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USING RS AND AI GIS IN LAND MANAGEMENT AND URBAN PLANNING IN MOSUL, IRAQ FOR SUSTAINABLE DEVELOPMENT

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Abstract. The importance of Remote Sensing (RS) and Geographic Information Systems (GIS) comes from the fact that they are means that have been proven effective in supporting and developing the decision-making process in the field of urban control. The city of Mosul in Iraq has been subjected to a tremendous change in the dynamics of land use due to the wars. This study aims to use RS techniques and Artificial Intelligence Geographic Information Systems (AI GIS), as the study relies on Sentinel-2 images and online data sources to evaluate the changes that occurred in the natural environment by comparing the years during and after the destruction. Four classification methods were used in this study; Support Vector Machine (SVM) learning, Scene Classification technique (SC), Normalized Difference Vegetation Index (NDVI), and Normalized Difference Water Index (NDWI). High classifications accuracies were obtained ranging between (92%–97%). The residential area had decreased, followed by vegetation, which was converted to bare land by 64% in the year 2017 due to the war effect. In 2023 some recovery of settlement and increasing in other sectors was observed. The approach highlights the capability of spatial technologies and the role of RS and GIS in sustainable development.

Keywords: AI GIS, SVM, SC, NDVI, NDWI, sustainable development.

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1. Introduction

Remote sensing, the acquisition of information about an object or phenomenon without direct physical contact, has emerged as a powerful tool in urban planning (Aggarwal, 2004; Cracknell, 2007; Campbell & Wynne, 2011; Weiss et al., 2020; Di & Yu, 2023; Mahmood et al., 2025). Satellite imagery and aerial photography provide planners with comprehensive and up-to-date data on land use, vegetation, infrastructure, and vital aspects of urban areas (Awad, 2019). Abou Samra and El-Barbary (2018) highlighted the importance of RS indices and GIS in assessing and mapping environmental changes in north Sinai in Egypt. The integration of RS and GIS data has been widely used in diverse types of global change studies (Pricope et al., 2019; Jumaah et al., 2025). There has been an improvement in the resolution and the ease of data supply and access of the remote sensing systems. The continuous flow of information from remote sensing contributes to updating the performance of sustainable land management, covering aspects such as disaster risk reduction and green infrastructure improvement (Taramelli et al., 2019; Khan et al., 2020). Lately, many studies have applied SVM, which represents one of the most robust classification algorithms that is used in various applications (Cervantes et al., 2020). SVM shows its ability to deal with unbalanced data, in addition, classification times of larger input datasets lengthen for other types more than for SVM, so authors recommend the use of SVM for being the easier and wieldy method that repeatedly achieves results with high accuracy and is over faster to execute (Boateng et al., 2020). Researchers underscore the major role of AI GIS and RS in land management and urban planning for example, Zhu et al. (2019) emphasized the achievable accuracy in urban planning developments using distinct data gained by high-quality remote sensors concerning infrastructure, vegetation cover, and land use. Despite the earlier RS-based indices still functioning very well, according to an assessment of the appropriateness and limitations of various satellite-derived indicators offered in some research for measuring sustainable development goals, however, they were used less, and novel indices were not investigated as much (Avtar et al., 2020). As well, Han et al. (2021) highlighted the significance of Intelligent GIS in investigating massive data and classifying spatial patterns guiding sustainable development strategies. Accordance to Jamal Jumaah et al. (2023) intelligent GIS, distinguished by advanced data analysis, machine learning, and artificial intelligence, supplements RS by converting comprehensive datasets into applicable insights for planners and policymakers. Akhtar et al. (2023) revealed that training data quality and the detection task frame are some of the parameters that shape how accurate an AI system is. For example, Mahmood and Jumaah (2023), used AI GIS mapping for fire detection in Mosul Park based on Sentinel-2 Images. The employment of open source and modern RS applications, involving satellite imagery (Ameen et al., 2021; Jumaah et al. 2023a), aerial photography, and Unmanned Aerial Vehicles UAV-based sensors (Jumaah et al., 2018; Jumaah et al., 2019; Park et al., 2019; Hamed et al., 2021; Li et al., 2023), advances a comprehensive and real-time interpretation of the urban land changes (Jamal Jumaah et al., 2023; Jumaah et al., 2023b, 2023c). In the case of the city of Mosul, a region characterized by historical importance and modern geopolitical challenges, the employing of RS datasets helps in assessing the dynamic spatial changes of the city land (Jumaah et al., 2021; Salman & Alkinani, 2023). It is worth noting that the application of satellite images allows monitoring changes in land use, which enhances a deeper understanding of the city's evolving needs thus managing and developing infrastructure, and modifying the negative environmental transformations that have occurred over time (Jumaah et al., 2022, 2023a).

In this study, we presented the effective methodology and application of advanced RS applications and AI GIS for a sustainable environment, as it presents current applications and explores the role and importance of satellite systems, whether new or future, in promoting more sustainable development. The city of Mosul in Iraq is used as an example to illustrate this phenomenon. Unlike in the earlier research work, this time technological tools such as RS, satellite imaging along with AI, and GIS have been used for measuring variations in the natural environment of the city. The study is going to explore the use of Sentinel-2 images and the entire complicated datasets to identify the variations of vegetation, water, and housing. These four methods of classification will take care of the task that has been assigned using SVM, SC, NDVI, and NDWI methods. Research is concerned with the evaluation of the accuracy of the classified maps as the study shows that it has high classification accuracy. The research respectively addressed land use in Mosul due to wars and their spatial dynamics especially in the residential areas and barre lands. The findings of the study are mixed with less of a recovery in some areas after they have been affected long ago.

Thus, the research shows the dynamic form of integrated tools of RS and GIS with AI for assessing the environmental consequences of wars on a city scale which becomes evident in the case of Mosul as the study example. These technological advances enable planners to comprehensively understand the urban environment, allowing them to formulate plans that balance conservation and growth. The unique challenges facing the city of Mosul, resulting from historical factors and contemporary conflicts, emphasize the significance of tailored methodologies to land management and urban development.

