ISSN: 0974-5823 Vol. 7 No. 1 January, 2022

International Journal of Mechanical Engineering

Change Detection in Land Use/Cover (LULC) for the Sustainable Development in Karbala, Iraq

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Abstract

Land use/Land cover change (LULCC) is critical to planning sustainable natural resource management, Given its extent, direction, and causes. To achieve this goal in Karblaa/ Iraq, we used ERDAS imagine 2015 to do the supervised classification using maximum probability technology. Adopting period from 2001 to 2017 as a time frame for studying LULCC dynamics. This satellite data is for Land Use/Land Cover (LULC) analyzed in the study area. Agricultural land, urban land, barren land and water bodies were identified using multispectral satellite data (Landsat 5 TM images and Sentinel-2 MSI images) for assessing rates of change, trends, and magnitude of changes in LULC between 2001 and 2017. The results showed that agricultural lands and urban lands increased during the adopted period by about 1.24% (60.686 km2) and 8.05% (393.6603 km2), respectively, while water bodies and barren lands decreased by about 6.89% (337.088 km2) and 2.40%. (117.258 km 2), respectively. Finally, the accuracy assessment was performed and its results showed that the overall accuracy of the images classified for the years 2001 and 2017 were 90.88% and 91.03%, respectively. The total Kappa values for the two rated images were 0.7820 and 0.7938 respectively. Hence, these figures show that the accuracy of LULC classes is within acceptable limits.

Keywords: Supervised classification, sustainable development, Karbala, land use/cover, change detection.

1. Introduction

The most intense contact between humans and environment takes place on and beneath the ground, which is the foundation of human existence [1]. Earth observation (EO) data is used to track resource efficiency and analyze progress toward reaching the Sustainable Development Goals (SDGs) [2]. Sustainability is a necessary requirement for human society to continue to exist. Because of the growing number of environmental issues, the subject of sustainable land use is becoming increasingly important [3]. That sustainability should be viewed as a socially and politically constructed idea that has also been influenced by business [4]. Following the 1987 Brundtland Report, Our Common Future, and the 1992 United Nations Conference on Environment and Development, SD as a concept gained traction (UNCED), also known as the Earth Summit. Though SD thinking is widely acknowledged to have its origins in the 1972 United Nations Conference on the Human Environment, environmental conservation, and social justice and inclusion[5]. Because of the recurring nature of the data collection, the digital format's suitability for computer processing, and the precision of the georeferencing processes, For detecting, quantifying, and mapping LULC patterns and fluctuations, satellite remote sensing is the most widely used data source. Using several multi-date photos, change detection and monitoring by remote sensing requires analyzing differences in LULC between picture acquisition dates induced by a variety of environmental circumstances and human activity [6]. For the first time in the 1990s, global datasets obtained from the AVHRR allowed for the mapping of large scale land cover based on land surface features seen through remote sensing [7]. (AVHRR) (Advanced High Resolution Radiometer) A multipath scanning device with five spectral bands, with an accuracy of 1.1 km, that scans the Earth twice a day (https://www.avl.class.noaa.gov/release/data_available/avhrr/index.htm). Due to diverse socio-economic activities and natural occurrences, the earth's surface is undergoing fast Land use/Land cover (LULC) changes [8]. The world's population has been increasingly concentrated in cities or towns as a result of urbanization. Rapid urbanization has become a serious concern in the twenty-first century; the world's urban population is anticipated to expand by 84 percent by 2050, from 3.4 billion in 2009[9]. It is important to review previous studies of the use of remote sensing to analyze and detect land use/land cover change, for example For the Erbil Governorate in Iraq's Kurdistan Region, Napas and Sarchel analyzed and predicted future LULC changes. Three LULC maps were created with various categories, and then a change detection analysis was performed [10]. Claudia and Ines investigated the change detection of two multispectral datasets for the Bostanlik District of Tashkent, Uzbekistan, using Landsat-5 TM data from 1989 and Landsat-8 OLI data from 2017. The results, which were divided into six land use classifications, could be useful to government officials and stakeholders in future land use planning operations [11]. We employed multispectral photos with customized selection bands to find change detection over a 16 year period in this investigation. In the territories of Karbala Governorate / Iraq, photographs taken in 2001 were analyzed and compared to images taken in 2017 in four categories of sustainable development.

2. Changes in Land Cover.

Significant progress has been made in the field of land use/cover change modeling since the Land Use/Land Cover Change (LULCC) project began in 1995. One of the main objectives of the project was to develop a new generation of land use/cover change models capable of recreating the key socio-economic and biophysical processes driving land use and land cover change, according to a scientific strategy[12]. The initial phase in the procedure entails determining the rates at which land cover changes over time for various development patterns[13]. Land Use/Land Cover Change (LULCC) are influenced by both natural and human activity[14]. Conversion is a term used to describe the process of completely replacing one land-use /land-cover type with another (i.e., entirely replacing one Land-Use /Land-Cover type with another) and alteration (i.e., more subtle changes to the Land Use /Land Cover character without affecting the overall classification) are the two types of LULCC [15].

