

Environmental Assessment For Mapping Land Degradation and Lands Changes Using Remotely Sensed Data with Geospatial Analysis

Ghaidaa Saba Yousef^{1*}, Hayder Dibs², Ahmed Samir Naje³

¹Water Resources Management Engineering Department, College of Engineering, Al-Qasim Green University, Babylon, 51013, Iraq

* Corresponding Author Email: Ghaida.m106416@wrec.uoqasim.edu.iq - ORCID: 0000-0001-8034-923X

²Water Resources Management Engineering Department, College of Engineering, Al-Qasim Green University, Babylon, 51013, Iraq

Email: Dr.hayderdibs@wrec.uoqasim.edu.iq - ORCID: 0000-0001-8034-9234

³Water Resources Management Engineering Department, College of Engineering, Al-Qasim Green University, Babylon, 51013, Iraq

Email: ahmed.sameer@wrec.uoqasim.edu.iq - ORCID: 0000-0001-8034-923Y

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Abstract:

Lands degradation is one of the problems that facing the humanity throughout the world as well as the abandonment of farming on their lands by farmers, in addition to the fragmentation of most orchards and agricultural fields and their conversion into residential areas, has a negative impact on the Economic, Environmental and Social (Reduced Agricultural Productivity, Economic Loss, Soil Degradation, Agricultural productivity. Water Scarcity, Biodiversity Loss, Rural-Urban Migration, Food Security, Conflict and Instability). However, in Karbala Province, Iraq, most the Agriculture lands are facing this dilemma since 2003. Therefore, in order to start solving this problem and, it is important to detect all the changes throughout the study area and then put recommendations for overcoming this dilemma. The aim of this study to monitor and detect the changes in LCLU the study area and detect the lands degradation and the reasons behind that. For that, Authors employed pixel based classification techniques (Maximum Likelihood Method) on four Landsat satellite (9 ,7 ETM+, TM5, TM4) images acquired at intervals (1990, 2000, 2010, and 2023). The first step in this research is applied the pre-processing stages (radiometric and geometric corrections) to correct the images, secondly, processing stage (layer stacking, and study area sub-setting) to all satellite images, then the corrected images classified using supervise classification to six regions. The results show that the desertification has markedly intensified in the city of Karbala since the last three decades. In 2023, the water volume, decreased by 14.21%, and both Urban area and dark soil increased by 3.05%, and 8.63% respectively, and that give a negative indicator about what happen in research area, it evidences of land degradation processes was seen, mostly due to Human activities such as urban expansion and unsustainable land use practices. The confusion matrix was applied to evaluate the results. The overall accuracy and kappa statistic were above the 90% and 0.90 respectively.

1. Introduction

Each year, approximately 20 million hectares of fertile land experience degradation, and 70% of potentially productive drylands face the threat of desertification, with 18% of Africa's arid regions already significantly affected by this process [1]. The United Nations Convention to Combat Desertification (UNCCD) defines land degradation

as the "reduction or loss of biological or economic productivity and complexity" in rainfed and irrigated croplands, pastures, forests, woodlands, and rangelands due to various land-use practices or a combination of processes. Since 1995, the UNCCD has identified desertification as a specific form of land degradation characterized by the decline in soil productivity in arid, semi-arid, and dry sub-humid regions [2,3].

Soil degradation, on the other hand, refers to the deterioration in the quality of soil and its biological, chemical, and physical attributes [4,5]. Both degradation and desertification are driven by human activities, natural events, or their interplay, reducing the capacity of land and soil to deliver essential ecosystem services. These ecosystem services, defined as “the benefits people derive from ecosystems,” are crucial for promoting sustainability and conservation efforts [6].

Land degradation is a multifaceted issue encompassing geographical, ecological, climatic, and socio-economic dimensions [7]. It imposes significant environmental and socio-economic challenges, particularly in developing nations [1,8]. Deep Learning Algorithm Design for Discovery and Dysfunction of Landmines was studied [9]. Effective monitoring of degradation and desertification is essential to prevent further environmental decline [10]. Despite the importance of these phenomena, there remains no universally accepted definition or standardized methodology for assessing them under the UNCCD framework. In the context of the Sustainable Development Goals (SDGs), an indicator for monitoring SDG 15 and its target 15.3 has been proposed. This indicator relies on three sub-indicators: land cover, land productivity, and carbon stocks, adhering to the statistical principle of “One Out, All Out.” However, the methodologies for calculating these sub-indicators lack precise guidance, with recommendations to utilize existing products, maps, and datasets with medium to coarse spatial resolutions (ranging from 300 meters to 1 kilometer) or national data sources. In cases where national data are unavailable or incomplete, earth observation data are recommended [11].

Remote sensing has emerged as a valuable tool for assessing land degradation and desertification, despite certain limitations and uncertainties [12]. It provides a cost-effective and reliable method for monitoring extensive areas over time, particularly in regions where historical data are scarce [1]. Remote sensing also enables access to time-series and near-real-time data, facilitating retrospective analyses and predictive modeling [13].

Over the past decade, bibliometric analyses of remote sensing applications for studying land and soil degradation have provided useful insights. However, these reviews have limitations, often emphasizing bibliometric indicators over the research content itself. They primarily focus on summarizing the state of the art in technological applications and thematic trends [14,15], with minimal critique or deeper analysis. Additionally, some reviews are restricted to specific geographic regions [4,12,16] or particular land cover types

[17,18]. Although certain studies have explored definitions and concepts related to land degradation and desertification, they often lack comparative analyses of their practical applications [1].

It offers “from eto” change information in addition to change location [19, 18]. There are presently a lot of satellite programs running. The Landsat program is unique for studies on change detection since it offers a continuous and historical collection of imagery [3, 4-7]. For LULC monitoring, mapping, and management, the ability to interpret Landsat photos to display land cover across vast desert expanses over extended periods of time is special and crucial [20]. Establishing a rational land use strategy necessitates the assessment of the trends and rates of land cover transformation [21, 22]. Numerous studies, especially those focused on semi-arid and arid areas, have aimed to utilize Landsat data to evaluate changes in land use and land cover. Another researcher utilized Landsat imagery to classify land use and land cover types in Egypt's coastal region. The overall classification accuracy enhanced by around 10% when supervised classification techniques were integrated with visual interpretation analysis. Analyzed alterations in land cover in a recently reclaimed region of Egypt from 1984 to 2008 using five Landsat images and a hybrid classification technique that combines unsupervised and supervised methods, in conjunction with the normalized difference vegetation index (NDVI) [23]. The remote sensing analysis can evaluate the impacts of these processes and furnish the knowledge necessary to formulate a national agricultural policy [24-27].