2. Materials and methods

2.1. Study area

The study location coordinates are bonded between (36° 15′ N – 36° 27′ N) and (43° 02′ E – 43° 16′ E). Figure 1 represents the study area (Mosul city location).

Mosul which is in northern Iraq, experiences summer temperatures between 20 and 40 degrees Celsius and winter temperatures between 5 and 15 degrees Celsius (Mahmood & Jumaah, 2023). Mosul was exposed to wars more than any of the cities in Iraq, as the city spent three difficult years under the conflict (2014–2017), which during that period destroyed many of its archaeological monuments. As a result of the wars during these years, residential buildings were destroyed and many of the city's landmarks changed. Therefore, it requires rehabilitating the city, creating scenarios, and rebuilding it using restoration plans and the knowledge of worldwide experiences in restoring and reconstructing damaged cities following the devastation.

In order to restore Mosul City's urban regions, modern RS and GIS technology can help create more precise, effective, and sustainable development strategies. Decision-makers in urban planning can make well-informed, data-driven choices by combining RS data and GIS. This results in a better overall plan for the restoration of urban areas and a more effective use of resources.

2.2. Methods and advanced techniques

Classification of remote sensing images plays a pivotal role in extracting actionable information for decision-makers. Some steps are involved in applying classification techniques to satellite imagery (Figure 2).

2.3. Data acquisition

Acquired data attributes were reported in Tables 1 and 2. Moreover, Acquired Sentinel-2 Images of the scenes were mapped in Figure 3.

Commence by obtaining high-resolution satellite imagery relevant to the study area. Some factors must be considered such as spatial and temporal resolution, as well as spectral bands that capture critical information for classification, such as land cover types, infrastructure, or population density.

We were based on two types of data; Sentinel-2 Images for three scenes (2015, 2017, 2023) by Copernicus from satellite Earth Observation and in-situ data, and the latest

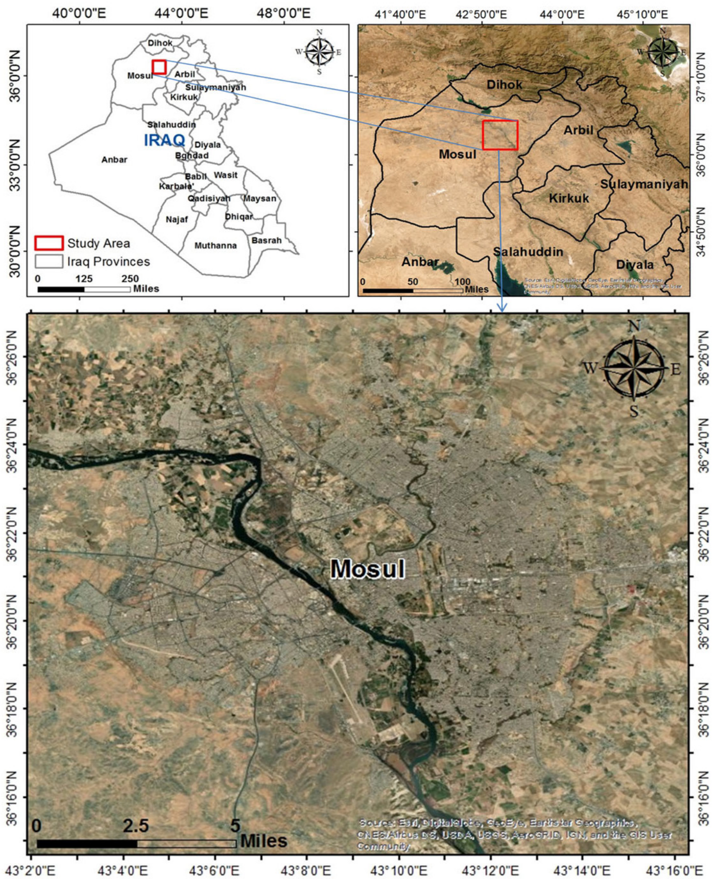

Figure 1. Mosul city location

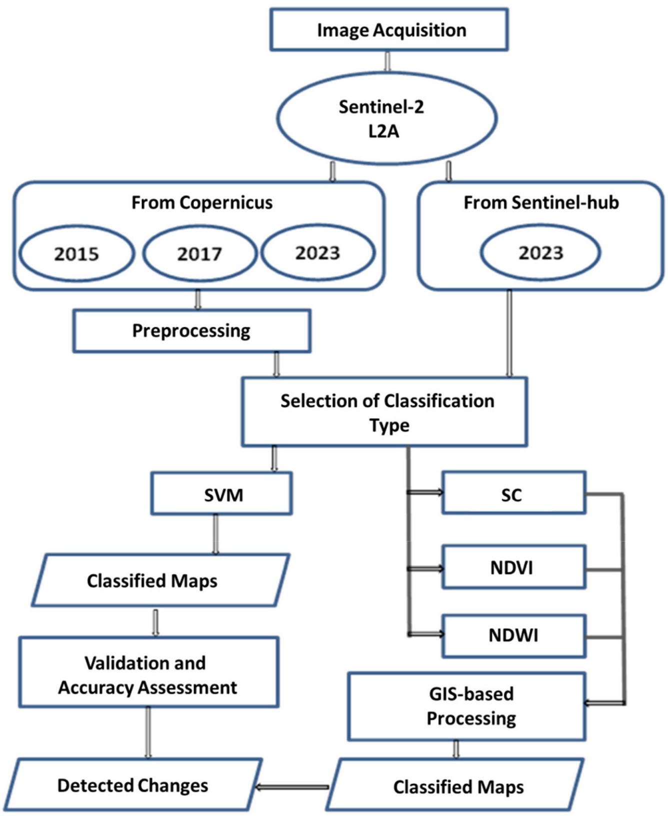

Figure 2. Classification techniques of Mosul Sentinel-2 imagery

Table 1. Acquired data attributes from Copernicus

Platform	Sensing date	Instrument	Resolution	Cloud cover	Orbit No.	Direction
SENTINEL-2	21-08-2015	MSI	10 m	0	847	Descending
SENTINEL-2	21-06-2017	MSI	10 m	0	10 428	Descending
SENTINEL-2	02-12-2023	MSI	10 m	0.03	35 196	Descending