2.1. Changes in Land Cover and Climate Conditions.

Land-Use And Land-Cover (LULC) changes caused by humans have a significant impact on climate and the environment. Urbanization is a particularly extreme example of LULC change[16]. Changes in the water balance and energy budget caused by Land Use and Land Cover change (LULCC) have an impact on regional climate. Variations in the amount and frequency of precipitation, as well as changes in surface temperatures, are common manifestations of these consequences [17]. In dry and semi-arid regions, Land Use/Land Cover change (LULCC) and climate change are to blame for ecological degradation. For any type of sustainable development studying ecological changes is very important, which LULCC as one of the most important inputs. Using remote sensing, the main objective is to assess the effects of LULCC and climate change on ecosystem vulnerability (ESV)[18].

2.2 The Land Cover Changed Due to political Conflicts .

The effects of armed conflict on ecosystems are complicated and difficult to evaluate due to restricted access to damaged areas during warfare, making satellite remote sensing a useful tool for analyzing conflict's direct and indirect environmental repercussions[19]. Shocks can cause abrupt changes in Land Use decisions, and warfare and armed conflicts are among the most severe and internationally common shocks[20]. Internal or international armed conflict is still a prevalent problem that impacts many parts of the globe. Can result in a violent struggle for scarce resources such as arable land and fresh water due to heavy population pressure in recent times[21]. Armed conflict can occasionally have a positive impact on biodiversity. When people avoid or flee places of violence or militarism, wildlife can be conserved. Since 1953, the demilitarized zone between North and South Korea has maintained thriving natural habitat and wildlife populations, is a notable example of this "refuge effect."[22]. Iraq was previously considered rich in water and had a semi-arid subtropical climate, but a lack of water resources has developed in recent years due to a variety of factors, among the issues to be addressed are climate change and dam construction by neighboring countries[23]. In addition to the shorting Governments that neglected these resources and did not take care of them, these cased the changing negatively on Land Use \ Land Cover in this country including the study area (Karbala governorate).

3. The Study Area .

Karbala is one of Iraq's religiously influenced cities, It influenced the urban and population structure of the city, which might be seen in the Land Use planning, agricultural area, water bodies represented by Al-Razzaza lake which is the biggest lake in Iraq, and the untapped resource represented by the bare area. All these give the study area significance which push us to study the change detection that has effect on sustainability development in this governorate. In central Iraq, Karbala is located in the Mesopotamian zone, With a total area of 5,034 km2, it is located west of the Euphrates River and about 100 kilometers southwest of Baghdad, between 44° and 40° longitude and 33° and 31° latitude. Anbar Governorate to the north and west, and Najaf Governorate to the south, form its borders, Babil Governorate, on the other hand, is located in the east[24]. Among the most important architectural and cultural monuments is the shrines of Imam Hussein and Imam Abbas (peace be upon them), in addition to being spiritual centers for Shiite Muslims. As a result, the old downtown district and the city of Karbala were directly affected by their location[25].(Fig .1) illustrates the chosen area.

Figure (1) Area of Research[26].

4. Materials and Methods.

4.1. Remote sensing and data preprocessing.

The USGS Earth Explorer website provided separate, cloud-free Landsat TM and MSI data for the study area in 2001 and 2017 (http://earthexplorer.usgs.gov/). This research used Landsat and Sentinel-2 images because they are inexpensive, readily available, and have medium to high spatial resolution[27]. Table (1) contains information regarding the data. The radiative flux recorded by the remote sensing device at different bands should, in theory, be an accurate depiction of the radiative flux that actually leaves a feature of interest on the Earth's surface (for example, soil, vegetation, water, or urban land cover). The overlapping atmosphere between the terrain in question and the remote sensing system generates a lot of noise because the energy captured by the sensor differs from the energy reflected or emitted by the terrain[28].

