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Accuracy Evaluation of Land Cover Classification Maps Using Remote Sensing and GIS. The Sea of Najaf-Iraq as a Case Study

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Abstract

Water scarcity is a growing concern, particularly in arid and semi-arid regions. Sea of Najaf in Iraq is one such region facing water scarcity, with the lake serving as a crucial water source for the local population. Remote sensing systems "RS" and geographic information systems "GIS" are important techniques for monitoring environmental and land cover changes. This paper focuses on Sentinel-2B imagery for surface water mapping in the Sea of Najaf and evaluating the performance of maximum likelihood (MLC) classification method. The study area encompasses Sea of Najaf and its immediate surroundings. Two images for Sentinel-2B one image on December,29, 2015 and December,29,2022, were used for training and validating the classification models. The MLC method was evaluated for surface water classification, with accuracy assessment results presented. The MLC method showed high accuracy in terms of overall accuracy and agreement with reference data over multiple years. Additionally, fluctuations in the surface area of Sea of Najaf, as observed from the classification maps, were analyzed. In 2015, the surface area was 74.36 square kilometers, which increased to 120.30 square kilometers in 2022. The fin, dings highlight the efficacy of the MLC method for surface water classification, indicating its superiority in accurately mapping and monitoring surface water in the Sea of Najaf.

Keywords: Surface water, Sea of Najaf, RS, GIS, Sentinel-2B, MLC.

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مجلة المخطط و التنمية

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Vol 30 Issue 1 2025/4/7

تقييم دقة خرائط تصنيف الغطاء الأرضي باستخدام الاستشعار عن بعد ونظم المعلومات الجغرافية. دراسة حالة بحر النجف ـ العراق

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المستخلص

تشكِّل ندرة المياه مصدر قلق متزايد، لا سيما في المناطق القاحلة وشبه القاحلة. تُعدُّ منطقة بحر النجف في العراق احدى هذه المناطق التي تواجه ندرة المياه، حيث تعمل البحيرة في تلك المنطقة كمصدر مهم للمياه للسكان المحليين. تُعدُّ أنظمة الاستشعار عن بعد ونظم المعلومات الجغرافية من التقنيات المهمة لرصد التغيرات البيئية والغطاء الأرضي. تركِّز هذه الدراسة على صور القمر الصناعي Sentinel-2B لرسم خرائط المياه السطحية في بحر النجف وتقييم أداء طريقة التصنيف MLC. تشمل منطقة الدراسة منطقة بحر النجف ومحيطها. تم استعمال صورتين للقمر الصناعي Sentinel-2B الأولى بتاريخ 29 ديسمبر 2015 والثانية بتاريخ 29 ديسمبر 2022 للتدريب والتحقُّق من صحة نماذج التصنيف. تم تقييم MLC لتصنيف المياه السطحية، مع عرض نتائج تقييم الدقة. أظهرت طريقة MLC دقة عالية عند استعمال overall accuracy، Kappa Coefficients. بالإضافة الى ذلك تم تحليل التغيرات في مساحة بحر النجف كما لوحظ ذلك من خلال خرائط التصنيف. ففي عام 2015 بلغت المساحة 74.36 كيلومتر مربع وارتفعت الى 120.30 كيلومتر مربع في عام 2022. بينت النتائج فعالية MLC في تصنيف المياه السطحية مما يدلُّ على تفوقها في رسم خرائط دقيقة ورصد المياه السطحية في بحر النجف.

الكلمات المفتاحية :

المياه السطحية، بحر النجف، الاستشعار عن بعد، نظم المعلومات الجغرافية، القمر الصناعي سينتيل ـ2، طريقة تصنيف الاحتمالية القصوى.

Introduction

Water is a scarce yet necessary resource for keeping life alive. Concern over water supply has increased recently, especially in arid and semi-arid areas. Iraq's Sea of Najaf serves as an example of a place with little water availability. As a vital water source for local populations, this lake is susceptible to climate change and other stressors. Accurate surface water mapping is imperative for effective water resource management. While a potent tool for detecting surface water, remote sensing can struggle to differentiate between water bodies like lakes, rivers, and wetlands. The wider spectral range of Sentinel-2B provides more information about surface water, which can be helpful for distinguishing between different types of water bodies (Ali &Jaber,2020). The higher spatial resolution of Sentinel-2B allows for more detailed mapping of surface water features. However, the lower spatial resolution can be advantageous for some applications, such as mapping large areas. The higher temporal resolution of Sentinel-2B allows for more frequent monitoring of surface water changes. This can be helpful for tracking seasonal changes in water levels or detecting water pollution events., which can be helpful for historical studies of surface water change. However, Sentinel-2B is a more recent satellite, so its image archive is still growing. Image classification is the process of categorizing and labeling the pixels in a digital image based on their spectral and spatial characteristics (Faraj&Mahmood,2018, Aziz&Alwan,2021). The accuracy and application of image classification approaches have been improved throughout time by the development of new algorithms and methodologies (Phiri&Ranagalage,2020). Several types of classification methods can be used, including supervised and unsupervised methods, pixel-based, object-based,