Table 2. Acquired data attributes from Sentinel-hub

Image	Sensing date	Resolution	Projection	Coordinates
SENTINEL-2	22-11-2023	2500×1775 px	WGS84/38N	lat.: 0.00019 deg/px (0.7sec/px) long.: 0.00023 deg/px (0.9sec/px)

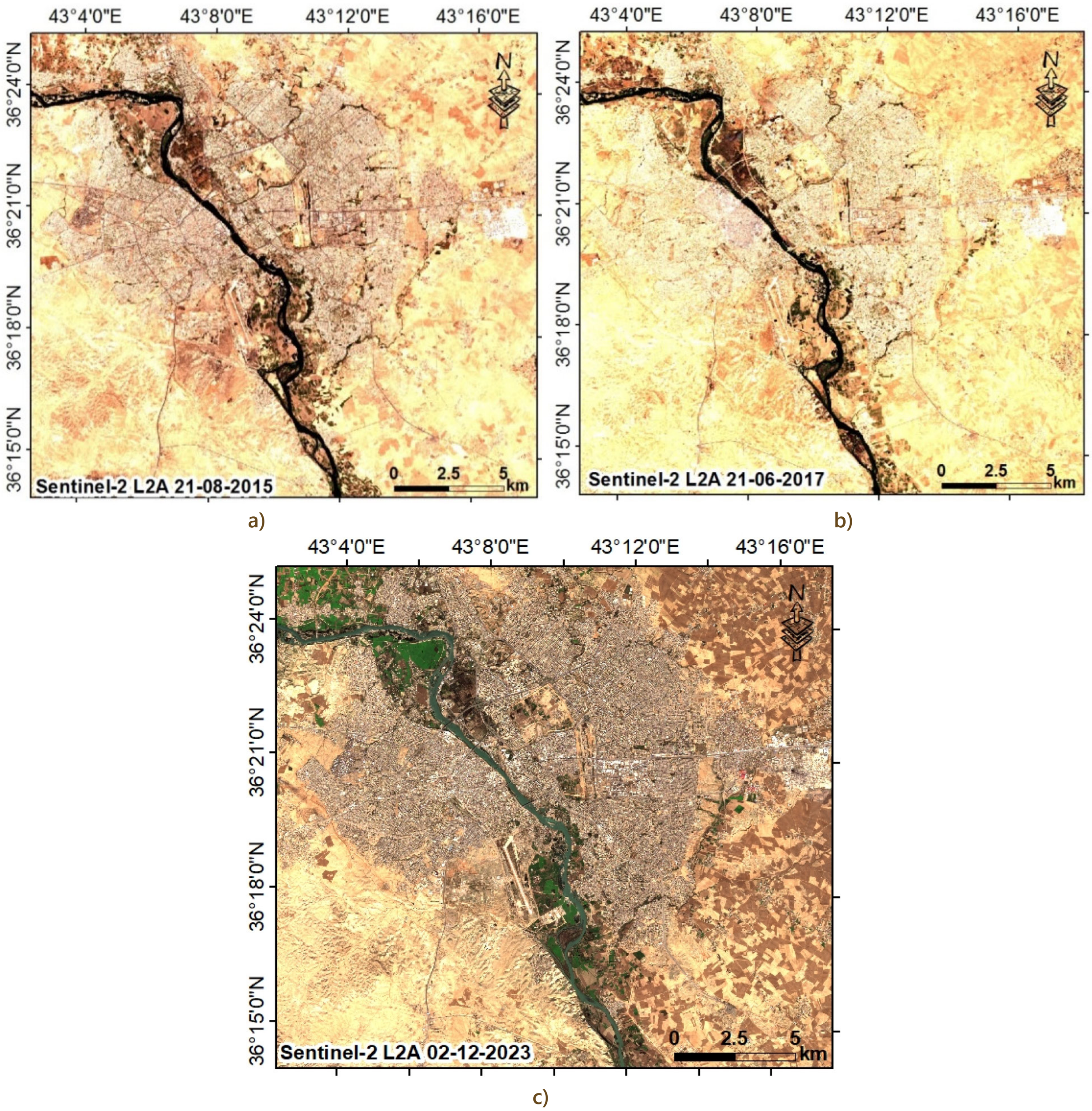

Figure 3. Maps of Sentinel-2 images: a) scene 2015; b) scene 2017; c) scene 2023

images for the year 2023 by Sentinel-hub which were used for mapping the indices.

2.4. Preprocessing

To create a standardized input for accurate classification it is important to fix the resolution and clean the acquired imagery through preprocessing steps to enhance its suitability for classification. This involves radiometric and atmospheric corrections, noise removal, and normalization to ensure consistency across the dataset.

Using Envi software we applied radiometric calibration on Sentinel-2 images for three scenes which represent the years 2015, 2017, and 2023 using calibration type as a radiance and applying the FLAASH model. The resulting calibrated map was then used to be corrected from atmospheric distortion using the FLAASH Atmospheric Correction tool. After selecting the sensor type as multispectral Sentinel-2A, the atmospheric correction proceeded and the image clarity was increased.

2.5. Applying classification types

We used SVM classification based on the specific objectives and characteristics of the dataset of the three scenes (2015, 2017, and 2023). Four classes have been identified in the classification processes; residential, water, vegetation, and land.

Based on AI GIS applications three classifications (SC, NDVI, and NDWI) were applied to the latest images from the Sentinel hub.

Afterward, applying the trained classifier to the entire satellite image. The SVM algorithm assigns pixels to specific classes based on the learned patterns. Post-classification refinement may be necessary to eliminate misclassifications and improve overall accuracy.

The algorithms of applied classifications can be set as follows;

SVM can be specified as (Jumaah et al., 2021, 2023a):

$$f(x) = sign\left(\sum_{i}^{r} \propto_i y_i x_i + b\right); \quad (1)$$

$$f(x) = sign\left(\sum_{i}^{r} \propto_i y_i k(x, x_i) + b\right). \quad (2)$$

A spectral response made up of a description of the class item (y_i) is represented by a vector (x_i) for each of the r training cases. $\propto_i$ (i = 1, ..., r) are Lagrange multipliers; the kernel's item is $k(x, x_i)$, and b denotes the hyperplane space from the beginning point.