Table (1) Details on the Satellite Data Used in This Study

Date of photography		**Sensor**	**Spatial Resolution of Reflective Bands**	**Number of Bands**	**Format**
2001	2001-03-10	Landsat 5 TM	30 m	7	Geo TIFF
	2001-03-10		30 m	7	
	2001-03-19		30 m	7	
2017	2017-03-10	Sentinel-2 MSI	(10,20,60)m	13	JPEG 2000
	2017-03-10		(10,20,60)m	13	
	2017-03-13		(10,20,60)m	13	
	2017-03-13		(10,20,60)m	13	

4.2. Methodology of Research.

(Fig.2) depicts the study's comprehensive methodological framework and data analysis, with the following aspects of methodology:

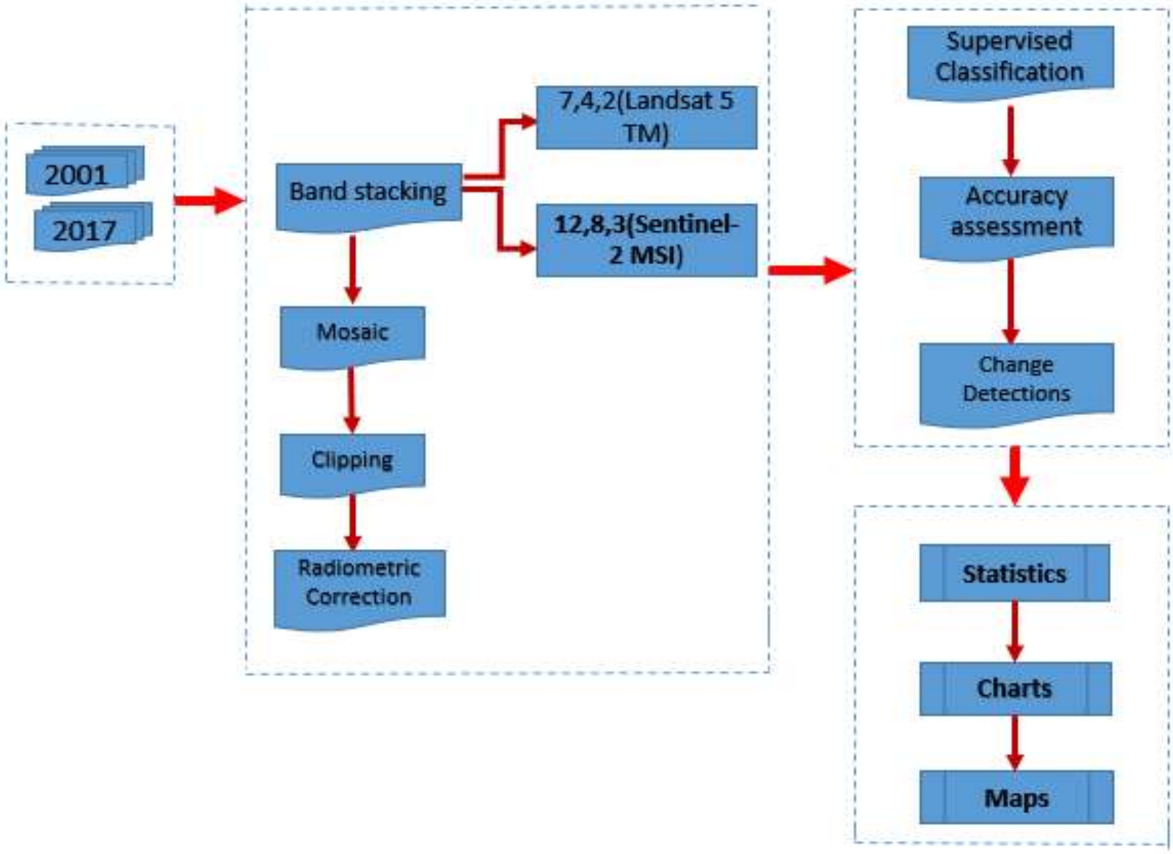

Figure 2: Land Use and Land Cover Change Monitoring Methodologies.

4.3. Classification process .

The classification process aims to classify all the pixels in a digital image for a land cover class or subject. Objective maps of the land cover present in the image can then be produced using this disaggregated data. The purpose of image classification is to identify and show the features that occur in the image in terms of the object or kind of land cover that these features truly represent on Earth as a distinct gray level (or color)[29]. Algorithms that "learn" patterns in data to predict a discrete related category are known as supervised classification approaches machine learning approaches refer to a group of flexible statistical prediction techniques. "The programming of computers to enhance a performance criterion using example or data from past experience" is how machine learning is defined[30].The classification is then supervised in the ERDAS Imagine 2015 using the maximum likelihood algorithm , which was used to analyze land use/cover change between 2001 and 2017 as shown in Figure (3-a,b).