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مجلة المخطط و التنمية

Journal of planner and development

Vol 30 Issue 1 2025/4/7

patch-based methods, and integrated methods. The most common classification algorithms are Maximum Likelihood (Ahmad&Quegan,2012) Random Forest (Belgiu&Dragut,2016), Decision Tree (Xu &Arora,2005), and Artificial Neural Networks (Mas & Flores,2008). The maximum likelihood algorithm is a widely used method for classifying images and is considered a boundary classification algorithm where it considers that each category is distributed normally with all ranges. Different techniques, such as maximum likelihood, support vector machines, decision trees, and random forests, can be used for supervised classification. The categorization of each pixel in an images using its spectral characteristics is known as "pixel-based classification" (Sekertekin & Akcin,2017). In pixel-based classification, the algorithm compares the spectral signature of each pixel to a set of pre-defined spectral classes or a statistical model, such as a Gaussian distribution. Classification models also useful for analyzing changes in satellite images and identifying patterns of changes over time (Fahad &Dibs,2020, Yousef& Jaber,2023 Dibs &Al-Ansari,2023). Sentinel-2 satellite imagery was used to assess the rise in water levels in the Sea of Najaf region in many studies (Maarez & Shareef,2023, Al-Helaly &Al-Hameedawi,2021) that used remote sensing techniques to evaluate and monitor surface water. Their research identified several land use classifications and discovered that crucial infrastructure, such as oil transmission components and pilgrimage roads, was vulnerable to floods. The authors advise government organizations to act right away to reduce future flood risks. Hung & Wu,2018) examined the developments in surface water detection and monitoring using satellite-based optical remote sensing. They called attention to difficulties such problems with spatiotemporal scale, integration with in-situ data, and the requirement for global-scale mapping, (Wasniewski&Chmielewska,2022) Indonesia.

(Tang & Wang,2022) used the Google Earth Engine to construct a region-adaptive random forest method for large-scale surface water mapping, and their findings were very precise and accurate. (Sogno & Kuenzer,2022) gave a thorough assessment of 233 scientific papers on monitoring inland surface water dynamics, outlining the sensors utilized, the geographical and temporal resolutions, the topic focuses, and the regional distribution of the investigations. used multi-temporal multispectral Sentinel-2B imagery with image recognition and fusion algorithms to identify changes in surface water. To separate water pixels and spot changes, their study used a variety of classification approaches, including Maximum Likelihood, Support Vector Machine, Artificial Neural Network, and Random Forest. Collectively, these research projects advance our knowledge of and ability to use remote sensing methods for surface water analysis and monitoring. However, more investigation is required to solve issues including overcoming cloud and vegetation obscuration, integrating hydrological and elevation data, and attaining accurate global mapping. The investigation into the analysis of Sentinel-2B for the purpose of surface water mapping holds considerable academic merit, as it has the potential to enhance the precision and effectiveness of such mapping endeavours. This, in turn, can yield substantial benefits for the management of water resources. The outcomes of this research will carry significant implications for water management practices specifically in the region of Sea of Najaf. By identifying the most optimal algorithm for surface water mapping within the lake, the findings will offer valuable insights into the variables that influence the performance of MLC technique in this context.

