Using Landsat data for detection the land cover changes between 2000 and 2021 in Al Najaf City, Iraq

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Abstract

Al Najaf city has encountered critical changes in the land use land cover LULC caused by human practices. This exacerbated land debasement and ecological problems. This research evaluates the rate and extent of changes in LULC Over the course of twenty-one years 21 years using a geographic information system (GIS) as well as remote sensing data to secure a quantitative comprehension of spatiotemporal elements of LULC. The multi-temporal data of Landsat 5 TM in 2000 and Landsat 8 OLI in 2021, were utilized to assess the land cover maps. The supervised classification of both remote sensing images was performed for the years 2000 and 2021 to extract the spatial pattern of land cover change. Overall accuracy and Kappa coefficient were calculated using 200 reference points. Change detection results utilizing Land Change Modeler between (2000-2021) showed a critical increment (7.75%) in the agricultural region from (25.11%) in 2000 to (32.86%) in 2021, followed by a remarkable increase (3.03%) in the urban zone from (6.36%) in 2000 to (9.39%) in 2021. On the contrary, bare soil and desert cover declined drastically by 8.66% and 8.43 % respectively. Based on change analyses, 129 km^2 and 71 km^2 of desert land and bare soil respectively were converted to Agriculture. This indicates a remarkable expansion in urban and agricultural land in this area. The other categories showed a slight transition of the land cover between 2000 and 2021. The overall accuracy results for 2000 and 2021were about 90.1 and 92 respectively, whereas kappa index for every year were 0.90. These work results can uphold decision-production towards reclamation proportions of land debasement and long-haul natural protection in the area.

Keywords: Landsat, LULC, Supervise classification, Kappa coefficient, Overall accuracy

Introduction

Human changes in land use and land cover (LULC) have led to significant changes in biological and geochemical systems on Earth, which exacerbated global environmental problems **(Prakasam, 2010; Firozjaei et.al., 2018).** Information on LULC changes can be used to make recommendations for the management of natural resources and local socioeconomic development in a particular region. Consequently, there is a need to monitor, analyze and understand the transformation of LULC changes to provide accurate and timely information on land-use properties and changes to the local authorities irrespective of sustainable development **(Reis et.al., 2018; Srivastava et.al., 2013; Pervez et.al., 2016; Liping et.al., 2018)**. Changes in the land surface are divided into two categories: Land use and land cover. The phrase "land use" refers to the use of a given piece of land for a certain purpose, such as urbanization, agriculture, mining, and so on. The expression "land cover" refers to the features located on the earth's surface, such as trees, pavement buildings, and so on Change detection is the quantitative analysis of changes in land cover classes using multi-temporal datasets. Traditional approaches and remote sensing technology can be used to detect changes. Traditional approaches are costly, time-consuming, and inaccurate, but remote sensing technology solves all of these issues **(Mishra et al., 2017)**. Remote sensing techniques along with systems of geographic information have been widely adopted as fundamental and beneficial tools for obtaining precise spatial data about LULC and measuring spatial data alternatives **(Nguyen et.al., 2020).** Several methods have been employed to detect changes in the land cover, for instance comparing classifications of land cover, multi-temporal classification, vegetation index differentiation, image differentiation, principal component analysis, and change vector analysis **(Coppin et al., 2004; Mei et al., 2016).**

This research aims to analyze changes in the land cover of Al Najaf Governorate for the period between 2000 and 2021 using Landsat images.

Study Area

Al-Najaf Governorate is laying in the Middle Euphrates zone of Iraq, about 161 km southwest of the capital, Baghdad. Geographically, sited between 32°15'- 29°50' " Latitudes and 44°44'-42°50' Longitude (Figure 1). The mean height of Najaf is approximately 70 meters above the level of the surface. A study area of 2,194 km2 was selected from the province of Najaf between the latitudes of 32°20'30" and 31°35'54" and the longitudes of 44°35' 22" and 43°58' 11" for this paper. The study region included urban, bare soil, desert, water bodies (lake and river), and agricultural land.