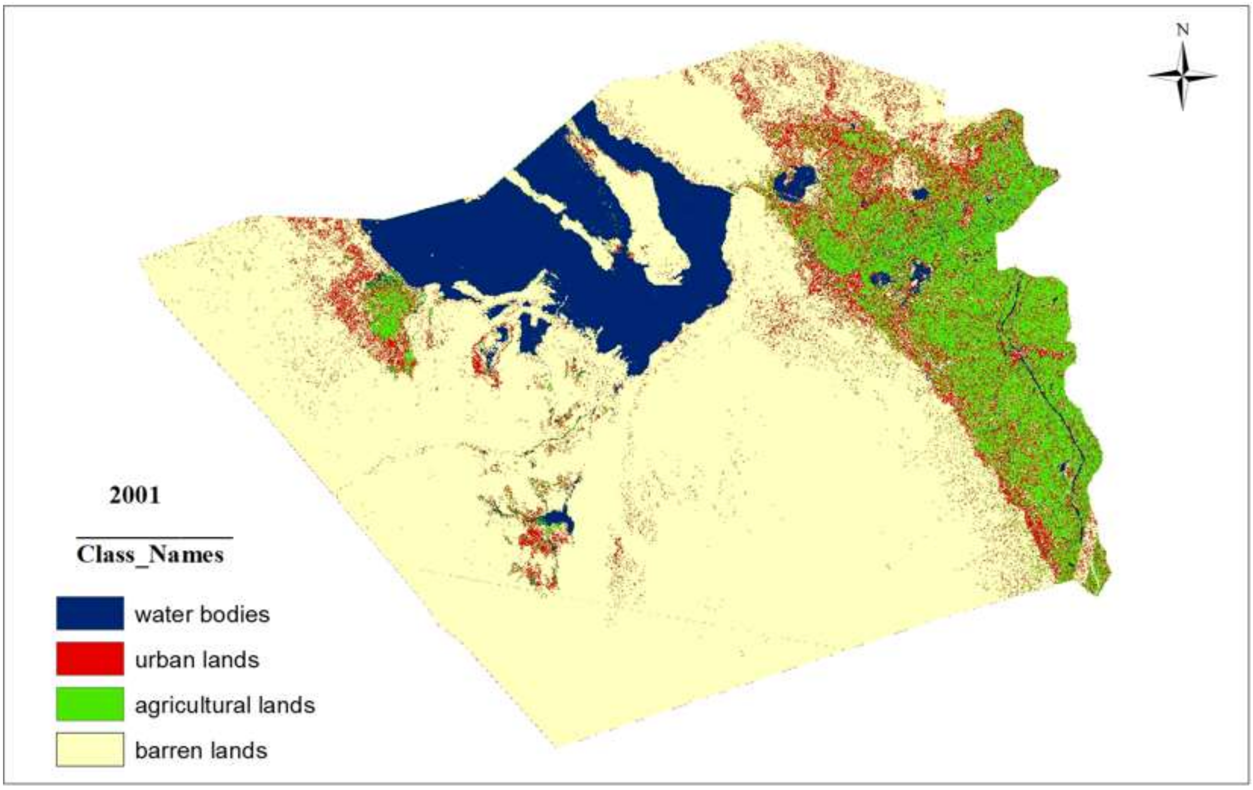

Figure (3-a)