P-ISSN: 1996-983X
E-ISSN: 2960-1908

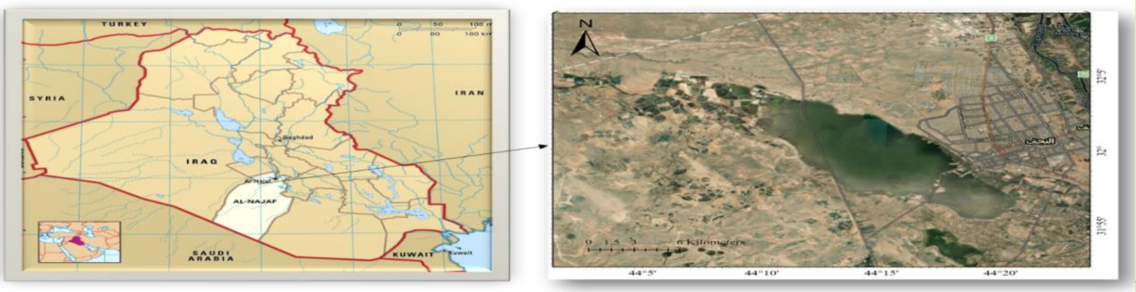
مجلة المخطط و التنمية

Journal of planner and development

Vol 30 Issue 1 2025/4/7

Study Area

Sea of Najaf and its surrounding areas, which together cover a total area of 2,000.2 square kilometers, make up the study site **Figure** 1. The principal channel, floodplains, and adjacent land regions that are directly impacted by the river's hydrological processes make up the research area, which is defined by the river's course. The Sea of Najaf is a well-known canal in southern Iraq that is extremely important to the area's ecology, socioeconomics, and culture (Al-Hamdani &Al-Shimmary,2020).The study area exhibits a wide range of characteristics, encompassing variations in topography, land cover types, and land use patterns. The course of the river may traverse through urbanized regions, agricultural fields, forests, and natural reserves. These distinct land cover types pose challenges when utilizing remote sensing data to monitor and estimate the surface area of Sea of Najaf. Furthermore, the study area is subject to both natural and anthropogenic factors that can impact the dynamics of the Lake. Natural elements, such as seasonal fluctuations, precipitation patterns, and geological processes, interact with human activities, including irrigation, dam construction, urbanisation, and deforestation. Comprehending and quantifying these influences on the lake's surface area are essential for effective water resource management and environmental conservation endeavours (Yousef & Jaber,2023).



FIG

URE 1. A geographical representation of Sea of Najaf (Yousef, 2023).

P-ISSN: 1996-983X
E-ISSN: 2960-1908
مجلة المخطط و التنمية
Journal of planner and development
Vol 30 Issue 1 2025/4/7

DATA UTILISED AND METHODOLOGY

Datasets

The utilization of Sentinel-2 data for mapping and estimating the surface area of Sea of Najaf offers numerous advantages and is well-suited for this study. Sentinel-2B missions provide extensive spatial coverage, capturing images globally with a repeat cycle of approximately 5 days for Sentinel-2B. This enables comprehensive coverage of the study area, ensuring that the entire extent of Sea of Najaf is captured. The evaluation of long-term trends and changes in the lake's surface area is made possible by the availability of several images spanning several years. A variety of spectral bands, such as visible, near-infrared, and short-wave infrared bands, are available from Sentinel-2B sensors. As they make it easier to identify and distinguish water bodies from other terrain features, these bands are crucial for water body study. By exploiting the unique spectral signatures of water, these sensors enable accurate estimation of Sea of Najaf surface area. This study used two images for training and validating the classification models including Sentinel-2B images (https://earthexplorer.usgs.gov/). Figure 2 shows the RGB composite of the two images. Upon visual interpretation of the true color composite images from 2015, and 2022, some key differences can be noted. By 2015, the lake area has significantly increased. The 2022 image indicates the lake has again substantially increased.

P-ISSN: 1996-983X
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مجلة المخطط و التنمية
Journal of planner and development
Vol 30 Issue 1 2025/4/7

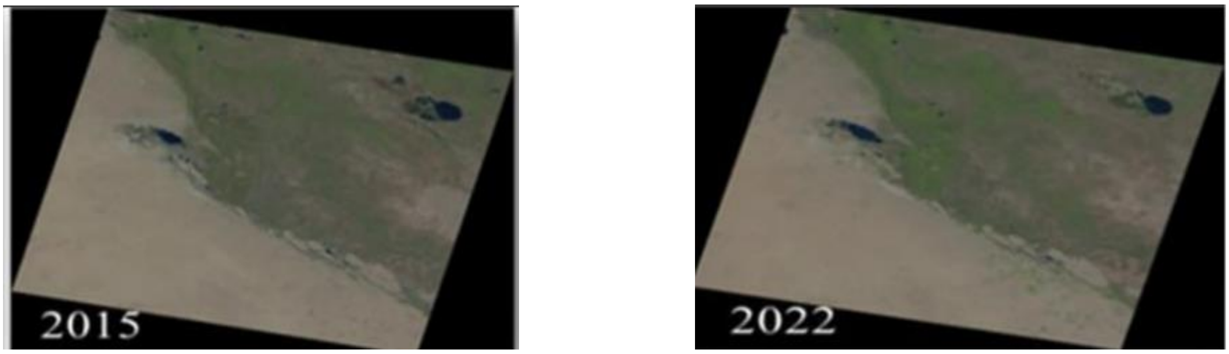

FIGURE 2. Land cover maps of the study area for the years 2015 and 2022(by Author).