These researches authors employed climatic data from Landsat 4 TM, Landsat 5 TM, Landsat 7 TM, and Landsat 9 ETM covering the period from 1990 to 2023. An investigation of the vegetative and agricultural cover in 2010 revealed fluctuations, marked by both gains and losses in vegetation, particularly in the southern and central regions. A comprehensive database and maps depicting the status of desertification and its progression since 2000 were developed through vegetation and agricultural research. Additionally, some strategies were proposed to mitigate the encroachment of desertification into urban areas and to reduce its adverse effects.

2. Methodology

This study utilized four satellite images to evaluate the effectiveness of multi-sensor datasets with varying resolutions in detecting changes in Land Use and Land Cover, as well as in monitoring desertification in Karbala city.

This study consists of several stages: (a) the pre-processing phase to correct geometric and radiometric inaccuracies and noise, (b) the processing stage involves delineating the study area through clipping and subsetting the images, (c) subsequent resampling of the satellite imagery, (d) fieldwork to gather ground control points, and (e) the selection of training and testing samples. In the post-processing step, the maximum likelihood method was utilized as a supervised image classification technique to generate the Land Use/Land Cover thematic maps. Subsequently, validate all acquired results with the confusion matrix method. Change detection was executed by a statistical comparison of all classified images from 1990 to 2023, resulting in statistical analysis and accuracy evaluation.

2.1 Study Area

The research study region is situated in central Iraq, approximately 100 km (62 mi) southwest of Baghdad and a brief distance east of Lake Milh, also referred to as Razzaza Lake. Karbala serves as the capital of Karbala Governorate, with an estimated population of 1,218,732 in 2018. The city, renowned for the Battle of Karbala in 680 AD and the shrines of Hussein and Al Abbas, is regarded as a sacred city for Shia Muslims. Millions of Shi'ite Muslims undertake a pilgrimage to the place biannually. Annually, millions of Shi'ites commemorate the martyrdom of Husain ibn Ali and Abbas ibn Ali. Figure 1 illustrates the map of the research area.

2.2 The Used Datasets

The enhanced spatial and spectral resolution of Satellite Landsat 9 for 2023, Satellite Landsat 7 ETM for 2000, Satellite Landsat TM 5 for 2010, and Satellite Landsat TM 4 for 1990. Satellite

imagery was employed to monitor, identify, and produce Land Use/Land Cover maps, as well as to evaluate urban expansion and growth in the study area for the years 1990, 2000, 2010, and 2023. All obtained satellite images were free of clouds, and all datasets were gathered during the summer season.

Table 1 delineates the attributes of the employed satellite pictures.

2.3 Image Pre-Processing

The methodology encompasses a pre-processing phase that entails radiometric and atmospheric correction, followed by image subsetting to identify changes within the study area. The satellite image must be geo-referenced to a coordinate system that aligns with real-world coordinates on the Earth's surface; hence, geometric correction was executed using ENVI Classic. The pre-processing of satellite pictures before change detection is crucial and aims to create a more direct relationship between the data and biophysical processes [25]. The methods employed for this

The research investigated multiple image pre-processing methods, encompassing geometric correction, augmentation, and interpretation. geometric rectification All Landsat data utilized in this study were obtained under clear atmospheric conditions (Figure 2). The images from 1990, 2000, and 2010 were geometrically corrected to correspond with the 2023 image using Envi 5.3 software. The 2023 image was previously geo-referenced using ground control points and terrain maps. Subsequent to the pre-processing phase, the research area exhibited multiple distinguishable classes from the images, which have been delimited and classified into six regions according to topographical variations, as demonstrated in Table 2.

Table 1. specifications of the adopted Datasets.

Satellite	Date	Spatial resolution	Spectral resolution (m)	Projection
Satellite Landsat 9	2023/09/02	30 m	11 Bands	UTM
Satellite Landsat TM5	2010/07/09	30 m	7 Bands	UTM
Satellite Landsat7 ETM+	2000/08/22	30 m	8 Bands	UTM
Satellite Landsat TM4	1990/07/10	30 m	7 Bands	UTM

Table 2. Classifications and Descriptions of the Research Area.

Class number	Class name	Description
1	Vegetation	Orchards, agricultural crops, deciduous and evergreen forests, and bushes.
2	Urban Area	Industrial and commercial, buildings, residential areas and houses, and all types of transportation facilities such as airports, and parking lots
3	Water Bodies	All types of water bodies, rivers, lakes, and other
4	Soil	Desert and sand area
5	dark soil	The lands were planted and which is prepared for agriculture
6	Salty soil	Salty soil