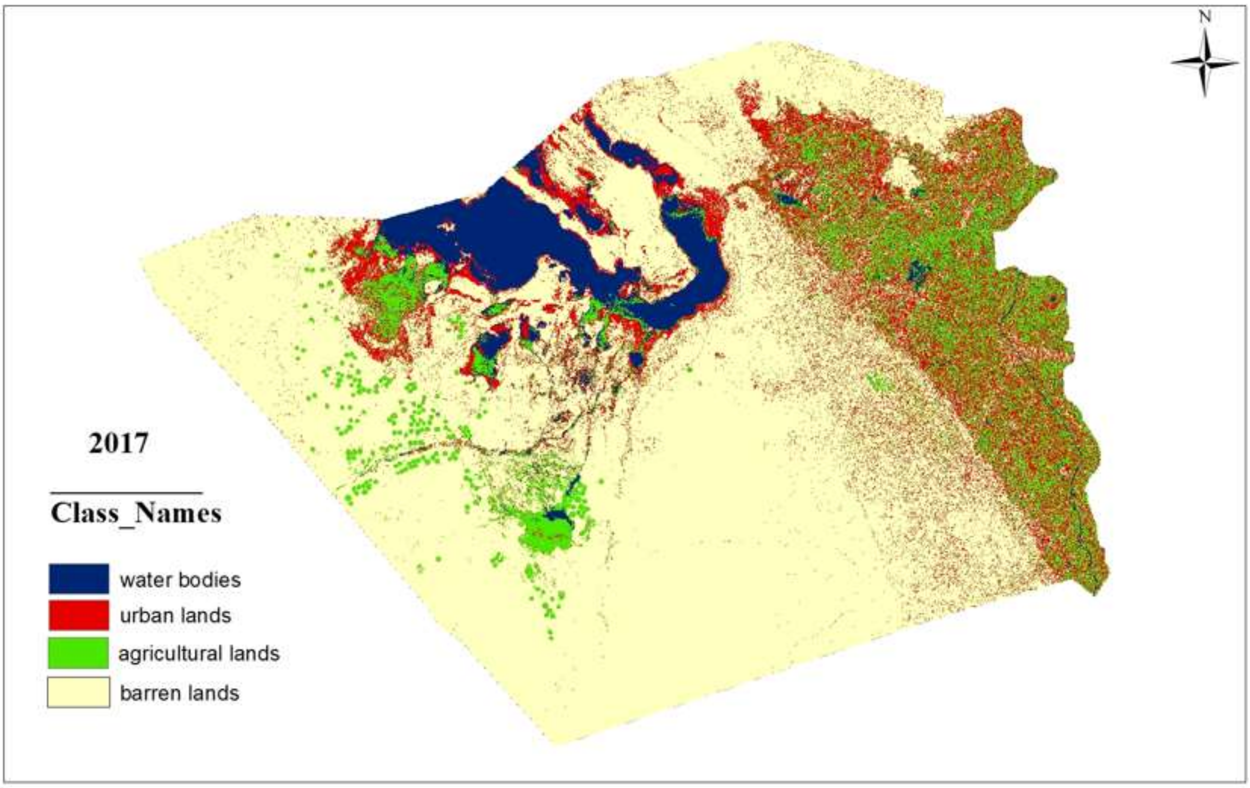

Figure (3-b)

Figure (3-a,b) Land use and land cover maps of Karbala Governorate in Iraq, based on the Landsat Thematic Satellite Chart and Sentinel-2 MSI from 2001 to 2017

5 .The Result and Discussion.

5.1. Analyze the changes in Land Use / Cover.

LULC was classified into four classes in the study area, (1) water bodies (2) agricultural land (3) urban land (4) barren lands, in (Fig. 4). The data show that in the 2001 picture, about 11.83% (579,335 km²) was water bodies, 10.31% (504,842 km²) was agricultural land, 8.13% (398,413 km²) was urban land, and 69.73% (3412.35 km²) was barren lands and all shown in (Fig. 5). While LULC was classified into four categories in the study area in the 2017 image, about 4.94% (242.247 km²) of water bodies, which decreased by 6.89% of the area as a result of the decrease in the waters of Lake Al-Razzaza during this period. 11.55% (60.686 km²) of agricultural land increased by 1.24%, while 16.18% (393.6603 km²) of urban land indicated an increase of 8.05% of area, and 67.31% (117.258 km²) of barren lands decreased by 2.40 % in the area. Compare with LULC 2001, respectively (Table 2).

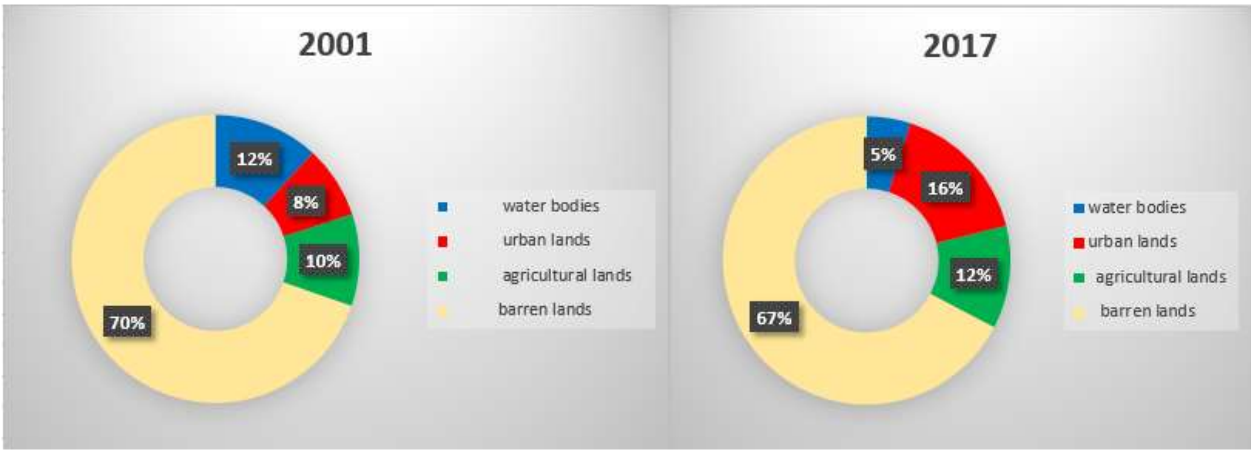

Figure (4) PI Diagram Showing the Percentage of Land Use Land Cover during the years 2001 and 2017.

