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Monitoring Land Use and Land Cover Changes Using Remote Sensing and GIS Techniques, A Case Study: Kufa and Najaf, Iraq

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Abstract

The rapid expansion of the population is a significant factor in the quick transformation rate of land use and land cover (LULC) in various locations worldwide. This approach led to a substantial exhaustion of natural resources. Consequently, continuous monitoring of LULC alterations has become crucial for efficiently administering natural resources and assessing the consequences of climate change. Land cover change (LULC) is widely recognized as a significant driver of environmental change that can affect human activities. Evaluating LULC change is the most accurate approach to understanding past land use patterns, identifying changes that need assessment, and establishing their substantial influence on urban environmental planning and management. Machine learning methods have become more critical for rapidly and accurately mapping LULC using remote sensing (RS) data. The main reason is the growing demand for LULC estimation in ecosystem services, natural resource management, and environmental management. Hence, assessing and contrasting the efficacy of different machine learning classifiers is crucial to attaining accurate LULC mapping. This study was conducted in the Kufa district using eight images, three from Landsat-8 in 2013, 2016, and 2019, to monitor change detection in LULC. Five classes were obtained: residential buildings, water bodies, orchards, bare lands, and agricultural land from a supervised classification using ERDAS Imagine 2015 connected with Google Earth Pro and ArcGIS 10.8 software. For LULC change detection 2013-2016, residential buildings increased by 4.04 km^2 to 0.77% of the total area, and bare lands decreased by 47.08 km^2 (10.17 % of Kufa's area), converted into agricultural lands. The orchard area decreased by 22.29 km^2 with a percent of 4.88%, which transfers into agricultural lands, and the latter increased by 67.40 km, which is 14.36 % of the total area. However, for LULC change detection 2016-2019, the bare lands increased by 30.66 km^2 to 6.63 % of the total area, while orchards increased by 29.67 km^2 with 6.47 % of the total area due to agricultural land converted into orchards. The residential buildings decreased by 20.93 km^2, with 4.41% of the total area transferred into agricultural lands. This study output is crucial for environmental scientists, land managers, decision-makers, and urban planners in Al Najaf province.

Keywords: ERDAS, GIS, LULC, remote sensing, Kufa

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مراقبة التغيرات في الغطاءالأرضي والابنية با ستخدام تقنتي الاستشعار عن البعد ونظم المعلومات الجغرافية ، دراسة حالة: الكوفة والنجف، العراق