The $NDVI$ algorithm for Sentinel-2 can be specified as (Mahmood & Jumaah, 2023):

$$NDVI = (B08 - B04) / (B08 + B04), \quad (3)$$

where, $B04$ is the band four/RED, and $B08$ is the band eight/NIR.

While $NDWI$ algorithm for Sentinel-2 can be specified as (Jumaah et al., 2023a):

$$NDWI = (B03 - B08) / (B03 + B08), \quad (4)$$

where, $B03$ is the band three/GREEN, and $B08$ is the band eight/NIR.

2.6. Validation and accuracy assessment

By dividing the dataset into training and validation sets. We used the training set to identify patterns associated with different classes. Then adjusting parameters and validating against the ground truth data until a satisfactory accuracy level is achieved. Accuracy assessment involved using ground truth control points using the confusion matrix method. A maximum of 100 random points have been selected in the study area of classified maps by SVM. By creating accuracy assessment points using segmentation and classification techniques within the ArcGIS spatial analyst tool, and then comparing them with the same points on earth. The points that were classified incorrectly were identified and corrected. The comparison was made and the confusion matrix technique was applied from the ArcGIS spatial analyst tool. Producer accuracy, user accuracy, overall accuracy, and kappa coefficient have been determined. All three SVM classified maps were validated by the accuracy assessment method. Moreover, we applied the same process of accuracy assessment on the classified maps of NDWI and NDVI.

2.7. GIS-based processing and geoprocessing

GIS-based processes and geoprocessing have been applied for the final classified maps for analyzing the outputs. ArcGIS version 10.8 was used for symbolization and raster conversions which have been applied in order to get final classified maps.

2.8. Detecting changes

The process of detecting changes in the way land is used over time is known as land use change detection (Jumaah et al., 2021). For this, a variety of approaches and techniques can be used; which one to use will depend on the required level of accuracy, the scale of the analysis, and the availability of data. After classifying the Sentinel-2 images the detected changes were identified.

The steps of our change detection methodology involved selecting classified images of each year and comparing their results using statistical analysis. The classified map areas were calculated using the field calculator within the ArcGIS environment. The area calculations can be determined using either Python or VBScript in the attributes table for each land use class. Based on the cell size of each raster and class count of each class we calculated the areas of all classes for each year within the classified maps. Besides a change detection analysis within Envi software was applied between the initial image (2015) and the final image (2023) to identify the accrued changes in this period. Using change detection statistics and defining the equivalent classes between 2015 and 2023 the changes have been detected.

3. Results and discussions

Based on the SVM algorithm and Sentinel-2 imageries, the classified (2015, 2017, and 2023) scenes were mapped in Figure 4.

Moreover, land cover changes shown in Figure 5. Figure 6, also represents the classified maps of Sentinel hub data of the different type indices (SC, NDVI, and NDWI).

Based on Figure 4, SVM classification maps the differences between each class can be seen visually. The classified map of 2017 in comparison with the 2015 map shows degradation in urban areas where as shown the residential areas decreased and barren lands increased. The 2017 year represents the postwar period in Mosul. A study conducted by Jumaah et al. (2021) based on data of prewar and postwar between 2003 and 2016 showed the consequence of the war on the land use dynamic of Mosul with increasing bare lands.

Furthermore, based on Mohammed et al. (2021), agricultural areas were decreased due to war consequences and population leaving, which confirm our results of vegetation decrease in the period 2015–2017.

Otherwise, in 2023 the classification shows some urban recovery and restoration of residential. Barren lands decreased frequently from the previous years, this was reported by Saleh and Ahmed (2021), by land decreasing.

Based on Figures 4 and 5, the maximum detected land cover changes of the years 2015, 2017, and 2023 were in the barren lands and residential areas. In 2015 residential was 14192.82 ha, which decreased to 13185.03 ha in 2017. Otherwise, a tremendous increase in lands was detected from 2015 to 2017 which was 28593.84 ha, and increased by 5% to 31146.87 ha to be decreased in 2023 and became 21790.32 ha. Some recovery of settlements was identified in 2023 where residential areas increased by 4% from barren lands.

War can have long-lasting social, economic, and environmental effects in addition to its immediate effects on the environment. Rebuilding and restoring such regions is a difficult undertaking that could take several years or perhaps decades. Reconstruction projects, the building of infrastructure, and attending to the social and economic requirements of the impacted population are usually part of efforts to rehabilitate metropolitan areas.

Vegetation is also affected by distraction many orchards have been converted to bare lands. In 2015 the vegetation area was 4982.44 ha while in 2017 it decreased to 3434.23 ha, while in 2023 vegetation increased to reach