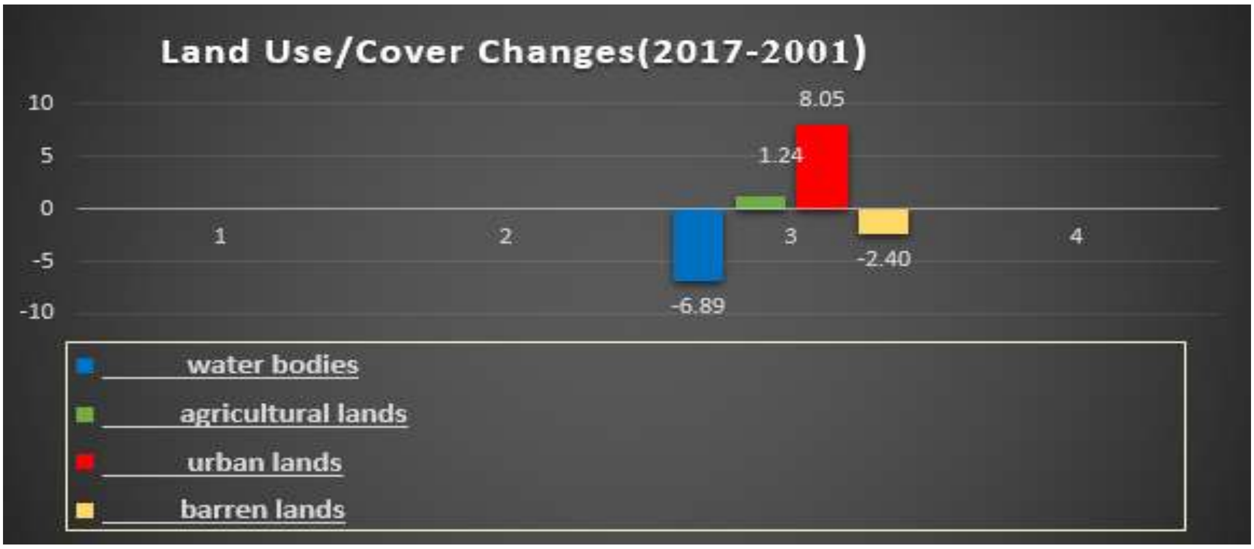

Figure (5) Changes in Land Use/Cover between 2017 and 2001.

Table (2) Area and percentage change in different usage/cover categories in Karbala Governorate / Iraq between 2001 and 2017

LULC	2001 (km2)	%	2017 (km2)	%	Change in Area(km2)	Change in %
water bodies	579.335	11.83	242.247	4.94	-337.088	-6.89
agricultural lands	504.842	10.31	565.528	11.55	+60.686	+1.24
urban lands	398.413	8.13	792.0733	16.18	+393.6603	+8.05
barren lands	3412.35	69.73	3295.092	67.31	-117.258	-2.40

5.2. Accuracy assessment.

In remote sensing applications, classification is a popular image processing technique for extracting thematic data for mapping. The classification process is influenced by a variety of factors. However, accuracy assessment is not possible without classification, And classification is only half of image processing, it is incomplete. The classification accuracy assessment indicates how well the categorization process was carried out[31]. As a result, an accuracy assessment for individual categorization is required, and an accuracy assessment was conducted for years of 2001 and 2017 photos to determine the quality of information generated from satellite data. The evolution of traditional RS accuracy assessment best practices was summarized . The importance of unbiased, randomized sampling for the generation of summary accuracy statistics is now widely acknowledged, This is usually presented in the form of a table known as a error matrix or confusion matrix. Summary metrics such as the overall accuracy (OA) and the Kappa coefficient statistic are computed using this table[32]. The cells of the error matrix summarize agreement and disagreement. Simple descriptive statistics or multivariate analytical statistical approaches can be used to assess the information in the error matrix. Confusion matrix (error matrix) is a square matrix of numbers with columns and rows that express the number of sample units assigned to each category compared to the true classification as specified in the field. The rows represent the categorization created from remotely sensed data, while the columns represent the reference data[33]. In image classification, the Kappa coefficient statistic is used to quantify the agreement between two sets of categorizations of a dataset while accounting for chance agreements between categories. This statistic is particularly valuable in landscape ecology and wildlife habitat studies for measuring the accuracy of prediction models by comparing the predictive model's agreement with a set of field-surveyed sample points. The Kappa statistic uses both the overall accuracy of the model and the accuracies within each category to account for chance agreement within categories, both in terms of the prediction model and the sample sites surveyed in the field[34]. In order to represent different types of land cover in the current study, a stratified random approach was used. The basepoint reference data was confirmed using previous satellite data from Google Earth, to assess accuracy for 2001 and 2017. Figure (6) and (7) show synchronization of Erdas images with Google Earth respectively. In addition to the confusion matrix (error matrix) (Table 3 and 4), Compare 450 reference points to the corresponding pixels for the LULC characteristics of the sorted photos to determine the user's correctness, All LULC classes' product accuracy and kappa coefficients, as well as overall resolution and Kappa aggregate coefficients. Table (5) represents the correctness of statistical data evaluation in 2001 and 2017, the total accuracy of categorised pictures was compared was 90.88 % and 91.03 %, respectively, according to the findings. The total kappa values for the categorized photos in 2001 and 2017 are 0.7820 and 0.7938, respectively. As a result, these data show that the rated LULC properties are accurate enough.