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الخلاصة

يعد التوسع السكاني السريع عاملاً مهمًا في معدل التحول السريع لاستخدام الأراضي والغطاء الأرضي في مواقع مختلفة حول العالم. وقد أدى هذا النهج إلى استنفاد كبير للموارد الطبيعية. وبالتالي، أصبح الرصد المستمر لتغيرات استخدام الأراضي والغطاء الأرضيأمرًا بالغ الأهمية لإدارة الموارد الطبيعية بكفاءة وتقييم عواقب تغير المناخ. من المعترف به على نطاق واسع أن تغير الغطاء الأرضي هو محرك مهم للتغير البيئي الذي يمكن أن يؤثرعلى الأنشطة البشرية. يعد تقييم استخدام الأراضي وتغير الغطاء الأرضي هو النهج الأكثر دقة لفهم أنماط استخدام الأراضي السابقة، وتحديد التغييرات التي تحتاج إلى تقييم، وتحديد تأثيرها الكبيرعلى التخطيط والإدارة البيئية الحضرية. أصبحت أساليب التعلم الآلي أكثر أهمية لرسم خرائط استخدام الأراضي والغطاء الأرضي بسرعة ودقة باستخدام بيانات الاستشعارعن بعدالسبب الرئيسي هو الطلب المتزايد على تقدير استخدام الأراضي والغطاء الأرضي في خدمات النظام البيئي، وإدارة الموارد الطبيعية، والإدارة البيئية. وبالتالي، فإن تقييم ومقارنة فعالية مصنفات التعلم الآلي المختلفة أمر بالغ الأهمية لتحقيق رسم خرائط دقيق لاستخدام الأراضي والغطاء الأرضي. تم إجراء هذه الدراسة في منطقة الكوفة باستخدام ثلاث land sat 8 Satellite) (imageللأعوام 2013 و2016 و2019 لرصد التغير في الغطاء الأراضي والمباني.تم الحصول على خمسة أصناف وهي المباني السكنية والمسطحات المائية والبساتين والأراضي العارية والأراضي الزراعية من طريقة التصنيف الموجه باستخدام Imagine 2015 (ERDAS) المرتبط ببرنامج google Earth pro وبرنامج ArcGIS 10.8. في بحثنا هذا نحن وجدناكشف التغير2013–2016ان المباني السكنية ازدادت بمقدار 4.04كم^2 وبنسبة 77% من المساحة الكلية و المناطق الجرداء قلت بمقدار 47.08 كم^2 وبنسبة 10.17% من المساحة الكلية التي تحولت الى أراضي زراعية. اما البساتين قلت بمقدار 22.29كم^2 وبنسبة الكلية4.88% من المساحة الكلية التي تحولت الى أراضي زراعية والتي بدورارها زادت بنسبة 14.36%. لكنكشف التغير 2016–2019 ان الأراضي الجرداء ازدادت بمقدار 30.66كم^2 وبنسبة 6.63% من المساحة الكلية والبساتين زادت بمقدار 29.67 كم^2 وبنسبة 6.47% من المساحة الكلية بسبب تحول أراضي زراعية الى بساتين. اما فيما يخص المباني السكنية فقد قلت بمقدار 20.93 كم^2 و بنسبة 4.41% من المساحة الكلية.

1. Introduction

Change detection is a technique employed to detect discrepancies in the state of a target or phenomenon by studying it at various time intervals [1].To effectively examine the changes in land cover of a specific area, it is essential to get data that precisely reflects its condition at different time intervals [2]. By utilizing satellite photos and a Geographic Information System (GIS) platform, change detection can be significantly achieved [3]. The process entails swiftly collecting data from multiple locations and documenting alterations in land surface across various scales with a high level of time precision [4]. Most cities' urbanization expanded during the twentieth century due to population increase and rural-to-urban migration. Urbanization at a fast pace significantly affects the management and growth of cities globally [4]. Metropolitan areas are seeing substantial urbanization and demographic expansion, while rural settlements, commonly called villages, are encountering accelerated growth and population increase. Once villages have grown into cities, they are rapidly approaching the threshold of being a city. Iraq has had multiple conflicts in the past, all of which impacted the country's economic, urban, and human recession [5]. This resulted in a massive urban sprawl and an expansion in the uses of built land. Overshot is the maximal capacity for city management in emerging nations. As a result, it appears that urban planning has a critical rule for managing cities' ability to accommodate population growth rates [6].

Remote sensing uses satellite or aerial images to generate various spatial data, including metropolitan areas, land use types, vegetated regions, water bodies, and other information about a region's utilities [7]. Conversely, GIS offers efficient and useful ways to produce, store, analyze, and display data from remote sensing [8]. When compared to previous methodologies, satellite remote sensing exhibits the potential to serve as a significant tool for monitoring land-use changes with enhanced temporal resolution and reduced financial burden [9]. The phrase "land use" describes the land's usage, including whether it is utilized for agricultural, residential, industrial, or other purposes [10]. When human operations are not being carried out on a piece of land, it is said to have a certain state or cover known as the land cover. Examples are natural pastures, rock-detecting areas, and riverbeds [11]. Earth's surface land use change detection through human activities for proper urban management is generally called LULC change detection [12]. Population density expansion and economic development undoubtedly influence land cover change, resulting in a discernible pattern in the LULC over time [13]. The rising urbanization rate in most emerging nations is one of the most pressing global issues, yet this transformation has important implications for future environmental and urban planning processes [14] [15].