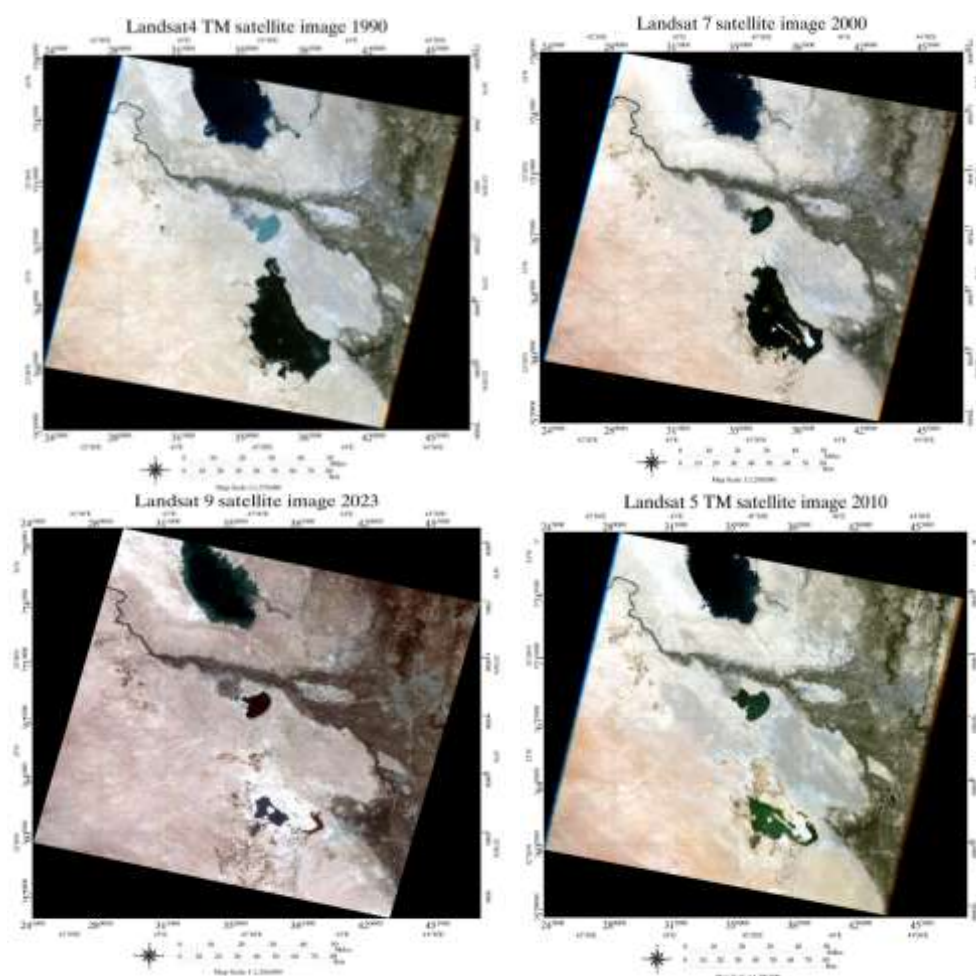


Figure 2. satellite images before processing.

2.4 Image Processing

The image processing phase involves cropping and subsetting images to modify pixel values, hence enhancing information visibility and improving visual interpretability by increasing the contrast between features. This study utilized picture subsetting to precisely delineate the research area within the four selected photographs for analysis. Prior to initiating the image classification procedure, the terrain was categorized into six distinct classifications using this technique. The six categories were determined using visual analysis of satellite imagery and corroborated by field surveys. The identification of these types was straightforward owing to the unique shapes and hues of the geological strata in the study area. Four maps of the area were created after this processing process as shown in Figure 3. They were later digitally classified through the classification process.

2.5 Images Classification

Six categories were assigned for the region of interest in the four images; a maximum likelihood

method was employed during the classification phase for each image to produce the theme map and to identify the changes between 1990, 2000, 2010, and 2023. The supervised classification was conducted with Envi 5.3 for the digital image processing of the designated Landsat datasets. Over 60 training sites were established for each category. Following the classification phase, the confusion matrix was employed to assess classification accuracy, and specific sample locations were collected for validation purposes. Figure 3 illustrates the thematic maps of land cover for each corresponding year. Training samples for each designated LULC type were chosen by delineating polygons around representative locations. We produced spectral signatures for the pertinent land cover classes from the pixels included within these polygons, as captured by the satellite photos. A spectral signature is deemed sufficient when there is minimal ambiguity regarding the land areas to be delimited. Subsequent to the validation of the spectral signature, we integrated it into the classification process. We employed the supervised maximum likelihood approach for categorization. Supervised classification produces a thematic raster layer (the categorized image) together with a

distance file. The thematic layer and the distance file were utilized for post-classification thresholding. Four preliminary land use and land

cover (LULC) maps were generated, as illustrated in Figure 4.

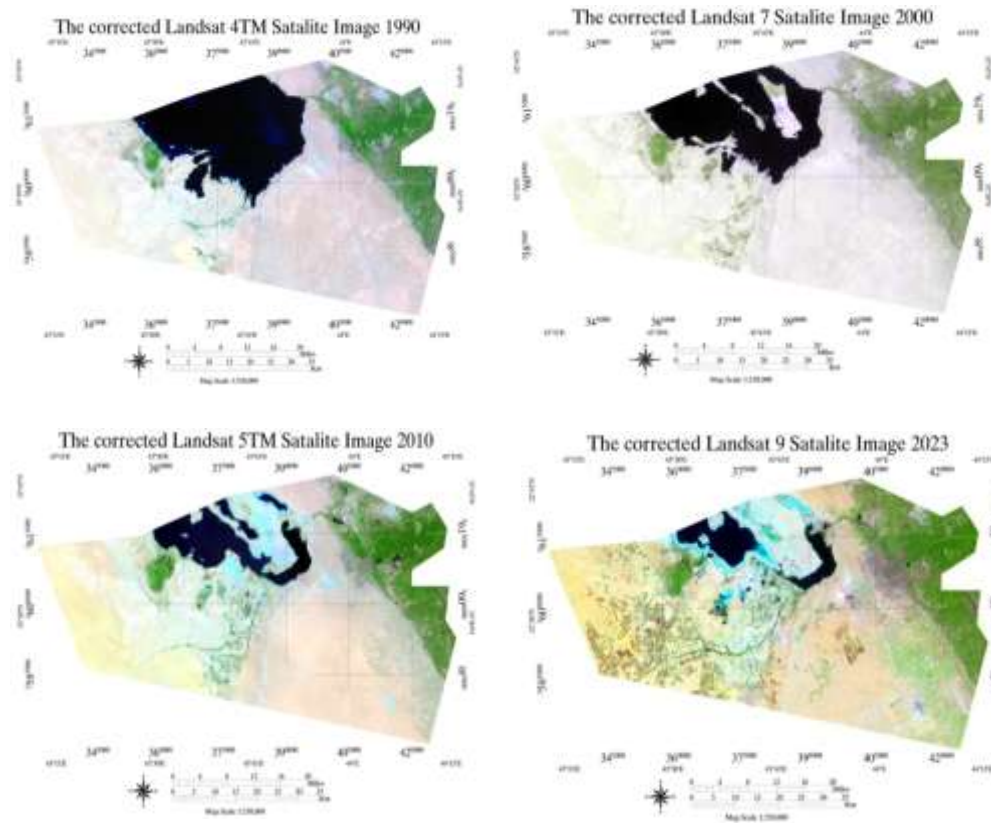


Figure 3. satellite images after processing.