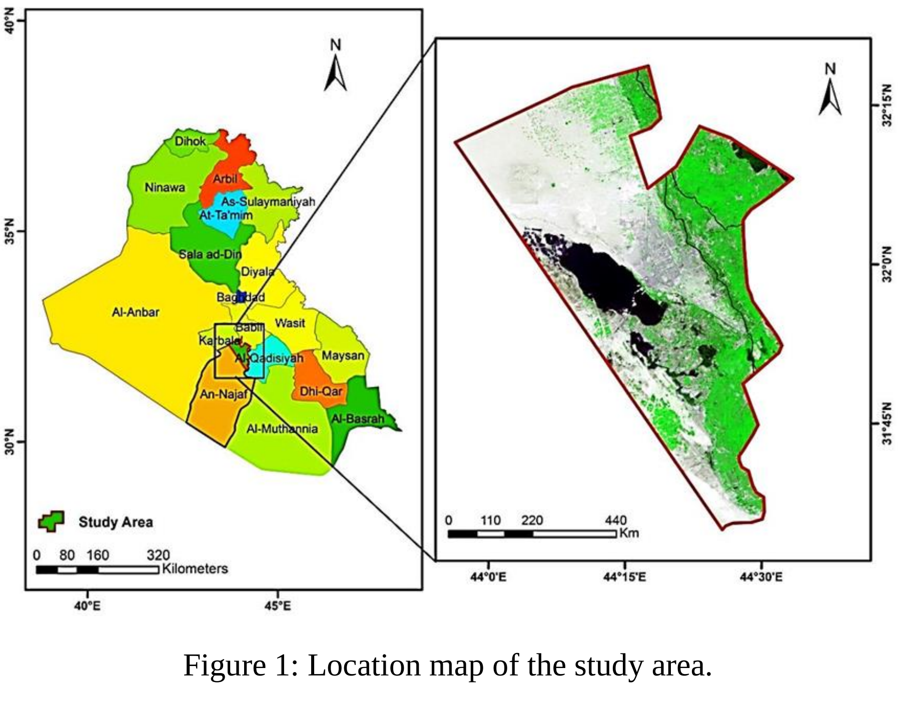

Figure 1: Location map of the study area.

1. Materials and methodology

3.1 Data acquisition

Two Landsat Imageries (Landsat 5 TM and Landsat 8 OLI) for 30 m resolution were obtained from the United States Geological Survey (http://earthexpolorer.usgs.gov/), significant information is summarized in Table 1. All these images were taken on satellite track path/row:168/038 and projection in UTM with WGS-84 datum 37 N.

Table 1: Summary of data acquisition

Type of Satellite sensor	Path/Row	Acquisition date	Resolution
Landsat 5 TM	168/038	February 29, 2000	30 m
Landsat 8 OLI	168/038	March 17, 2021	30 & 15 m

3.2 Image classification and mapping

Supervised classification is the most commonly used procedure for quantitative analysis of remote sensing image data. Supervised classification methods are based on the external knowledge of the area **(Khan, 2013)**. Supervised methods require input from the user before applying the selected algorithm. These inputs may be derived from fieldwork, analysis of aerial images, reports, or study of appropriate maps of the area of concern. The maximum probability classification for more accurate land-use changes detection studies, **(Lu, et al. 2007 and Otukei, et al 2010)** is therefore adopted in this research in the study area classification. Pixel units are classified into the category with the highest probability of belonging **(Perumal,et al, 2010).** The main advantage of ML is that it takes into account not only the average or the rate in the classification process but also the variation of brightness values in each category. In addition, ML is considered flexible and useful under any condition and may provide the most effective means of classifying land use. This is because the ML classifier assesses the variation between categories and the variation in spectral response patterns of the category in quantification.

3.3 Arrangement Accuracy Assessment

A precision evaluation indicates how well the basic actuality appears on the equivalent classified imagery. As land use maps derived from image classification usually contain some errors, the accuracy of the resulting classification results should be evaluated. An evaluation of classification accuracy provides confidence in the outcomes and the detection of the subsequent changes **(Nguyen, et al 2015).** In order to assess the accuracy, the classified map was compared with basic truth information. The reference points for 2000 and 2010 were gathered from Google Earth, maps, and original Landsat images. For the 2021 image, the field survey was conducted using GPS and included Google Earth, original Landsat images, and field observations of random reference locations in various LULC categories. The common and most effective method used to measure the accuracy of the classified image from remotely sensed imagery is an error/confusion matrix **(Lucia, et al, 2019).** Overall accuracy, producer accuracy, user accuracy, and kappa statistics are all provided by the confusion matrix. Equation (1) was used to compute the Kappa coefficient **(Jenness, et al, 2015)**. A kappa coefficient worth less than 0.4 indicates poor agreement, while a value between 0.4 and 0.8 shows moderate agreement, and a value more than 0.8 depicts a strong agreement **(Mishra, et al,2016).**