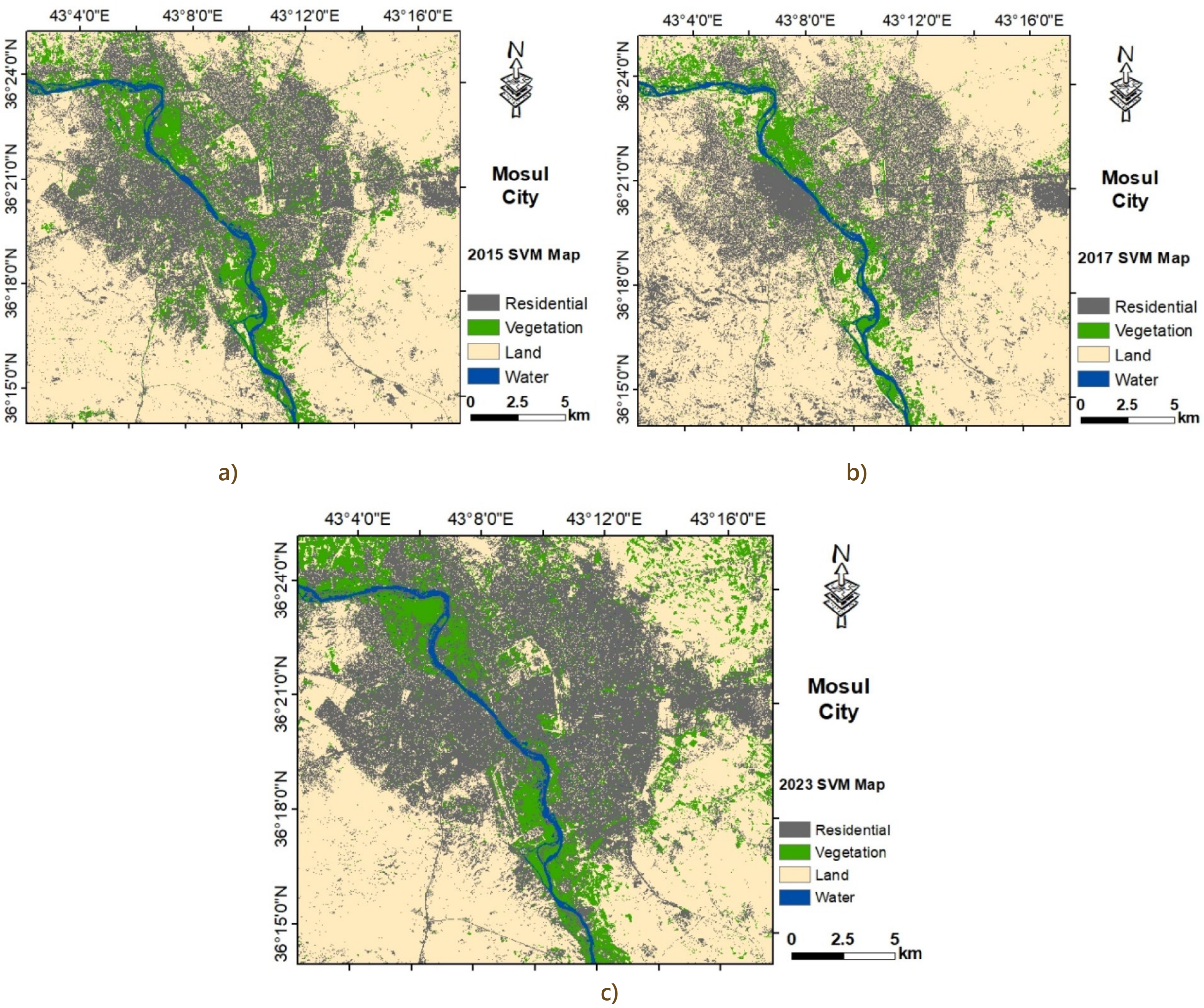

Figure 4. SVM classification maps of the years: a) 2015; b) 2017; c) 2023

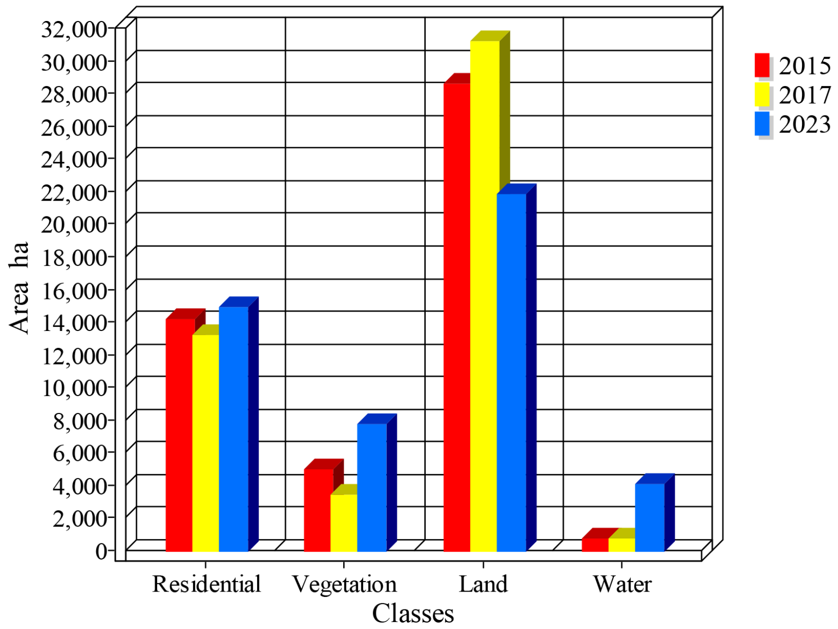

Figure 5. Land cover changes in the years 2015 and 2017

7708.52 ha. There is little doubt that the war has had a significant impact on Mosul, Iraq's agriculture. This region's agriculture is heavily dependent on infrastructure, like roads, storage facilities, and irrigation systems; the effects of war on this sector include farmer displacement and infrastructure destruction. Long-term effects on agriculture may result from contamination as well as from changes in land usage, ecosystem degradation, and long-term environmental impact. It can take time and effort to rehab and return the land to its pre-war state. In post-conflict settings, efforts to reconstruct agricultural systems frequently entail collaboration between non-governmental organizations, local governments, and foreign aid in order to support, rehabilitate, and restore agricultural output.

Water class was 758.49 ha, and 761.46 ha in 2015, and 2017 respectively. The water body in the study area has kept in little changes depending on the rainfall amount and meteorology. Based on the study region area it represented 2% of the total area in the three years. Based on Jumaah et al. (2022), Iraq suffering from water scarcity. The obtained percentage represents lower levels of the city water demands. In 2023 water became 4107.22 ha, this increase is due to rainfall increasing in 2019 (Hadi et al., 2022). The increased value still represents lower levels of the city water demands.

In Figure 6 the classified maps are based on AI GIS applications and Sentinel hub data and performed as SC map, NDVI map, and NDWI map.

The following are made possible by the SC algorithm; creation of a classification map with six distinct categories for vegetation, soils/deserts, water, snow, and clouds, and four classes for clouds in addition to the supply of quality indicators that are correlated with likelihood maps for clouds and snow. In our study area, we applied three classes in this case vegetation, not vegetated, and water as shown in Figure 6a.