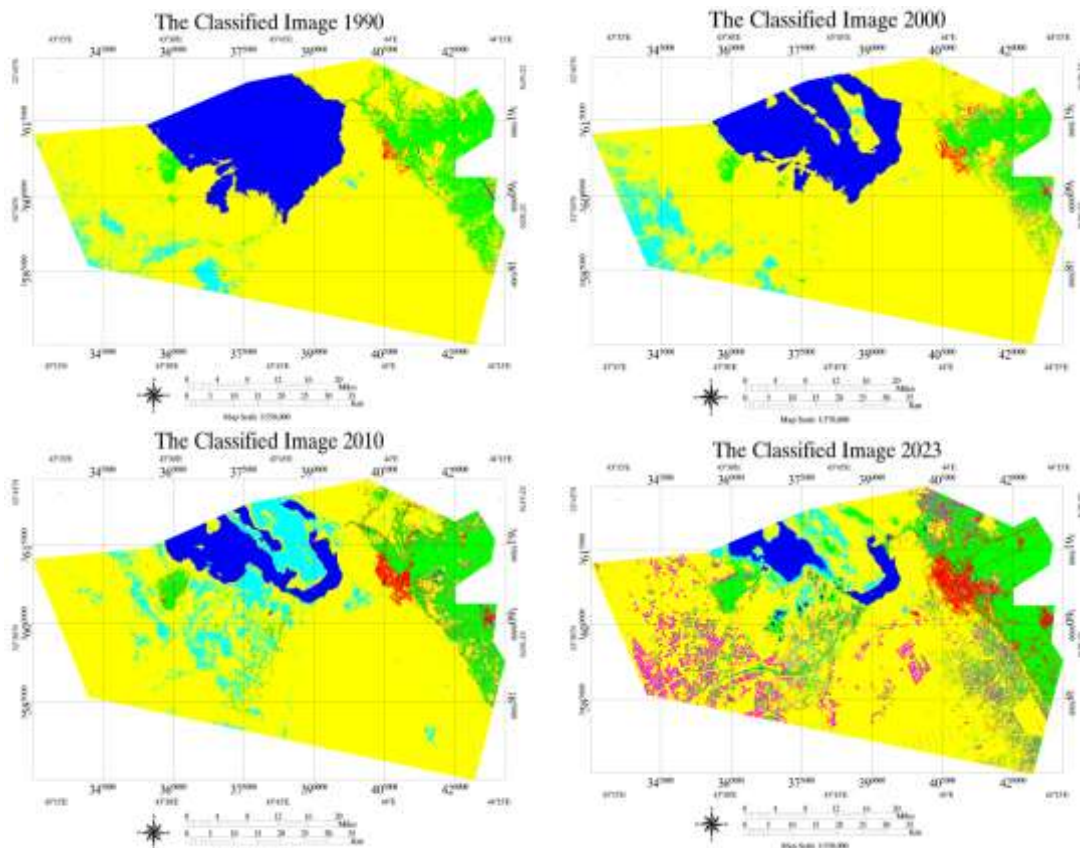


Figure 4. satellite images after classification

3. Results and Discussion

The examined photographs, following pre-processing and supervised categorization, revealed distinct land use and land cover patterns in the investigated area (Figure 5). The alterations in various land use and land cover categories in the examined regions from 1990 to 2023 were influenced by variables such as urban expansion and land reclamation (Table 2 and Figure 6). The primary impact of human activities on land degradation in the examined regions was urban sprawl. The classification explained the changes that occurred in the six classified areas in the study area, as in the table 3,4,5,6. The total area of the study area is 4262137 pixels. The Area of study area = 4262137pixels *900.

The used satellite images were Landsat. So, the area of the one pixel = 30 x30 m=900m²

Therefore, the total area of the study area is =4262137pixels *900 = 3,835,923,300 m² =3,835.92 km²

Table 3. Areas of the classified areas of the study area in km & % in 2023.

No.	Classes2023	Percent %	Area (km2)
1	Vegetation	19.13	733.81
2	Water bodies	04.40	168.78
3	Soil	61.19	2347.20
4	Dark soil	08.78	336.79
5	Salty soil	03.00	115.08
6	Urban area	03.50	134.26
7	Sum	100	3,835.92

Table 4. Areas of the classified areas of the study area in km & % in 2010

No.	Classes2010	Percent%	Area (km2)
1	Vegetation	10.03	384.74
2	Water bodies	06.85	262.76
3	Soil	70.89	2719.29
4	Dark soil	0.73	28.00
5	Salty soil	09.66	370.55
6	Urban area	01.84	70.58
7	Sum	100	3,835.92

Table 5. Areas of the classified areas of the study area in km & % in 2000

No.	Classes 2000	Percent%	Area (km2)
1	Vegetation	06.58	252.40
2	Water bodies	13.64	523.22
3	Soil	74.23	2847.40
4	Dark soil	0.59	22.63
5	Salty soil	04.33	166.10
6	Urban are	0.63	24.17
7	sum	100	3,835.92

Table 6 . Areas of the classified areas of the study area in km & % in 1990

No.	Classes 1990	Percent	Area (km2)
1	Vegetation	09.23	354.06
2	Water bodies	18.61	713.87
3	Soil	68.83	2640.26
4	Dark soil	0.15	5.75
5	Salty soil	02.73	104.72
6	Urban area	0.45	17.26
7	Sum	100	3,835.92