$$K = \frac{The\ total\ sum\ of\ correct - Sum\ of\ all\ the(row\ total \times column\ total)}{Total\ squard - Sum\ of\ all\ the(row\ total \times column\ total)}$$

1. Results and Discussion

4.1 Image Classification

In this study, the unsupervised classification of the study area was applied using the Maximum Probability Classifier in the ArcGIS 10.8 program for s Landsat images (TM and OLI/TIRS) obtained in 2000 and 2021. The study area was classified into five land cover categories (water, Agriculture, Bare soil, Desert area, and urban areas). Table (2) shows the areas and percentages of the different land cover categories for the two years 2000 and 2021.

Figure (2) represents the spatial distribution of land cover patterns for the years 2000 and 2021. In 2000, the desert areas occupied the highest percentage of the total study area, with an estimated area of 795.7km^2 and a percentage of 36.27%. It is followed by the bare soil land, with an area of about 650.98 km^2 (29.67%) of the total area considered, agricultural land, with 551.7 km^2 (25.15%) of the area. The water bodies covered 128.86 km ^{2} (5.87%). In 2021, agricultural areas covered the first of the net studied area of 720.95 km ^{2} (32.86%), followed by arid lands, which occupied 621.89 km^2 (27.93%). It was followed by the bare soil land about of 461.25 km^2, (21.03%) of the area of study, water bodies with an area of 192.62 km^2 (8.78%), and urban areas of 206.1km^2 (9.40%) of the total area.

Table 2. Area and percentage of land cover categories for years 2000 and 2021

Classification	2000		2021	
	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)
Water bodies	128.86	5.87	192.62	8.78
Agricultural land	551.71	25.15	720.95	32.86
Bare soil	650.98	29.67	461.25	21.03
Desert	795.71	36.27	612.89	27.93
Urban areas	66.49	3.04	206.04	9.40
Total	2193.75	100	2193.75	100

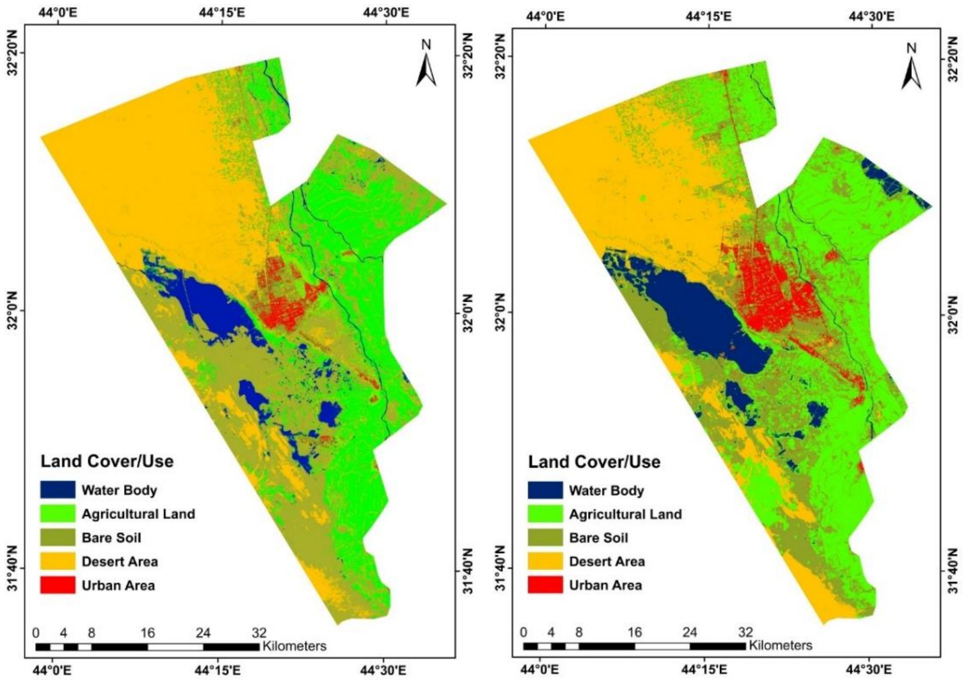

Figure 2: The distribution of LULC of the Al Najaf city in left 2000 and right 2021.