According to Figure 6b an easy-to-use yet efficient index for measuring green vegetation is the normalized difference vegetation index NDVI. It scales the health of the vegetation by looking at how plants reflect different wavelengths of light. The NDVI has a value range of –1 to 1. Water is represented by NDVI values that are negative (numbers that are close to –1). Arid patches of rock, sand, or snow are typically represented by values near zero (–0.1 to 0.1). Shrub and grassland are represented by low, positive values (between 0.2 and 0.4), while temperate and tropical rainforests are represented by high values (values close to 1) (Mahmood & Jumaah, 2023).

According to Figure 6c and for mapping water bodies, the normalized difference water index NDWI is the most suitable. Water bodies have values greater than 0.5. The values of vegetation are smaller. Positive values for built-up features range from 0.2 to zero (Jumaah et al., 2023a).

AI GIS applications and advanced remote sensing technologies are becoming more and more significant in a variety of sectors. AI GIS applications integrate geographic data with AI algorithms to provide advanced spatial analysis. Through the identification of patterns, trends, and linkages among spatial datasets, this integration facilitates better decision-making. When AI is combined with advanced remote sensing technology, data from several sources, including satellite imaging, aerial surveys, and ground-based sensors, can be combined. As a result, spatial information is more accurate and of higher quality. In addition to environmental management and monitoring, AI-powered remote sensing enables the monitoring of

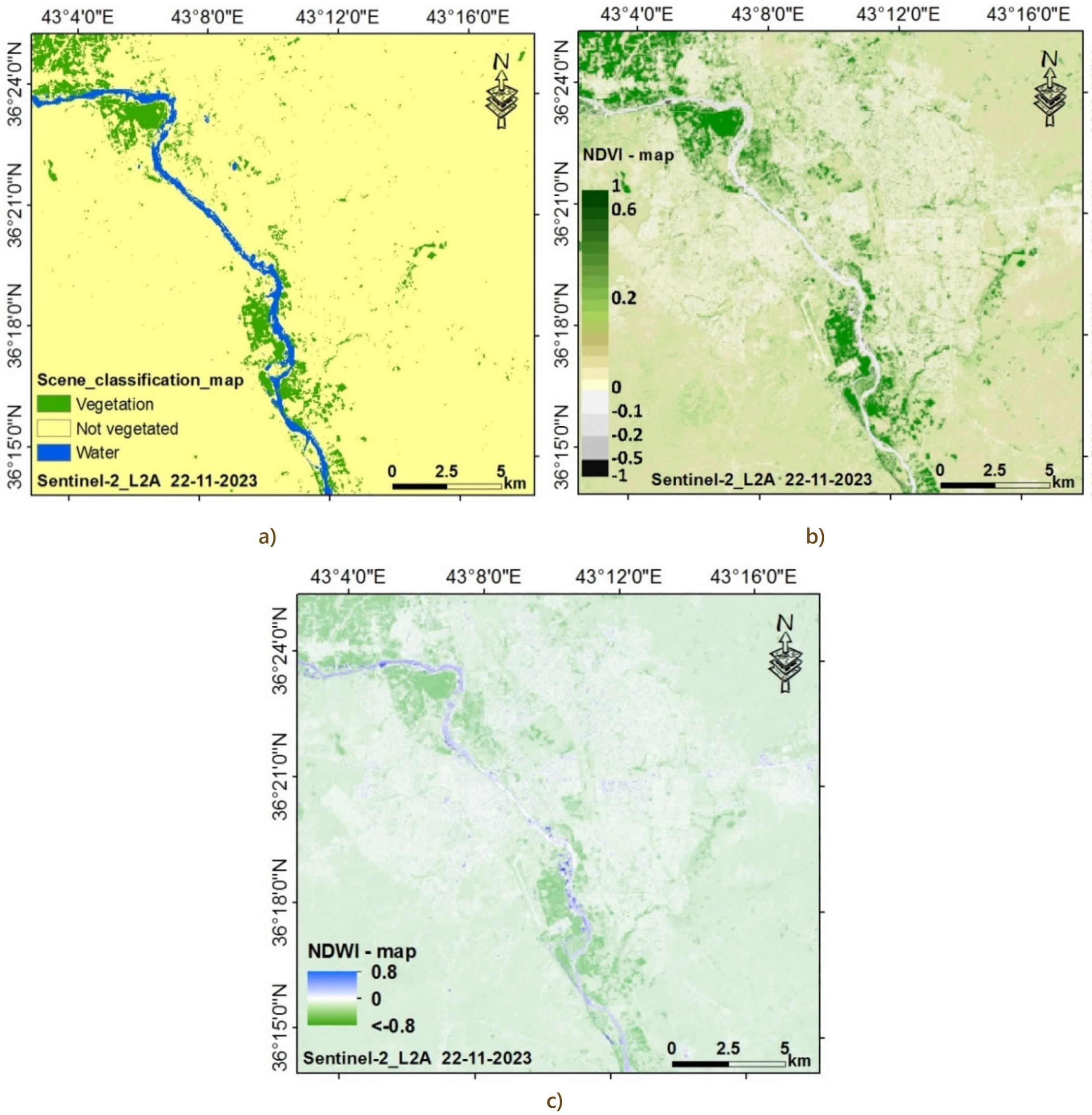

Figure 6. Classified maps of Sentinel hub data: a) SC map; b) NDVI map; c) NDWI map

environmental changes over time. One example of this is change detection. This is essential for evaluating changes in land use, urbanization, deforestation, and other environmental variables. Furthermore, accuracy assessment results were obtained based on the confusion matrix method and reported in Table 3.

Based on Table 3, a maximum of 100 points is used for accuracy assessments for each year. In 2015 residential was classified 93% precisely where 26 points of ground truth represented classified points from 28 tested points. Three points were out of vegetation classification and represented residential and land. Then the user accuracy of vegetation classification was 73%. For land accuracy assessment 60 points are classified by 95% with three points classified as residential while their ground truth is land. Based on the random method selection of testing points water was classified properly. The overall accuracy of the 2015 classification was 92% with a kappa coefficient of 0.85.