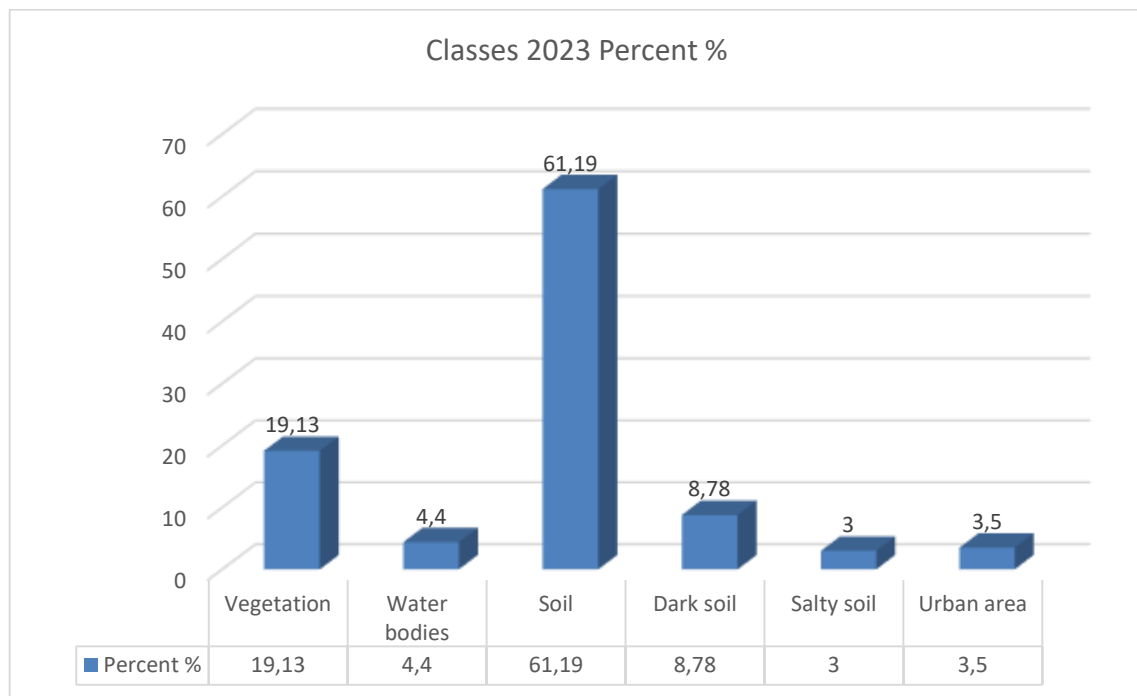


Figure 5. Areas of the classified areas of the study area in % in 2023.

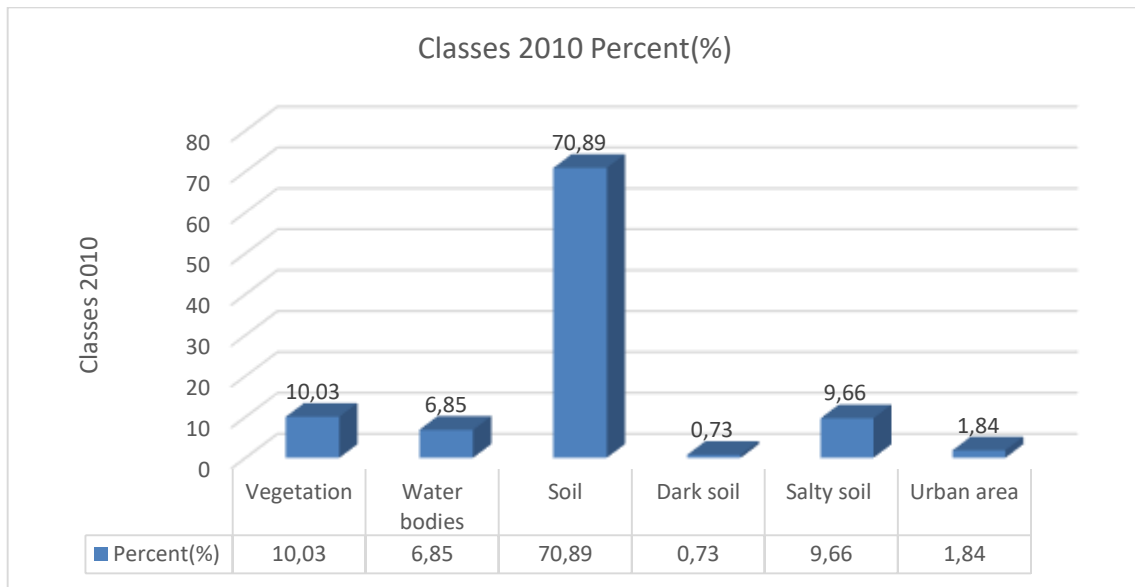


Figure 6. Areas of the classified areas of the study area in % in 2010.

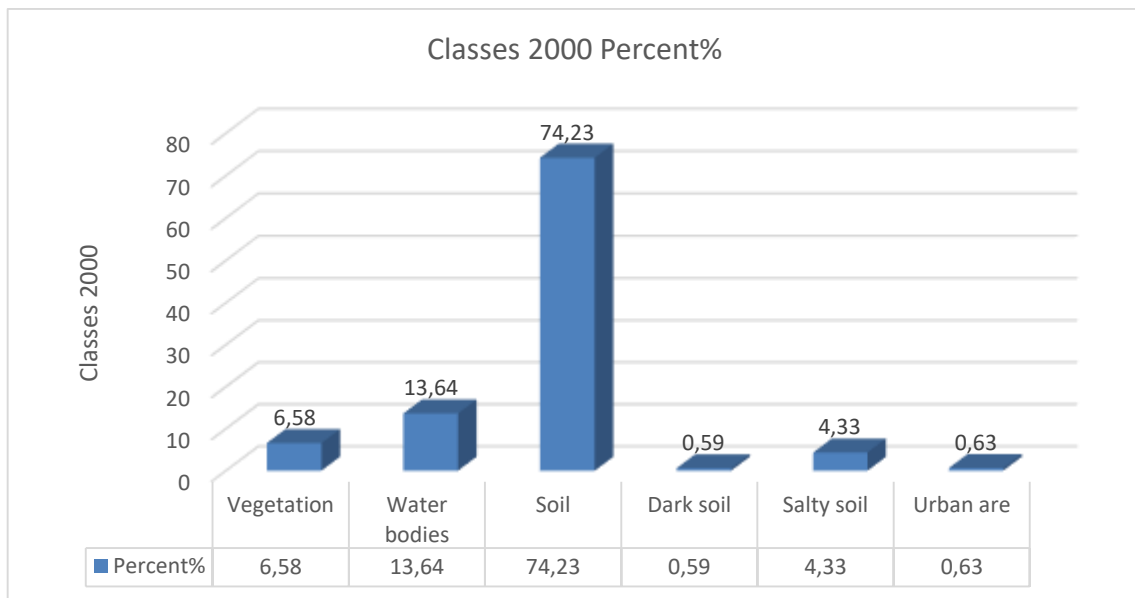


Figure 7. Areas of the classified areas of the study area in % in 2000.