Software

Software in this section, we will discuss the topic of software. Software refers to a collection of programmers, data. The geographical analysis and mapping in this work were conducted using ArcGIS Pro 3.03. Additionally, satellite image processing and correction were performed using SNAP9.0.0. ArcGIS Pro 3.03 gives analysts and GIS specialist's cutting-edge tools for handling spatial data and creating outputs and maps of the highest caliber. New capabilities for geographical analysis, data visualization, and mapping processes are included in this June 2022 version. A new task-based user interface (UI) for version 3.03 walks users through common tasks and adds more graphics and 3D capabilities. SNAP9.0.0 is an open-source tool maintained by the European Space Agency for working with Sentinel and other satellite data. Key functionalities include preprocessing, algorithm development, geospatial analysis, and time series processing. We utilized SNAP for converting Sentinel-2 scenes to surface reflectance and applying topographic normalization. SNAP is widely used in the remote sensing community for satellite image preparation and analysis. Their toolsets allowed us to efficiently process the Sentinel images to a standardized, analysis-ready state prior to water classification and change detection.

P-ISSN: 1996-983X
E-ISSN: 2960-1908
مجلة المخطط و التنمية
Journal of planner and development
Vol 30 Issue 1 2025/4/7

Methodology

Figure 3 presents the flowchart of the proposed methodology for image classification and comparison of satellite images of Sea of Najaf. The first step is data acquisition and organization. Landsat scenes covering the study area should be downloaded from reputable data repositories such as the USGS Earth Explorer. These scenes should be properly organized, and metadata including acquisition dates, sensor information, and file locations should be recorded for reference. The second step is to remove the effects of scattering and absorption in the atmosphere, as the correction of the atmosphere is a crucial step in preprocessing, allowing accurate measurements of surface reflection in this study using SNAP9.0.0 software. Atmospheric correction for the Sentinel-2B images was performed using the Sen2Cor processor. Telespazio VEGA Deutschland GmbH developed the atmospheric correction processor Sen2Cor on behalf of ESA (Sentinel-2B Toolbox). “Sen2Cor is a Level2A processor the main purpose is to correct single-date Sentinel-2 Level-1C TopOf-Atmosphere (TOA) products from the effects of the atmosphere in order to deliver a Level-2A Bottom-Of-Atmosphere (BOA) reflectance product. This correction compensates for atmospheric scattering and absorption, ensuring more accurate analysis and estimation of the Sea of Najaf surface area. Several atmospheric correction models and algorithms can be applied, such as the Dark Object Subtraction (DOS) method.

P-ISSN: 1996-983X
E-ISSN: 2960-1908
مجلة المخطط و التنمية
Journal of planner and development
Vol 30 Issue 1 2025/4/7