There are many studies on mapping and monitoring LULC, like mapping and assessing LULC Change in the Laylan sub-district, Kirkuk province [16], LULC changes of Kufa monitoring [17], detecting and monitoring the vegetal cover of Karbala Province areas mapping [18], predicting land cover changes in Al Najaf Province [19], land cover changes of Al Najaf [20], monitoring of LULC areas of Al-Kut city [21], mapping of detecting desertification in the northeastern part of the Al-Najaf province areas [22], and the expansion of urbanized and open land and the degradation of the vegetative areas, [23]. This research aims to detect and monitor the changes in LULC during 2016-2019 in the Kufa district employing the supervised classification technique. The supervised classification technique was applied using ERDAS Imagine 2015 connected with Google Earth Pro and ArcGIS 10.8 software indices from Landsat satellite data for the 2013, 2016, and 2019 periods.

2. Material and Methods

2.1 Description of the Study Area

Kufa is located in Southwest Iraq and Northeast of Najaf within the alluvial plain, which has mixed clay soil (Fig. 1). The coordinates of the research area are 44°37′30″ – 44°19′30″ eastern longitude and 32°13′0″ – 31°57′0″ northern latitude. The area covers 466.26 km^2, including agricultural land, residential buildings, rivers, orchards, and bare lands. Kufa district consists of the Abasia sub-district and Al-Hurria sub-district, Fig (1), and the Euphrates River and its branches (the rivers of Al-Kufa and Al-Abasia) and their streams include all districts nearly.

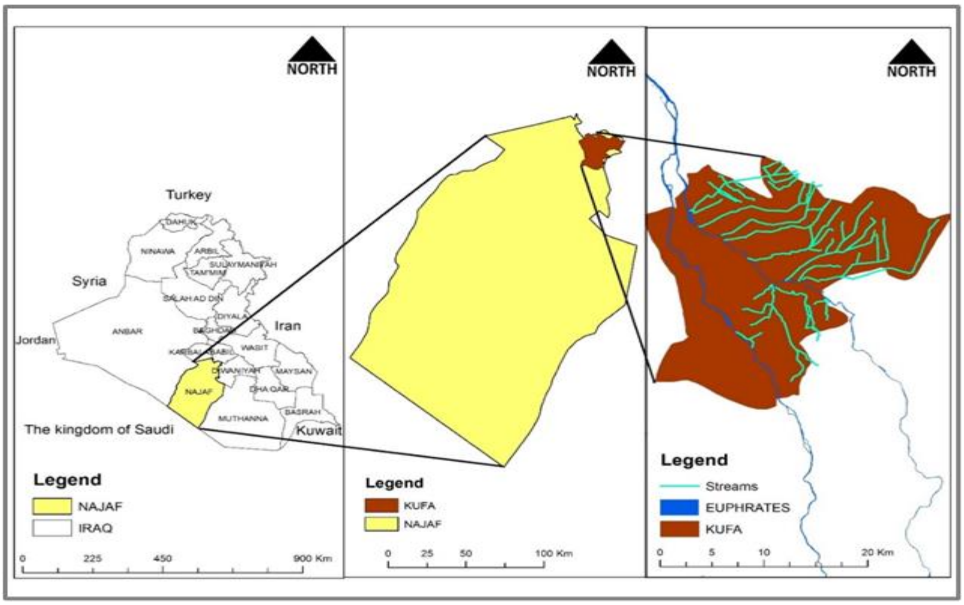

Figure 1: The location of the study area represents part of the holy city of Najaf, located in southwest central Iraq

2.2 Data source

Landsat 8 OLI imagery data for the study area were acquired for three periods: July 26, 2013, July 18, 2016, and July 27, 2019, with a resolution of 30 m. All the images were brought to the Universal Transverse Mercator (UTM) projection, Zone 38N, and World Geodetic System 1984 (WGS-84) datum. Data were analyzed using ERDAS Imaging 2015 and ArcGIS 10.8 software packages. Images were acquired from Earth Explorer's United States Geological Survey (USGS) website. The diagram of the procedure can be summarized in (**Fig. 2**).