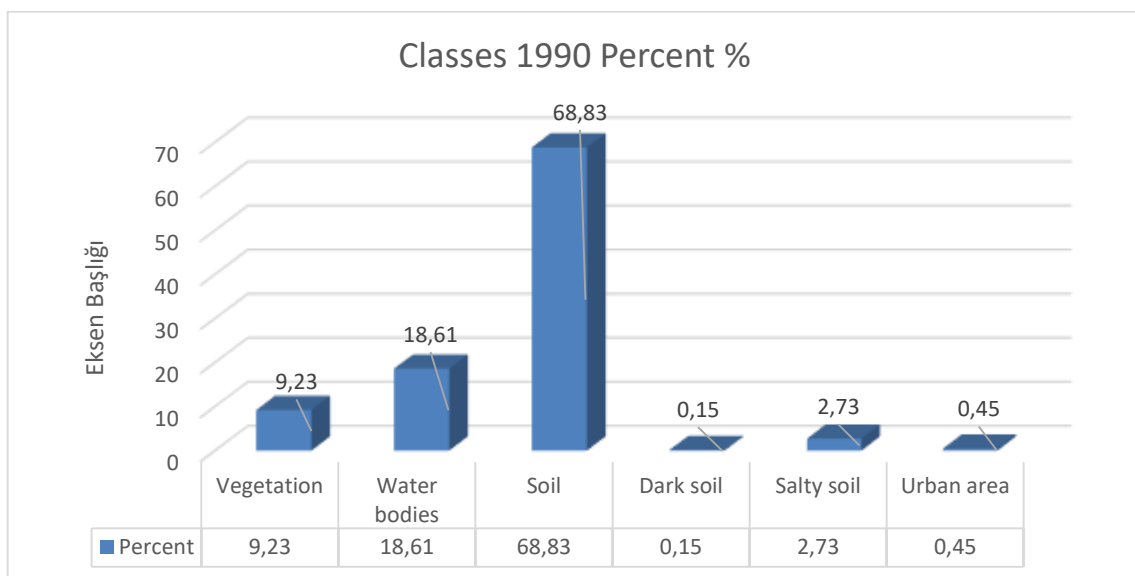


Figure 8. Areas of the classified areas of the study area in % in 1990.

The results exhibited a consistent pattern that defined the alterations in all land use and land cover categories. The cultivated regions in the vegetative zone experienced a notable and steady rise from 2010 to 2023. The observed change rate increased by 9.1% from 2010 to 2023, whereas the agricultural decline was roughly 2.65% from 1990 to 2000. The aggregate rate of change documented from 1990 to 2023 was 9.9% and 379.75 km² (Table 8, 9). The repercussions stem from the growth of agriculture through arid land reclamation and the transformation of former aquatic ecosystems into agricultural zones. A distinct pattern was noted in aquatic habitats, with the greatest extent recorded in 1990, followed by a decline in 2000, 2010, and 2023. The change detection findings indicated a decrease in waterlogged areas, with a decline of 4.97% from 1990 to 2000, 6.79% from 2000 to 2010, and 2.45% from 2010 to 2023. Between 1990 and 2023, the total change amounted to 545.09 km², reflecting a decline of 14.21%. The highest soil numbers were documented in 2000, followed by a fall in 2000, 2010, and 2023. The land area increased by 207.14 km² from 1990 to 2000, with an annual growth rate of 5.4%. It subsequently decreased by 128.11 km² from 2000 to 2010, at a rate of 3.34%, and further shrunk by 372.09 km² from 2010 to 2023, at a pace of 9.7%. From 1990 to 2023, the overall change was 293.06 km², indicating a 7.64% growth. The results for the Dark Soil region revealed that 2023 had the most extensive area, succeeded by 2010, 2000, and 1990. The change detection results revealed that the natural vegetation area increased by 0.44% from 1990 to 2000, by 0.14% from 2000 to 2010, and by 8.05% from 2010 to 2023. From 1990 to 2023, the total change was 331.04 km², indicating an increase of 8.63%. Salty Soil had a steady increase from 1990 to 2010, followed by a decrease in 2023. The recorded growth rates were 1.6% from 1990 to 2000, 5.33% from 2000 to 2010, and a decrease of -6.66% from 2010 to 2023, culminating in an overall change rate of 0.27% and a total area alteration of 10.36 km² from 1990 to 2023. In urban situations, the year 2023 had the greatest value, succeeded by 2010, 2000, and 1990. The urban ratio increased by 0.18% from 1990 to 2000, by 1.21% from 2000 to 2010, and by 1.66% from 2010 to 2023. The cumulative increase from 1990 to 2023 was 3.05% and 177 km² (Table 8, 9). The results can be attributed to urban expansion, resulting in the reduction of agricultural land, mostly driven by rapid population growth and internal migration. Additionally, enhanced land reclamation projects, desert agriculture, and the farming of once aquatic areas also play a role in these results. The reduction of water bodies may

stem from evaporation caused by rising temperatures, together with the conversion of certain water bodies into agricultural and aquacultural zones, thereby diminishing the overall area of water bodies. Concerning the soil area, The recent reduction in soil areas is due to their transformation into agricultural and residential zones, as agricultural expansion has intensified in the desert of the study area, alongside a rise in cultivated land and lakes. As for dark soil, these results can be attributed mainly to the increase in soil use, its rehabilitation and preparation for agriculture, as the cultivated lands have increased in recent years in order to improve the soil and prepare it for the agricultural seasons. As for salty soil, its decrease in recent years can be attributed to the conversion of part of it into agricultural lands and human activities in the study area, unlike what happened in the previous periods from 1990 to 2000 and 2000 to 2010, when it increased as a result of the lack of land exploitation and rehabilitation. The urban area has had a substantial rise in residential zones recently, due to urban expansion, increased human activity from population growth, and major migration from rural regions to urban centers. The findings reveal that the examined area has experienced substantial modifications in land cover, especially for aquatic bodies.

3.1 Assessment of Classification Accuracy

To assess the accuracy of the classification, each land cover and land use map was compared with a data source. The source data was taken from a study of historical data collected from random sample points on Google Earth and topographic maps, thereby validating the accuracy of the categorization through ground samples. The accuracy ratings for the years 1990, 2000, 2010, and 2023 were 94.46%, 93.82%, 91.06%, and 92.13%, respectively. The kappa score for the analyzed years exceeds 60%, indicating that the map categorization for 1990, 2000, 2010, and 2023.

Table 7. overall accuracy and kappa statistic.