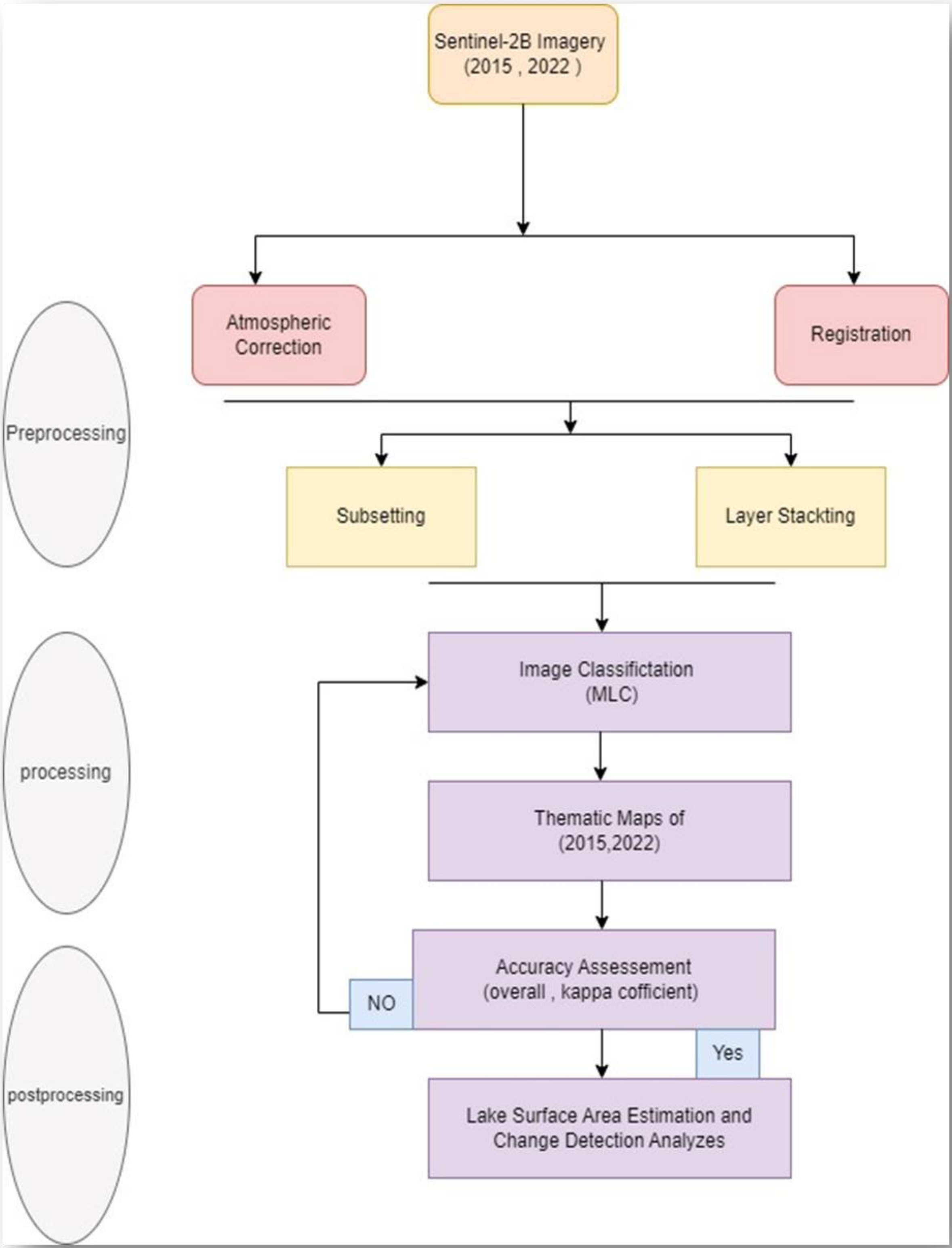

FIGURE 3. displays the flowchart illustrating the proposed methodology.

P-ISSN: 1996-983X
E-ISSN: 2960-1908

مجلة المخطط و التنمية
Journal of planner and development
Vol 30 Issue 1 2025/4/7

Supervised Classification

Selection of Training Samples

The acquisition of training samples via a visual interpretation procedure is crucial for the implementation of supervised classification and accuracy assessment. Training samples refer to pixels or regions within the imagery that are designated into specific categories, such as water and barren, through manual classification. These samples serve the purpose of training classification algorithms and verifying the precision of the resulting land cover or water extent maps. The visual interpretation process entails visually inspecting the imagery and assigning suitable class labels to the chosen samples. This process can be expedited by utilising geographic information system (GIS) software tools that facilitate efficient sample collection and labelling.

Maximum Likelihood Classification (MLC)

MLC is a commonly used supervised classification method in remote sensing (Sun&Qu,2013). The basic idea behind MLC is to find the class that maximizes the likelihood that the observed pixel values are drawn from that class's probability distribution Figure 4. The likelihood function is calculated based on the statistics of the training samples for each class. The following is the MLC mathematical equation: The following formula is used to determine how likely each pixel in the image is to belong to a certain class:We figure out the probability that each pixel in the image falls into class j as follows:

$$L_{i,j} = \frac{1}{(2\pi)^{\frac{k}{2}}|C_j|^{\frac{1}{2}}} exp\left(-\frac{(x_i - u_j)^T C_j^{-1}(x_i - u_j)}{2}\right) \ldots\ldots (1) \ldots.. (\text{Sun\&Qu}, 2013)$$

where:

$L_{i,j}$ is the likelihood that pixel i belongs to class j

x_i is the vector of observations (e.g., spectral values) for pixel i

u_j is the mean vector for class j, calculated from the training samples

C_j is the covariance matrix for class j, also calculated from the training samples

k is the number of bands (i.e., the dimensionality of the feature space)

$^\wedge T$ denotes the transpose of a matrix

exp is the exponential function

The pixel is then allocated to the class with the highest likely value after the likelihood values for each class have been determined. This can be mathematically stated as:

$$C_i = argmax_j(L_{i,j}) \ldots\ldots\ldots (2) \ldots. (\text{Sun\&Qu}, 2013)$$

where:

C_i is the class label assigned to pixel i

$argmax_j$ denotes the class j that maximizes the likelihood value $L_{i,j}$.