As same as 100 points were selected randomly from the classified 2017 map. The comparison with ground truth resulted in high accuracy assessment analysis with an overall accuracy of 94% and a kappa coefficient of 0.87. From a total of 20 residential testing points 2 points were classified as land with 91% user accuracy. From 9 vegetation points 2 points are classified as land and residential. The vegetation user accuracy resulted at 78% and the producer accuracy of 87%. A total of 68 points represented land classification testing. The user accuracy was 97% and producer accuracy was 96% with two points classified as residential. One point represented water and classified without errors.

Table 3. Accuracy assessment results of confusion matrix method

2015								
Classes	Residential	Vegetation	Land	Water	Ground truth	Accuracy		
						User	Producer	Overall
Residential	26	0	2	0	28	0.93	0.87	0.92
Vegetation	1	8	2	0	11	0.73	1	
Land	3	0	57	0	60	0.95	0.93	
Water	0	0	0	1	1	1	1	
Total	30	8	61	1	100	Kappa	0.85	
2017								
Residential	20	0	2	0	22	0.91	0.87	0.94
Vegetation	1	7	1	0	9	0.78	1	
Land	2	0	66	0	68	0.97	0.96	
Water	0	0	0	1	1	1	1	
Total	23	7	69	1	100	Kappa	0.87	
2023								
Residential	39	1	0	0	40	0.98	0.97	0.96
Vegetation	0	15	1	0	16	0.94	0.88	
Land	1	1	41	0	43	0.95	0.98	
Water	0	0	0	1	1	1	1	
Total	40	17	42	1	100	Kappa	0.94	
NDVI								
Residential	37	0	1	0	38	0.97	0.97	0.97
Vegetation	0	16	0	0	16	1	0.94	
Land	1	1	42	0	44	0.95	0.98	
Water	0	0	0	2	2	1	1	
Total	38	17	43	2	100	Kappa	0.95	
NDWI								
Residential	37	1	0	0	38	0.97	1	0.97
Vegetation	0	16	1	0	17	0.94	0.90	
Land	0	1	42	0	43	0.98	0.98	
Water	0	0	0	2	2	1	1	
Total	37	18	43	2	100	Kappa	0.95	

In 2023 residential was classified 98% precisely where 40 points of ground truth represented classified points from tested points. One point was classified as vegetation instead of residential. Also, one point was out of vegetation classification and represented land. The user accuracy of vegetation classification was 94% while producer accuracy was 88%. For land accuracy assessment 43 points were classified by 95% with two points classified as residential and vegetation. Water also was classified properly. The overall accuracy of the 2023 classification was 96% with a kappa coefficient of 0.94. Resultant maps of testing points performed by ArcGIS 10.8.

High overall accuracies were obtained by accuracy assessment of NDVI and NDWI maps which was 97% with a kappa coefficient of 0.95. This indicates that AI-based classification is more precise than others.

In the NDVI classification map residential was classified 97% precisely where 37 points of ground truth represented classified points from tested points. One point was classified as land instead of residential. Also, two points were out of land classification and represented residential and vegetation from 44 ground truths. The user accuracy of vegetation classification was 100% while producer accuracy was 94%. Water also was classified properly with 100% user accuracy and producer accuracy.

In the NDWI classification map residential was classified 97% precisely where 37 points of ground truth represented classified points from tested points. One point was classified as vegetation instead of residential. Also, one point was out of land classification and represented vegetation from 43 ground truths. The user accuracy of vegetation classification was 94% while producer accuracy was 90%. Water also was classified properly with 100% user accuracy and producer accuracy.

Resultant maps of testing points performed by ArcGIS 10.8. Figure 7 represents the accuracy assessment points of classified maps which are compared with ground truth points.

Integrating the classified remote sensing data with decision support systems ensures that the information extracted from the imagery contributes directly to informed decision-making processes, improving the efficiency and effectiveness of interventions. Implement a system for continuous monitoring of the classified imagery to detect new developments or changes in the landscape, and regularly updating the classification model based on new ground truth data and evolving conditions on the ground can derive meaningful insights, and streamline decision-making.

This study makes an effective contribution by integrating advanced spatial techniques to analyze the natural environment and assess the impacts of war on cities, which enhances understanding and paves the way for better decision-making in the field of urban planning and city management.

So the limitation can be defined as:

- Highlighting the importance of RS technologies and AI GIS as effective means to support and develop