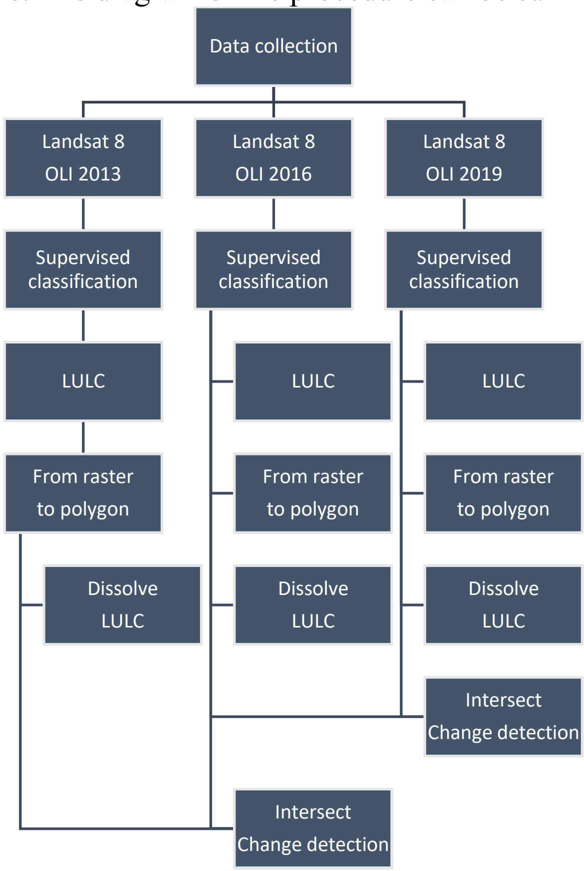

Figure 2: The diagram flowchart of the methodology

2.3 Landsat 8 imagery classification and accuracy

The used image was classified according to the supervised classification approach and the maximum likelihood algorithm. The four bands that were most effective in differentiating between each class were composite bands created with ArcGIS 10.8. Residential buildings, water bodies, orchards, bare lands, and agricultural land were used to categorize the satellite pictures' land use and cover. The reference data were chosen using Google Earth in conjunction with ERDAS. In the current study, laminated arbitrary testing samples of 256 pixels were related to the reference data from Google Earth. Overall accuracy, Producer's accuracy, User's accuracy, and Kappa ($k^\wedge$) statistic are the accuracy assessment measures generated from the confusion matrix.

The sum ratio of the main transverse numbers (i.e., the acceptably categorized) and the total number of pixels in the mistake matrix were used to calculate the classification's overall accuracy. Producer accuracy (a measure of the error of omission) was calculated by selecting the fraction of the numeral of pixels correctly classified for a class to the total number of pixels in the reference data. User's accuracy is defined (the amount of commission error) as the fraction of pixels correctly classified for a category to the total number of pixels in that category. Kappa statistic is considered a standard for accuracy [24] [25]. User Precision Commission error determines the probability that a pixel represents the class to which it was assigned, and it was calculated by dividing the number of correctly classified pixels in each category by the total number of pixels in that category (row total). The overall resolution was calculated by dividing the total number of correctly classified pixels (the sum of the principal diagonals) by the total number of pixels tested [26]. Using ERDAS imaging, the kappa coefficient (KC) is another characteristic coefficient obtained from the error matrix that considers the pixels that have not been correctly classified outside the main diagonal, with values ranging from 0 (worst) to 1 (best). From the relationship, the kappa coefficient can be calculated [27]:

$$k^\wedge = \frac{N\sum_{i=1}^{r} s_{ii} - \sum_{i=1}^{r}(s_{i+} . s_{+i})}{N^2 - \sum_{i=1}^{r}(s_{+i})}$$

Where the Kappa coefficient table is used to measure accuracy.

r, represents the row number of the error matrix, $s_{ii,}$ present observations in row i and column i (on the major diagonal), s_{i+} , present a total of observations in row i (exposed as marginal full to right of the matrix), s_{+i} , a total of remarks in column i (shown as marginal total at the lowest of the matrix), N, a total number of remarks involved in the matrix.