P-ISSN: 1996-983X
E-ISSN: 2960-1908
مجلة المخطط و التنمية
Journal of planner and development
Vol 30 Issue 1 2025/4/7

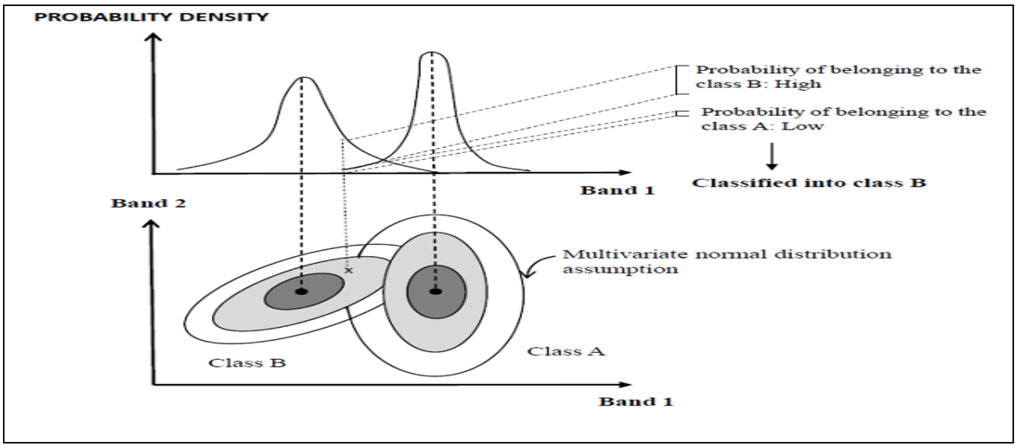

FIGURE 4. An illustration of MLC concept for land cover classification (Sun&Qu,2013).

Accuracy Assessment

Several measures, including Overall Correctness (OA) and Kappa coefficient, were used to assess the accuracy of the categorization findings. While the Kappa coefficient evaluates the agreement between observed and predicted classifications while taking into account chance agreement, (OA) estimates the percentage of properly categorized pixels. A distinct set of validation data, made up of independent samples not utilized in training, was created to assess classification accuracy. To evaluate the consistency between identified classes and reference data, these validation samples were compared to the classification findings, and (OA) and Kappa coefficients were computed. These accuracy evaluation criteria were used to evaluate the (SVM) classifier's performance and reliability in categorizing the Sea of Najaf surface region, giving important insights into the correctness and validity of the generated land cover map.

The percentage of correctly recognized pixels throughout the whole image is measured by the overall accuracy (OA) statistic (Grandini& Visani,2020). It is calculated by dividing the total number of pixels in the picture that were properly

P-ISSN: 1996-983X
E-ISSN: 2960-1908

مجلة المخطط و التنمية
Journal of planner and development
Vol 30 Issue 1 2025/4/7

identified by the total number of pixels in the image. In order to account for the possibility of chance agreement, the Kappa coefficient measures the degree of agreement between the observed and anticipated classifications (Grandini& Visani,2020).

$$OA = \frac{TP+TN}{TP+TN+FP+FN} \ldots\ldots (1)$$

where TP is the true positives, TN is the true negatives, FP is the false positives, and FN is the false negatives.

$$Kappa = \frac{c \times s - \sum_k^K pk \times tk}{s^2 - \sum_k^K pk \times tk} \ldots\ldots (2)$$

where:

- $c = \sum_k^K C_{kk}$ the total number of elements correctly predicted
- $s = \sum_i^K \sum_j^K C_{ij}$ he total number of elements
- $pk = \sum_i^K C_{ki}$ the number of times that class k was predicted (column total)
- $tk = \sum_i^K C_{ik}$ the number of times that class k truly occurs (row total)

Results and Discussions

Results of Image Classification

This section focuses on the results of the image classification procedure using satellite images from Sentinel-2B taken in 2015, and 2022. Figure 6 refer to (MLC) for more details. Maximum Likelihood Classification was one supervised classification model that was used in the analysis (MLC).

Figure 7 shows the training samples that were collected to train the maximum likelihood classifier (MLC) for supervised land cover classification in this study.

P-ISSN: 1996-983X
E-ISSN: 2960-1908

مجلة المخطط و التنمية
Journal of planner and development
Vol 30 Issue 1 2025/4/7

The goal of the classification was to differentiate between water and barren (non-water) land cover types.Therefore, two distinct sets of training samples were gathered. First, water samples were collected from locations across the study area that contained water bodies, such as rivers, lakes, reservoirs, and other standing water features. Care was taken to sample different types of water bodies across the landscape to capture the spectral variability within the water class. Second, barren training samples were taken from locations that lacked water and represented arid/barren land, urban built-up areas, roads, and other non-water land covers. The sample focused on spectrally homogeneous sites with uniform land cover. By collecting representative and spectrally distinct training samples for each class, the MLC classifier can learn the spectral characteristics that differentiate water from barren land covers. This allows the models to accurately classify unknown pixels when mapping the entire study area. The training samples form the foundation for supervised classification, and proper training data collection is crucial for producing accurate land cover maps.