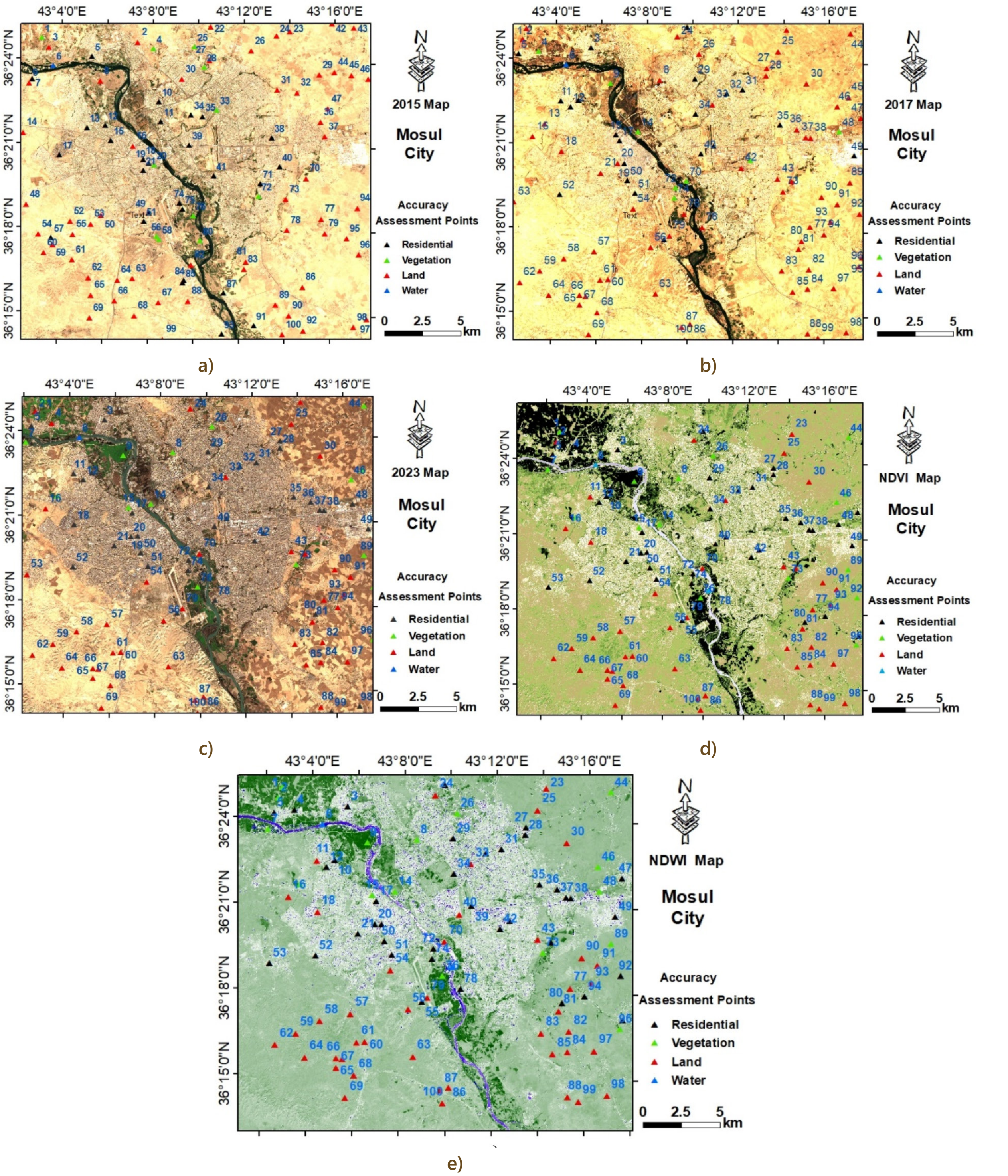

Figure 7. Accuracy assessment points of the classified maps: a) 2015; b) 2017; c) 2023; d) NDVI; e) NDWI

the decision-making process in city management and urban control, the unique context of the city of Mosul as a result of wars that affected land use dynamics.
- Using Sentinel-2 images and various classification techniques.
- Evaluating the accuracy of the classification enhances the reliability of the results.
- Detecting the main changes in the lands, analyzing them, and determining the percentage of decrease and increase in areas.
- Monitor settlement recovery, reflecting the potential positive impacts of reconstruction efforts.
- Highlighting the role of RS technologies and AI GIS in urban planning and land management assessment for sustainable development.

Numerous advantages can result from the rehabilitation of Mosul City's urban planning regions through the application of GIS and enhanced RS. Aerial photography and satellite images offer precise and current data regarding the condition of urban areas. This leads to an easier understanding of the city's infrastructure and the changes that have taken place on the city's land. The outputs of AI GIS and RS aid planners and decision-makers in examining and understanding data in a spatial context. As a result, it permits the selection of the best sites for infrastructure construction, and other facilities, which is a fundamental urban planning demand. Green spaces, roads, and other utilities and public services can be efficiently planned and monitored with the use of RS and GIS as an urban infrastructure. In the case of Mosul city using remote sensing to monitor environmental changes and evaluate how the natural ecosystems are affected by urbanization changes is an efficient and significant methodology. The practical and methodological analysis that is applied through GIS on the city of Mosul helps identify locations with specific requirements or priorities and eases the effective distribution of resources. This targeted approach verifies that rehabilitation efforts must concentrated in the sites that require the most.

4. Conclusions

In the context of sustainable development and to formulate relevant policies and decisions, rapid, effective, and efficient access to data from different sources and topics is required. In addition to accurate processing strategies, and modern data capture, particularly from cutting-edge and open-source software for high-resolution satellite imagery, this includes information obtained by remote sensing in this study including land cover data.

Through the use of several classification techniques in this study, several characterizations of land cover changes based on multi-temporal satellite data were deduced. Choosing the best classification gives accuracy and appropriate characterization of changes. The research concluded that previous activities and destructive operations that have taken place in the city during the war from 2014 to 2017 have caused high changes in the land cover, especially in residential areas and vegetation which were destroyed because of the effect of war, impacting the Mosul city's ability for sustained development. Despite the recovery of some residential in 2023, it still required rehabilitation for other sectors. Consequently, the study findings offer indispensable insights to the local government to initiate policies and make informed decisions. Through the use of advanced technologies, we can deal with the data and maps used in the planning and development process with high efficiency. The combination of RS and GIS technologies plays a vital role in ongoing project monitoring and assessment. This authorizes real-time evaluation strategy, identifying potential issues, and implementing necessary modifications. Consequently, this approach leads to more efficient utilization of resources and an enhanced overall plan for rehabilitating metropolitan areas. By incorporating modern RS and GIS in the urban planning regions of Mosul City, we can achieve more accurate, efficient, and sustainable development methods. Prioritizing the integration of these technologies into urban development strategy will help governments and municipal planners keep environmental sustainability as a primary consideration in the decision-making undertaking.

This study encourages future research to direct its attention toward war-affected cities. Also, the findings of this study inspire researchers to integrate remote sensing techniques with artificial intelligence and their efficiency in analyzing environmental changes. As well as, Directing attention to urban planning, agricultural land management, and optimal exploitation of water resources. The diversity of methods used in this study encourages researchers to improve and develop image classification and accuracy assessment methods to achieve more accurate and detailed results in future research. Integrating information in the context of crises and wars to understand environmental and social impacts. Thus encourages the expansion of research in sustainable development. Overall, this study can advance understanding of the impacts of war on cities and direct future research towards using spatial technologies to deal with environmental and social challenges in the context of crises.

To completely tap into the potential of Intelligent GIS and RS in urban planning, stakeholders are urged to fund cooperative projects, data infrastructure development, and capacity building.

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Author contributions

HJ and AJ designed the study and developed the data analysis. ZK was responsible for data collection. AG was responsible for data interpretation. HJ wrote the final copy of the article.

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