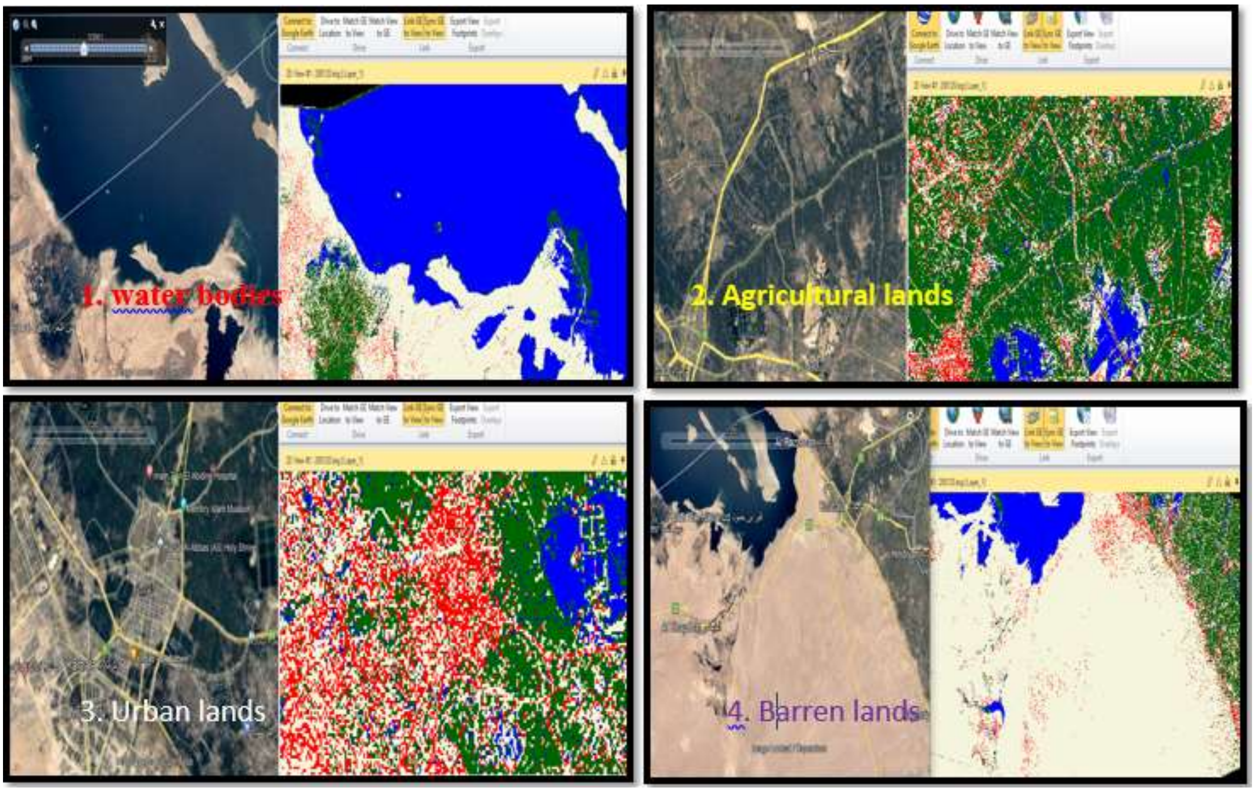

Figure (6) Synchronization of the ERDAS Images 2015 with Google Earth for the year 2001