The study presented the results of image classification through the use of classification maps for each of the three years Figures 8 and 9. These maps visually represent the spatial distribution of the water and barren classes within the study area. The classification maps offer valuable insights into the extent and changes in water bodies over time, enabling a comprehensive analysis of land cover dynamics in Sea of Najaf. Through examination of the classification maps, it becomes possible to identify the presence or absence of water bodies in specific areas during each of the three years. Additionally, comparing the classification maps from different years allows for the evaluation of temporal changes in land cover patterns, thereby highlighting areas where water bodies have expanded or contracted.

P-ISSN: 1996-983X
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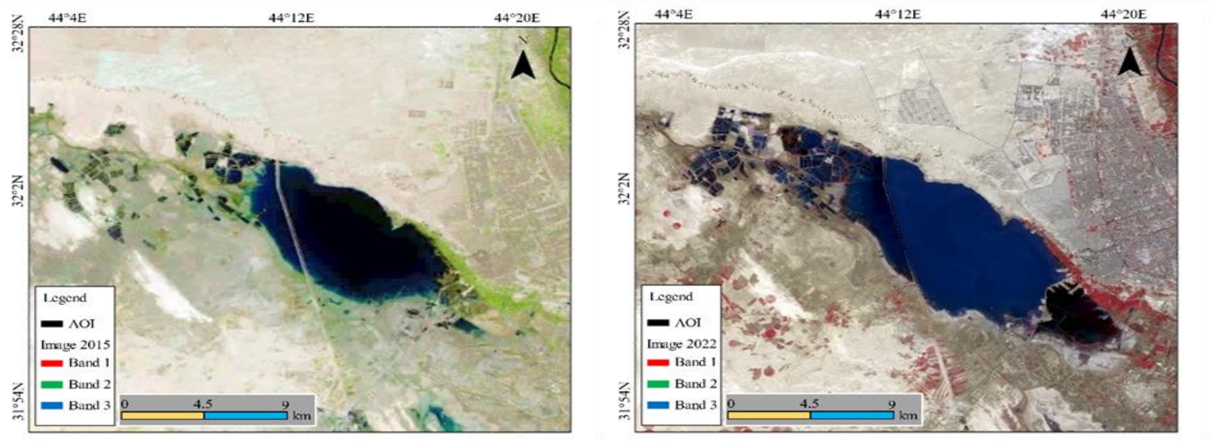
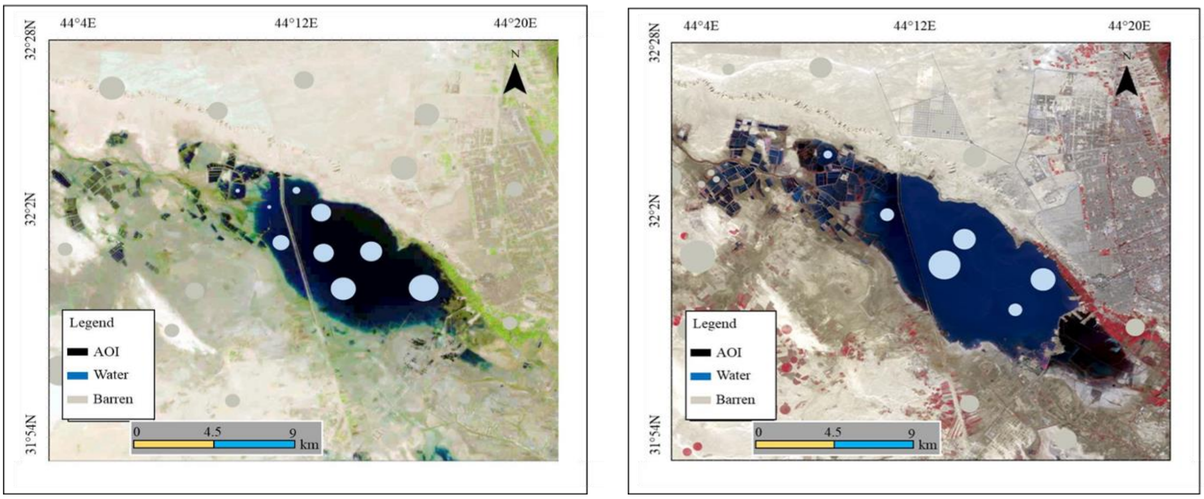
مجلة المخطط والتنمية
Journal of planner and development
Vol 30 Issue 1 2025/4/7



(a) (b)

FIGURE 6. Thematic maps for the study area used for image classification and change detection for (a) 2015, (b) 2022.