4.2 Accuracy Assessment

The assessment of image classification accuracy is an important step in determining the reliability of the results obtained **(Lilesand 2008).** The classification accuracy assessment was carried out using the random sampling technique for each land cover category of the disaggregated maps for the years 2000 and 2021. Approximately 200 random points per study area were taken from all land cover categories. Then, using data from the Sentinel-2 satellite in RGB (Red, Green, Blue) color and a Google Earth map, the points of verification have been visually interpreted. The error matrix table 4 has been used to calculate the Kappa coefficient and total accuracy.

Table 4: Error matrices.

			2000			
Land Classes	Water body	Farmland	Bare soil	Desert Area	Urban	Total (User)
Water body	27	0	3	0	0	30
Farmland	0	42	3	0	0	45
Bare soil	0	0	45	4	1	50
Desert Area	0	0	3	44	0	47
Urban	0	0	6	0	24	30
Total (Producer)	27	42	60	48	25	202

	2021					
Land Classes	Water body	Farmland	Bare soil	Desert Area	Urban	Total (User)
Water body	27	2	1	0	0	30
Farmland	0	48	1	0	0	49
Bare soil	0	0	37	3	1	41
Desert Area	0	0	2	46	1	49
Urban	0	0	5	0	26	31
Total (Producer)	27	50	46	49	28	200

Table 3 shows the accuracy of the classified maps for the two years (2000, 2021) the values of total accuracy were (90.1 and 92) respectively, and the Kappa coefficient value was 0.9 for each of 2000 and 2021. Based on **(Anderson,1976),** total accuracy for determining land cover categories must be at least 85%, which means that the classification accuracy obtained in this study was at a high level of accuracy.

Table 3: Accuracy assessment of classified LULC maps for 2000 and 2021.

LULC Class	Producer's Accuracy%		User's Accuracy%	
	2000	2021	2000	2021
Water	100	100	90	90
Agriculture	100	96.0	93.3	98
Bare soil	75	80.4	90	90.2
Desert	91.7	93.9	93.6	93.9
Urban	96	92.9	80	83.9
Total Accuracy	OA%		K	
	90.1	92.0	0.90	0.90

4.3 LULC Change Analysis

The LULC changes study provides a good understanding of alteration or loss of natural landscape elements such as vegetation clearance, agricultural land, and water bodies as valuable information for land use planning and environmental management (Wang et al., 2021). Land cover data with a 21-year interval, from 2000 to 2021, was used to conduct the LULC change analysis. The dynamics of land cover change have been relatively high over the last 21 years. The desert area and bare soil were continuously decremented by 183 km^2 and 190 km^2 with a negative annual rate of changes of 8.71 and 9.3 km^2/year respectively. On the other hand, agricultural land has expanded considerably around 169 km2 at an annual average of change of 8.05 km^2, followed by Urban land which increased by 140 km^2 at an annual average of change of 6.65 km^2 per year. A smaller increase has been detected in the water bodies, which is 64 km2 with an annual rate of changes of 3.05 km^2/ year. The important LULC changes that took place within the study zone between 2000 and 2021 are summarized in Table 4 and Figure 3.

