323-325, 2024. [Online]. Available: <https://www.researchgate.net/publication/385248912>
- [17] M. R. Mahmood, B. I. Abraham, H. J. Jumaah, H. A. Alalwan, and M. M. Mohammed, "Drought monitoring of large lakes in Iraq using remote sensing images and normalized difference water index (NDWI)," *Results in Engineering*, vol. 25, 2025. <http://doi.org/10.1016/j.rineng.2024.103854>
- [18] I. B. Jonah and T. M. Aketi, "Atmospheric Correction of Landsat Image," *Journal of Environmental and Geographical Studies*, vol. 2, no. 1, pp. 1-24, 2023.

- <http://doi.org/10.58425/jegs.v2i1.120>
- [19] K. Themistocleous, "Improving atmospheric correction methods for aerosol optical thickness retrieval supported by in-situ observations and GIS analysis," Doctoral dissertation, Department of Civil Engineering and Geomatics, Faculty of Engineering and Technology, Cyprus University of Technology, 2011. <https://hdl.handle.net/20.500.14279/878>
- [20] D. G. Hadjimitsis, G. Papadavid, A. Agapiou, K. Themistocleous, M. G. Hadjimitsis, A. Retalis, S. Michaelides, N. Chrysoulakis, L. Toullos, and C. R. I. Clayton, "Atmospheric correction for satellite remotely sensed data intended for agricultural applications: Impact on vegetation indices," *Natural Hazards and Earth System Science*, vol. 10, no. 1, p. 89–95, 2010. <http://doi.org/10.5194/nhess-10-89-2010>
- [21] R. Mueller, T. Behrendt, A. Hammer, and A. Kemper, "A new algorithm for the satellite-based retrieval of solar surface irradiance in spectral bands," *Remote Sensing*, vol. 4, no. 3, pp. 622–647, 2012. <https://doi.org/10.3390/rs4030622>
- [22] H. N. Vu, M. H. Nguyen, and C. Pham, "Masked face recognition with convolutional neural networks and local binary patterns," *Applied Intelligence*, vol. 52, no. 5, pp. 5497–5512, 2022. <https://doi.org/10.1007/s10489-021-02728-1>
- [23] R. R. Ismail, B. Q. Al-Abudi, and Z. F. Hussein, "Land cover change detection using satellite images based on modified spectral angle mapper method," *Plant Archives*, vol. 20, no. 1, pp. 2363–2371, 2020.
- [24] R. Khatami, G. Mountrakis, and S. V. Stehman, "Predicting individual pixel error in remote sensing soft classification," *Remote sensing of environment*, vol. 199, pp. 401–414, 2017. <https://www.sciencedirect.com/science/article/pii/S0034425717303437>
- [25] N. A. Fazaa, A. B. Ali, A. J. M. AL-Jabinawi, R. Francksen, and M. J. Whittingham, "Land use change in Baghdad City and assessment of the Jadriyah and Umm Al-Khanazeer Island Important Bird Area (IBA) from 1984 to 2020," *Baghdad Science Journal*, vol. 19, pp. 1471–1486, 2022. <http://doi.org/10.21123/bsj.2022.7033>
- [26] Y. You, J. Cao, and W. Zhou, "A survey of change detection methods based on remote sensing images for multi-source and multi-objective scenarios," *Remote Sensing*, vol. 12, no. 15, p. 2460, 2020. <https://doi.org/10.3390/rs12152460>
- [27] P. Gupta, S. Kanga, V. N. Mishra, S. K. Singh, and T. Sivasankar, "A Comparative Study and Machine Learning Enabled Efficient Classification for Multispectral Data in Agriculture," *Baghdad Science Journal*, vol. 21, no. 7, p. 2462–2484, 2024. <http://doi.org/10.21123/bsj.2023.8952>
- [28] P.P. Adhikary, D. Barman, M. Madhu, Ch. J. Dash, P. Jakhar, H. C. Hombegowda, B. S. Naik, D. C. Sahoo and K. Beer, "Land use and land cover dynamics with special emphasis on shifting cultivation in Eastern Ghats Highlands of India using remote sensing data and GIS," *Environmental monitoring and assessment*, vol. 191, no. 5, p. 315, 2019. <https://doi.org/10.1007/s10661-019-7447-7>
- [29] K. B. Al. Paruany, M. H. Al-Kubaisi, S. O. Al-Heety, and A. A. Jassaim, "Assessment of water quality of Al-Habbaniya Lake by using statistical techniques (Cluster and factor analysis)," *In IOP Conference Series: Earth and Environmental Science*, vol. 1222, no. 1, p. 012001, 2023. <http://doi.org/10.1088/1755-1315/1222/1/012001>
- [30] S. M. Abdulkareem, and A. A. Al-Hadithy, "Isotopic composition of Al-Habbaniya lake and groundwater surrounding it, Al-Anbar Governorate, Iraq," *Biochemical & Cellular Archives*, vol. 22, no. 1, 2022. <https://connectjournals.com/03896.2022.22.2739>