2.4 Change detection

Change detection analyses describe and quantify variations between photographs taken several times of a similar scene. The categorized photos of the three times can be used to estimate the area of several land covers and path changes in the data span. This analysis is highly beneficial for classifying changes in different land use types, such as an increase in built-up urban areas or a decrease in agricultural land, etc. [28]. Many methods are available to detect change [28][28], and each differs depending on the sort of images, the planned use of the variation image, and the change type to be detected. The post-classification comparison methodology was used in the case study [29] [30] [31]. This method is the only one that allows from and to classes to be considered for each reformed page, and consents were required to compare independently categorized images from each relevant date. To intersect various photos and obtain the results of the change detection.

3. Result and discussion

3.1 LULC classification and accuracy assessment analysis

According to the classification technique (LULC), patterns such as residential buildings, water bodies, orchards, agricultural lands, and bare lands were classified, as in the four Figures 3, 4, 5,6, and 7.

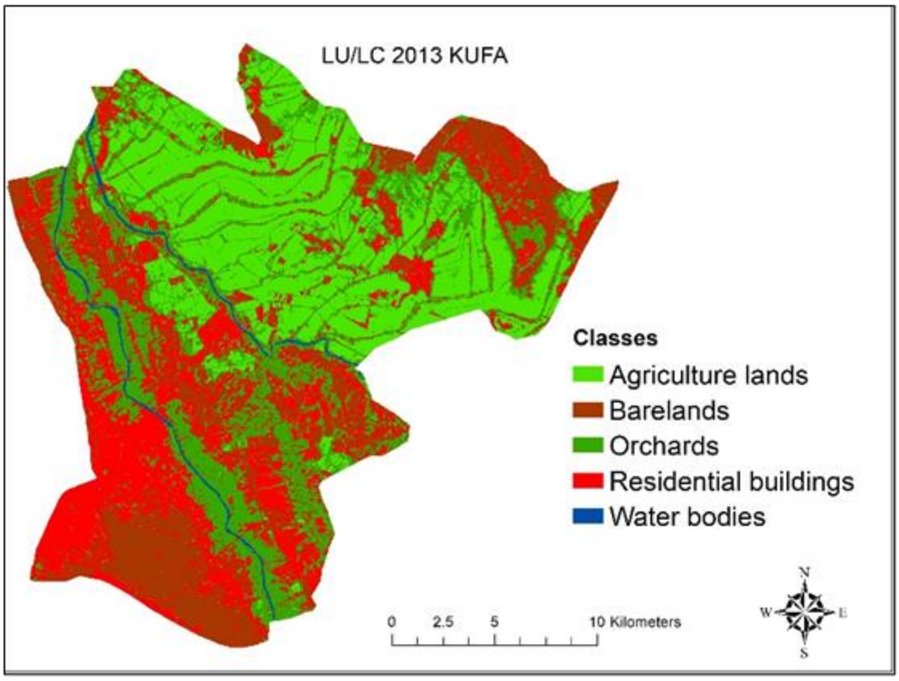

Figure 3: LULC map of Kufa in 2013

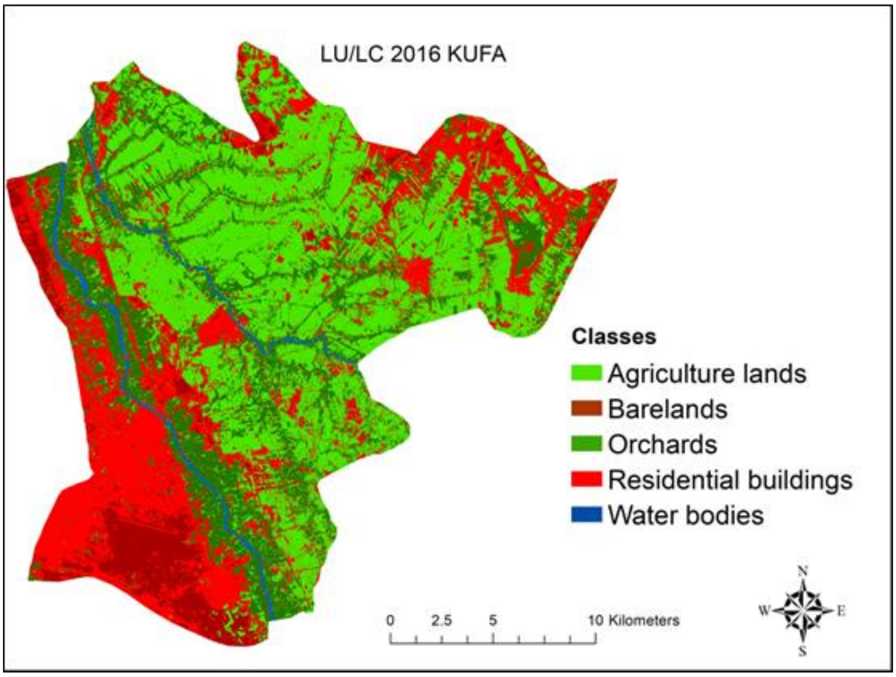

Figure 4: LULC map of Kufa in 2016

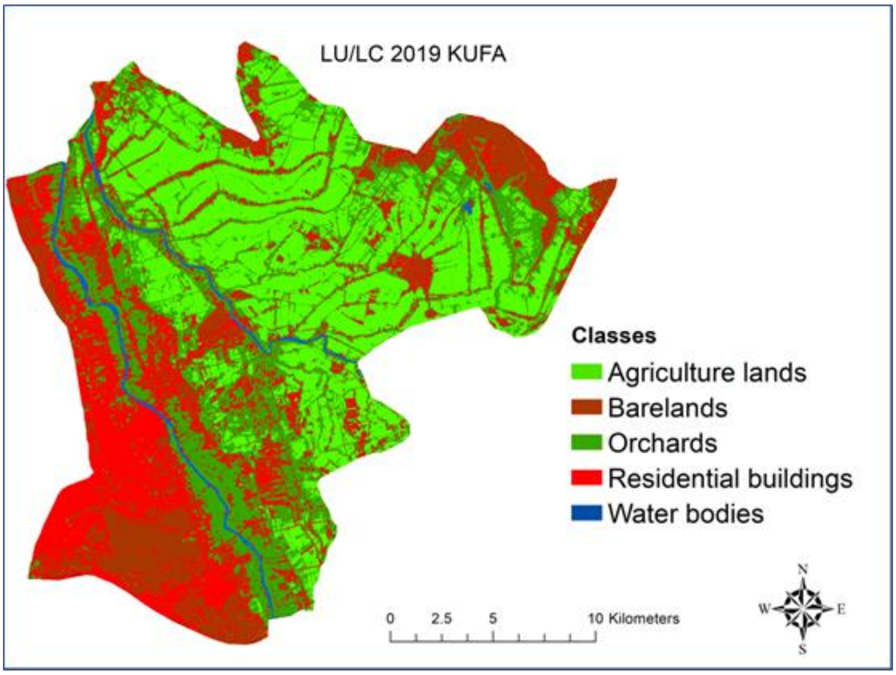

Figure 5: LULC map of Kufa in 2019

From Table 3, in 2013, residential buildings contributed an area of 120.74 km^2 with a percent of 26.0%, bare- lands contributed an area of 83.46 km^2 with a percent of 17.97 while water bodies area covered 5.52 km^2 with a percent of 1.19%. Orchards, the most significant area before agricultural land has been covered, is about 126.49 km^2, which contributes 27.24%, and agricultural land occupies the largest area of 128.20 and 27.61%.