Years	Overall Accuracy	Kappa Coefficient
1990	94.46%	0.9386
2000	93.82%	0.9255
2010	91.06%	0.9058
2023	92.13%	0.9090

3.2 Detection of Spatial-Temporal Changes

The discrepancies in land cover and land use observed in this study were derived from the statistics.

Derived from the thematic maps of Karbala city. The changes in land cover during the study period (1990 to 2023) are depicted in Figure 7 and Tables 7,8,9. Figure 8 is areas of the classified areas of the study area in % in 1990. Vegetation and water bodies decreased in 2000 by 2.65% and 4.97% and increased soil and urban area by 5.4% and 0.18% as in the Table 10. In 2010, water bodies and soils

decreased by 6.79% and 3.34% percent, while Vegetation and Urban area increased by 3.45% and 1.21% percent, as shown in the Table.11. In 2023, water bodies and soils also decreased by 2.45% and 9.7% percent, while vegetation and Urban area increased by 9.10% and 1.66% percent, as shown in the Table 12.

Table 8. Percentage of areas classified by km² over the four years.

No.	Class	Area in 1990 (Km ²)	Area in 2000 (Km ²)	Area in 2010 (Km ²)	Area in 2023 (Km ²)
1	Vegetation	354.06	252.40	384.74	733.81
2	Water bodies	713.87	523.22	262.76	168.78
3	Soil	2640.26	2847.40	2719.29	2347.20
4	Dark soil	5.75	22.63	28.00	336.79
5	Salty soil	104.72	166.10	370.55	115.08
6	Urban area	17.26	24.17	70.58	134.26
7		3,835.92	3,835.92	3,835.92	3,835.92

Table 9. Percentage of areas classified by % over the four years.

No.	Class	Area in 1990 Percent (%)	Area in 2000 Percent (%)	Area in 2010 Percent (%)	Area in 2023 Percent (%)
1	Vegetation	09.23	06.58	10.03	19.13
2	Water bodies	18.61	13.64	06.85	04.40
3	Soil	68.83	74.23	70.89	61.19
4	Dark soil	0.15	0.59	0.73	08.78
5	Salty soil	02.73	04.33	09.66	03.00
6	Urban area	0.45	0.63	01.84	03.50
		100	100	100	100

Table 10. Increasing and Deceasing (%) between 1990 & 2000.

No.	Class	Area in 1990 Percent (%)	Area in 2000 Percent (%)	Increasing and Deceasing (%)
1	Vegetation	09.23	06.58	-2.65
2	Water bodies	18.61	13.64	-4.97
3	Soil	68.83	74.23	+5.4
4	Dark soil	0.15	0.59	+0.44
5	Salty soil	02.73	04.33	+1.6
6	Urban area	0.45	0.63	+0.18

Table 11. Increasing and Deceasing (%) between 2000 & 2010 .

No.	Class	Area in 2000 Percent (%)	Area in 2010 Percent (%)	Increasing and Deceasing (%)
1	Vegetation	06.58	10.03	+03.45
2	Water bodies	13.64	06.85	-06.79
3	Soil	74.23	70.89	-3.34
4	Dark soil	0.59	0.73	+0.14
5	Salty soil	04.33	09.66	+05.33
6	Urban area	0.63	01.84	+1.21

Table 12. Increasing and Deceasing (%) between 2010 & 2023.

No.	Class	Area in 2010 Percent (%)	Area in 2023 Percent (%)	Increasing and Deceasing (%)
1	Vegetation	10.03	19.13	+09.10
2	Water bodies	06.85	04.40	-2.45
3	Soil	70.89	61.19	-09.70
4	Dark soil	0.73	08.78	+08.05
5	Salty soil	09.66	03.00	-6.66
6	Urban area	01.84	03.50	+01.66

4. Conclusions

This study aimed to assess the detection and monitoring of desertification developments in Karbala city from 1990 to 2023. Remote sensing was employed to identify these discrepancies and analyze changes in satellite imagery data. Data were acquired from USGS, including Landsat images from Landsat 9, TM5, 7ETM, and 4TM. A supervised classification of the images was employed to identify changes across six categories: vegetation, aquatic bodies, soil, dark soil, saline soil, and urban regions. The classification accuracies for the years 1990, 2000, 2010, and 2023 were 94.46%, 93.82%, 91.06%, and 92.13%, respectively. Analysis reveals a 9.9% increase in vegetation over the previous thirty years, alongside a 14.21% drop in water bodies, a 7.64% reduction in soil areas, an 8.63% expansion of dark soil, a 0.27% rise in saline soils, and a 3.05% growth in urban areas.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