Table (4) Change in land cover for the period (2000-2021)

LULC Classes	2000	2021	Change between 2000-2021		Annual Rate change 2000-2021	
	Area (km^2)	Area (km^2)	MC (KM^2)	PC % (km2)	MC (Km^2/year)	PC% (km^2/years)
Water body	128.86	192.62	63.76	49.48	3.04	2.36
Agriculture land	551.71	720.92	169.24	30.67	8.06	1.46
Bare soil	650.98	461.25	-189.73	-29.15	-9.03	-1.38
Desert Area	795.71	612.9	-182.81	-22.97	-8.71	-1.094
Urban Area	66.49	206.04	139.55	209.88	6.64	9.99
Total	2193.75	2193.7				

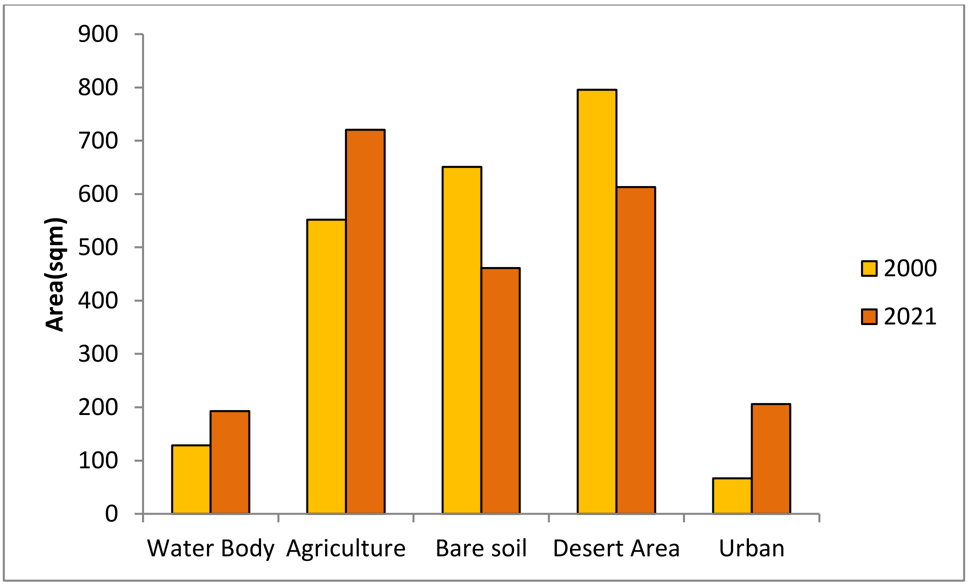

Figure 3. Comparison of existing LULC category by statistical area in km2

4.4 LCLU Transition matrix

The likelihood of changing from one land cover category to another is known as the transition probability (Susilo et al, 2011). The transition matrix for changes between 2000 and 2021 was built to have a better understanding of the LULC changing kinds in the zone under study. The spatiotemporal land cover change evaluation was cross-tabulated between the previous and subsequent land cover maps. Cross-tabulation is employed to specify the magnitude of change and transfers between diverse land cover types. A transition matrix for land cover conversion for all classes between 2000 and 2021 is summarized in Table 4. In the years 2000–2021 (Table 5), 62 km of Desert land and 53 km2 of bare soil were converted to urban areas, on the other hand, 129 km2 of desert land and 71 km2 bare soil were converted to Agriculture. This indicates a remarkable urban and agricultural expansion in this area. The other categories showed a slight transition of the land cover between 2000 and 2021 (Table 5)

Table 5: transition matrix of land cover change (in km^2) from 2000 to 2021

Land Cover		2021					
		Water	Agriculture	Bare soil	Desert	Urban	**Total**
2000	Water	115.71	10.65	1.9	0.3	0.3	128.86
	Agriculture	11.6	508.4	2.3	1.3	28.1	551.71
	Bare soil	63.3	70.78	453.3	10.34	53.36	650.98
	Desert	1.2	129.42	2.15	600.74	62.2	795.71
	Urban	0.7	1.7	1.6	0.21	62.28	66.49
	Total	192.6	720.95	461.25	612.89	206.4	2193.75

4 Conclusion

The change study was carried out using five land cover classes derived from the classified images for the years 2000 and 2021. The assessment results of classification land cover types in the study area obtained for 2000 and 2021 showed satisfactory accuracy with high agreements of over 90% and 0.9%, for overall accuracy, and Kappa statistics respectively. Because Al Najaf city experienced population and socio-economic growth, the majority of the land conversion in the research region was to agricultural, urban land. RS and GIS have been shown to be efficient tools for monitoring LULC change and providing multi-temporary land cover databases to aid decision-makers in land use planning and environmental policy.

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