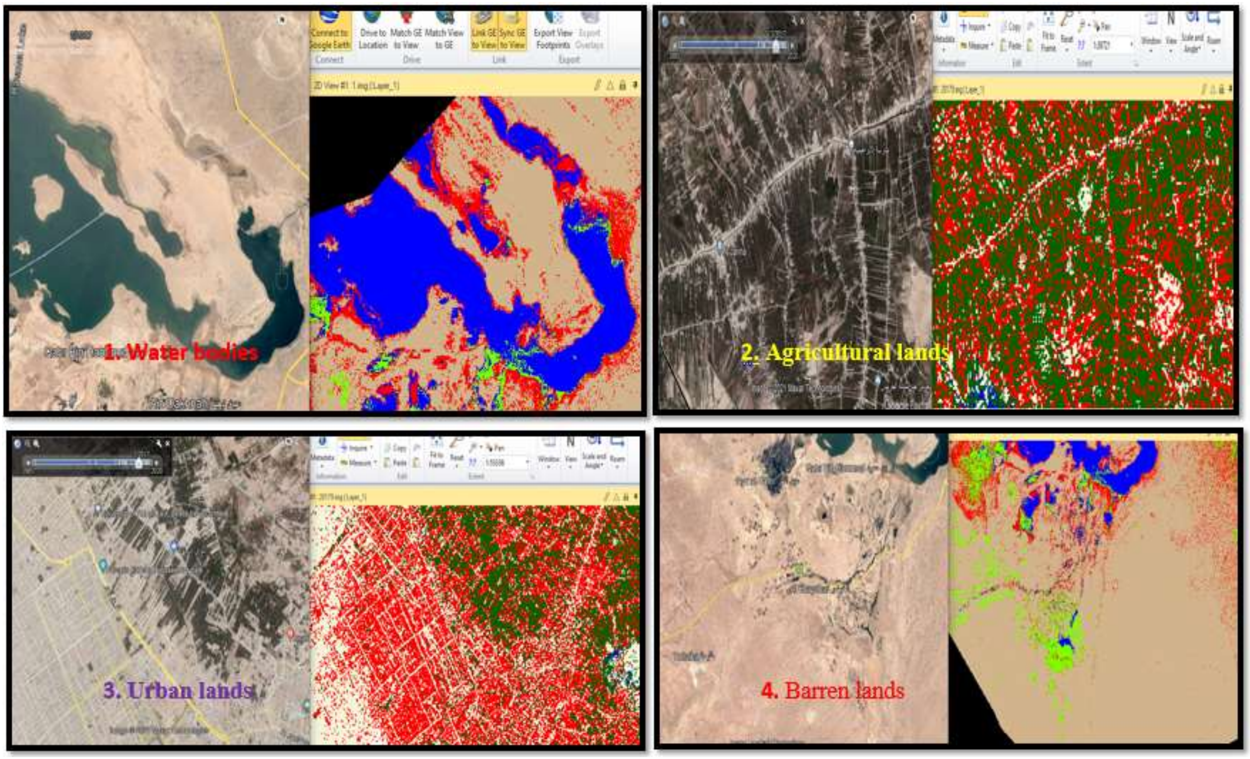

Figure (7) Synchronization of ERDAS Images 2015 with Google Earth for the year 2017.

Table 3: The Accuracy Assessment of Supervised Classification in 2001 is represented as an error matrix

S. No.	LULC	water bodies	agricultural lands	urban lands	barren lands
1	water bodies	28	1	0	2
2	agricultural lands	1	22	1	2
3	urban lands	0	1	5	0
4	barren lands	6	4	6	195

Table 4: The Accuracy Assessment of Supervised Classification in 2017 is represented as an error matrix.

S. No.	LULC	water bodies	agricultural lands	urban lands	barren lands
1	water bodies	7	0	0	3
2	agricultural lands	0	38	3	4
3	urban lands	0	1	23	4
4	barren lands	0	5	8	216

Table 5: Assessment of Accuracy of Supervised Classified Landsat 5 and Sentinel-2 Satellite Images for 2001 and 2017

S. No.	LULC	User Accuracy in %		Producers Accuracy in %	
		2001	2017	2001	2017
1	water bodies	85.71	70.00	80.00	100.00
2	agricultural lands	84.62	84.44	78.57	86.36
3	urban lands	83.33	82.14	38.46	67.65
4	barren lands	92.42	94.32	97.99	95.15
Total corrected reference points				274	312
Overall classification accuracy				90.88	91.03
Overall Kappa coefficient				0.7820	0.7938

6. Conclusions.

This study has given changes detection in Land Use/Land Cover that serve the sustainable development in Karblaa governorate. Where has explained the reality of the changes whether these changes are positive or negative. Remote sensing and geospatial approaches were shown to be crucial in identifying satellite sensor data in this study. using the supervised classification of maximum likelihood algorithm, it is accurate, simple and effective to monitor LULC changes during 2001, 2017. The current study reveals that the proportion of water bodies decreased by 6.89% (337.088km2). Agricultural land increased by 1.24% (60.686 km²), urban land increased by 8.05% (393.6603 km²), and barren lands decreased by 2.40% (117.258 km²). Finally, we came to the conclusion that the supervised classification findings obtained by GIS and remote sensing explained the significant changes in land surface features in the current research area over the course of 16 years. The results of this study share for introducing useful information to the sustainability development in Karbala governorate as part from the globally sustainability development goals (SDGs) that should be verified in the period (2015-2030) according to the Paris conference agreement about this issue.

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