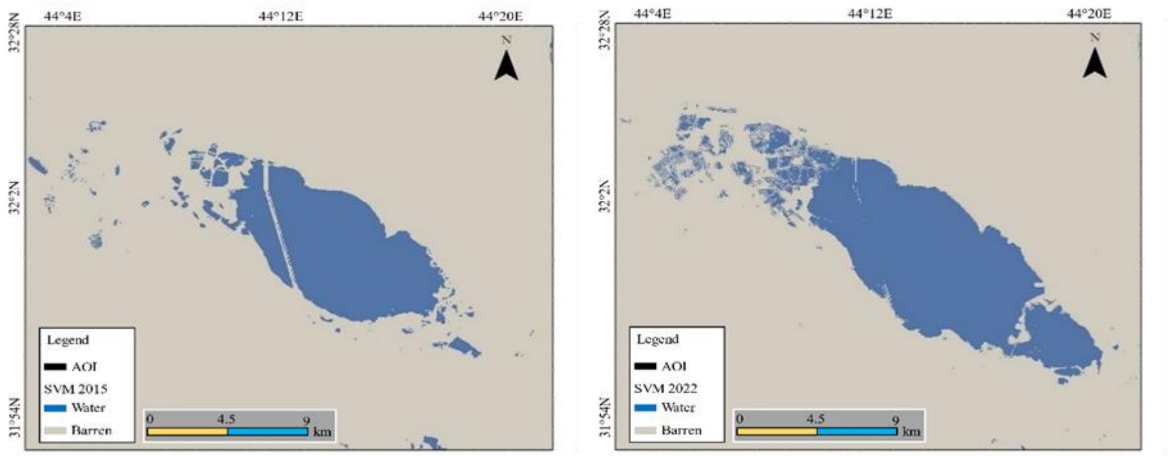


(a) (b)

FIGURE 7. Training samples used to train the MLC model for the year (a) 2015, (b) 2022.

P-ISSN: 1996-983X
E-ISSN: 2960-1908

مجلة المخطط و التنمية
Journal of planner and development
Vol 30 Issue 1 2025/4/7



(a) (b)

FIGURE 8. Classification map of the study area based on MLC for the year (a) 2015, (b) 2022.

The performance of one classification method, MLC, was evaluated for surface water classification. The accuracy assessment results for the method is presented in Table 2. In terms of overall accuracy (OA), the MLC method attained an accuracy of 80.24% in 2015, and 79.61% in 2022. To further assess the agreement between the classified results and the reference data, the Kappa statistic was calculated. The MLC method yielded Kappa values of 0.780 in 2015, and 0.774 in 2022.

TABLE 2. **presents analysis of the accuracy evaluation for surface water classification utilizing Maximum Likelihood Classification (MLC) approache**.

Image	MLC	
	OA	Kappa
2015	80.24	0.780
2022	79.61	0.774

P-ISSN: 1996-983X
E-ISSN: 2960-1908
مجلة المخطط و التنمية
Journal of planner and development
Vol 30 Issue 1 2025/4/7

Results of Surface Area Estimation

Sea of Najaf lake is a hydrological feature located within the Najaf Governorate in Iraq. Analysis of classification maps and calculations of water area reveal temporal fluctuations in the surface area of Sea of Najaf lake over the years. Specifically, in 2015, a significant expansion in the surface area of Sea of Najaf lake occurred, resulting in a rise to 74.36 square kilometers. Finally, in 2022, another substantial increase in the surface area of Sea of Najaf was observed, with it reaching 120.30 square kilometers.

CONCILSIONS

By observing the results of the study, it is clear the effective contribution of land cover/land used monitoring and water management through the use of GIS techniques and remote sensing together. The results demonstrate the effectiveness of using the (MLC) approach to precisely monitor water bodies and determine their surface areas.This study developed utilized the satellite images to map the surface water of Sea of over two periods 2015, and 2022. Thematic maps of the study area were created using (RS) and supervised classification techniques. In addition, surface area estimation of Sea of Najaf lake was performed using Sentinel-2B data. The study successfully estimated the surface area of the lake, providing a benchmark for future assessments of surface water changes in the area. The MLC method, with accuracy percentages of (80.24%), (79.61%), in 2015, and 2022, respectively. The Kappa statistic values of (0.780) and (0.774) in the corresponding years. Overall, these results highlight the superiority of the SVM method in terms of accuracy and agreement with the reference data, making it more effective for surface water classification in this study.

The implications of the study's findings hold substantial importance for the management and conservation of water resources in Sea of Najaf. Nevertheless, there are several recommendations that can be put forth to enhance the practises of water resource management in this region. Firstly, it is advisable to explore more sophisticated classification techniques, such as deep learning, to augment the accuracy of surface water classification within the study area. Secondly, it is crucial to formulate comprehensive plans for integrated water resource management, taking into account the identified factors that contribute to alterations in surface water. These plans should encompass strategies to regulate land use practises, control human-induced activities, and promote sustainable water utilisation practices.

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