- [1] Abdel Rahman, M.A.E. (2023). An Overview of Land Degradation, Desertification and Sustainable Land Management Using GIS and Remote Sensing Applications. *Rendiconti Lincei. Scienze Fisiche e Naturali*. 34, 767–808. <https://doi.org/10.1007/s12210-023-01155-3>
- [2] UNCCD. (1994). Elaboration of an International Convention to Combat Desertification in Countries Experiencing Serious Drought and/or Desertification, Particularly in Africa; UN: Bonn, Germany,.
- [3] Rivera-Marin, D., Dash, J., Ogutu, B. (2022). The Use of Remote Sensing for Desertification Studies: A Review. *Journal of Arid Environments*. 206, 104829. <https://doi.org/10.1016/j.jaridenv.2022.104829>
- [4] Krasilnikov, P., Makarov, O., Alyabina, I., Nachtergaele, F. (2016). Assessing Soil Degradation in Northern Eurasia. *Geoderma Regional*. 7(1);1–10. <https://doi.org/10.1016/j.geodrs.2015.11.002>
- [5] Montanarella, L., Badraoui, M., Chude, V., Costa, I.d.S.B., Mamo, T., Yemefack, M., et al. (2015). Status of the World's Soil Resources: Main Report. FAO: Rome, Italy. ISBN 978-92-5-109004-6.
- [6] Reid, W.V., Mooney, H.A., Cropper, A., Capistrano, D., Carpenter, S.R., Chopra, K., et al. (2005). *Ecosystems and Human Well-Being: Synthesis, Millennium Ecosystem Assessment (Program)*, Ed., Island Press: Washington, DC, USA, 2005, ISBN 978-1-59726-040-4.
- [7] Sengani, D., Ramoelo, A., Archer, E. (2023). A Review of Fusion Framework Using Optical Sensors and Synthetic Aperture Radar Imagery to Detect and Map Land Degradation and Sustainable Land Management in the Semi-Arid Regions. *Geocarto International*. 38(1). <https://doi.org/10.1080/10106049.2023.2278325>
- [8] Hermans, K., McLeman, R. (2021). Climate Change, Drought, Land Degradation and Migration: Exploring the Linkages. *Current Opinion in Environmental Sustainability*. 50;236–244. <https://doi.org/10.1016/j.cosust.2021.04.013>
- [9] S. Leelavathy, S. Balakrishnan, M. Manikandan, J. Palanimeera, K. Mohana Prabha, & R. Vidhya. (2024). Deep Learning Algorithm Design for Discovery and Dysfunction of Landmines. *International Journal of Computational and Experimental Science and Engineering*, 10(4). <https://doi.org/10.22399/ijcesen.686>
- [10] Ferrari, G., Ai, P., Alengebawy, A., Marinello, F., Pezzuolo, A. (2021). An assessment of nitrogen loading and biogas production from Italian livestock: A multilevel and spatial analysis. *Journal of Cleaner Production*. 317, 128388. <https://doi.org/10.1016/j.jclepro.2021.128388>
- [11] SDG Indicator Metadata. (2024). Available online: <https://unstats.un.org/Sdgs/Metadata/Files/Metadata-15-03-01.Pdf> (accessed on 18 June 2024).
- [12] Mbow, C., Brandt, M., Ouedraogo, I., De Leeuw, J., Marshall, M. (2015). What Four Decades of Earth Observation Tell Us about Land Degradation in the Sahel? *Remote Sensing*. 7(4);4048–4067. <https://doi.org/10.3390/rs70404048>
- [13] Dubovyk, O. (2017). The Role of Remote Sensing in Land Degradation Assessments: Opportunities and Challenges. *European Journal of Remote Sensing*. 50(1);601–613. <https://doi.org/10.1080/22797254.2017.1378926>
- [14] Xie, H., Zhang, Y., Wu, Z., Lv, T. (2020). A Bibliometric Analysis on Land Degradation: Current

- Status, Development, and Future Directions. *Land*. 9(1), 28. <https://doi.org/10.3390/land9010028>
- [15] Costa, D.P., Herrmann, S.M., Vasconcelos, R.N., Duverger, S.G., Franca Rocha, W.J.S., Cambuí, E.C.B., et al. (2023). Bibliometric Analysis of Land Degradation Studies in Drylands Using Remote Sensing Data: A 40-Year Review. *Land*. 12(9), 1721. <https://doi.org/10.3390/land12091721>
- [16] Erdanaev, E., Kappas, M.W., Pulatov, A., Klinge, M. (2015). Short Review of Climate and Land Use Change Impact on Land Degradation in Tashkent Province. *International Journal of Geoinformatics*, 11(4);39–48. <https://journals.sfu.ca/ijg/index.php/journal/article/view/909>
- [17] Al-bukhari, A., Hallett, S., Brewer, T. (2018). A Review of Potential Methods for Monitoring Rangeland Degradation in Libya. *Pastoralism*. 8(1). <https://doi.org/10.1186/s13570-018-0118-4>
- [18] Wang, Z., Ma, Y., Zhang, Y., Shang, J. (2022). Review of Remote Sensing Applications in Grassland Monitoring. *Remote Sensing*. 14(12), 2903. <https://doi.org/10.3390/rs14122903>
- [19] Yuan, F., Sawaya, K. E., Loeffelholz, B., & Bauer, M. E. (2005). Land cover classification and change analysis of the Twin Cities (Minnesota) metropolitan area by multi temporal Landsat remote sensing. *Remote Sensing of Environment*. 98(2–3), 317–328. <https://doi.org/10.1016/j.rse.2005.08.006>
- [20] Jensen, J. R., & Lulla, K. (1987). Introductory digital image processing: A remote sensing perspective. *Geocarto International*. 2(1);65–65. <https://doi.org/10.1080/10106048709354084>
- [21] Wulder, M. A., White, J. C., Goward, S. N., Masek, J. G., Irons, J. R., Herold, M., et al. (2008). Landsat continuity: Issues and opportunities for land cover monitoring. *Remote Sensing of Environment*. 112(3);955–969. <https://doi.org/10.1016/j.rse.2007.07.004>
- [22] Shalaby, A., & Tateishi, R. (2007). Remote sensing and GIS for mapping and monitoring land cover and land-use changes in the Northwestern coastal zone of Egypt. *Applied Geography*. 27(1);28–41. <https://doi.org/10.1016/j.apgeog.2006.09.004>
- [23] Kheiralipour, K., Al-Ansari, N., Dibs, H. (2024). Monitoring air quality using ground and remote sensing based imaging techniques. *The Future of Imaging Technology*. 21–40. <https://urn.kb.se/resolve?urn=urn:nbn:se:ltu:diva-110047>
- [24] Al-Janabi, A. M. S., Dibs, H., Sammen, S. Sh., Yusuf, B., Ikram, R. M. A., Alzuhairy, S. H., & Kisi, O. (2024). Comparison Analysis of Seepage Through Homogenous Embankment Dams Using Physical, Mathematical and Numerical Models. *Arabian Journal for Science and Engineering*. <https://doi.org/10.1007/s13369-024-09224-x>
- [25] Hashim, F., Dibs, H., & Sabah Jaber, H. (2022). Adopting Gram-Schmidt and Brovey Methods for Estimating Land Use and Land Cover Using Remote Sensing and Satellite Images. *Nature Environment and Pollution Technology*. 21(2);867–881. <https://doi.org/10.46488/nept.2022.v21i02.050>
- [26] Hashim, F., Dibs, H., & Jaber, H. S. (2021). Applying Support Vector Machine Algorithm on Multispectral Remotely sensed satellite image for Geospatial Analysis. *Journal of Physics: Conference Series*. 1963(1), 012110. <https://doi.org/10.1088/1742-6596/1963/1/012110>
- [27] E. Selvamanju, & V. Baby Shalini. (2024). 5G Network needs estimation & Deployment Plan Using Geospatial Analysis for efficient data usage, Revenue Generation. *International Journal of Computational and Experimental Science and Engineering*, 10(4). <https://doi.org/10.22399/ijcesen.692>