In 2016, residential buildings covered an area of 124.77 km^2 with a percent of 26.77%; bare lands contributed an area of 36.37 km^2 with a percent of 7.80%, while water bodies occupied 5.19 km^2 with a percent of 1.11%. Orchards have a covered area of about 104.20 km^{2,} contributing 22.35%, and agricultural land area of 195.61 and 41.96 %.

In 2019, residential buildings occupied an area of 103.85 km^2 with a percent of 22.36%, bare lands contributed an area of 67.03 km^2 with a percent of 14.43while water bodies area covered 6.52 km^2 with a percent of 1.40%. Orchards, the most significant area before agricultural land, covered an area of about 133.86 km^2, contributing 28.82%, and agricultural land occupied an area of 153.14 with a percentage of 32.98%.

3.2 Change detection and Post classification matrix analysis

From Table 4 and maps in Figure 6,7 during 2013-2016, residential buildings increased by 4.04 km^2, 0.77% of the total area. At the same time, bare lands were decreased by 47.08 km^2, 10.17 % of the total area, which was converted into agricultural lands. The orchard area decreased by 22.29 km^2 with a percentage of 4.88%, which transferred into agricultural lands, and the latter increased by 67.40 km, which is 14.36 % of the total area. In 2016-2019, in the northeastern part of the study area, the population was evacuated and compensated so that the residential areas became agricultural and other to bare land. Therefore, residential buildings decreased by 20.93 km^2, 4.41% of the total area. The bare lands increased by 30.66 km^2 to 6.63 % of the total area. Orchards increased by 29.67 km^2, with 6.47 % of the total area due to agricultural land converted into orchards.

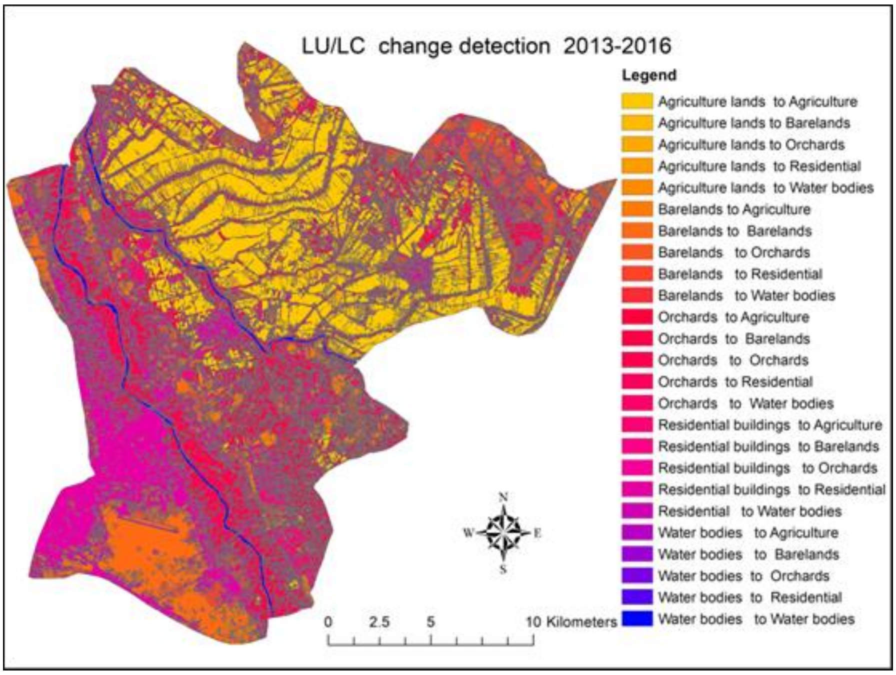

Figure 6: LULC map of change detection during 2016-2019

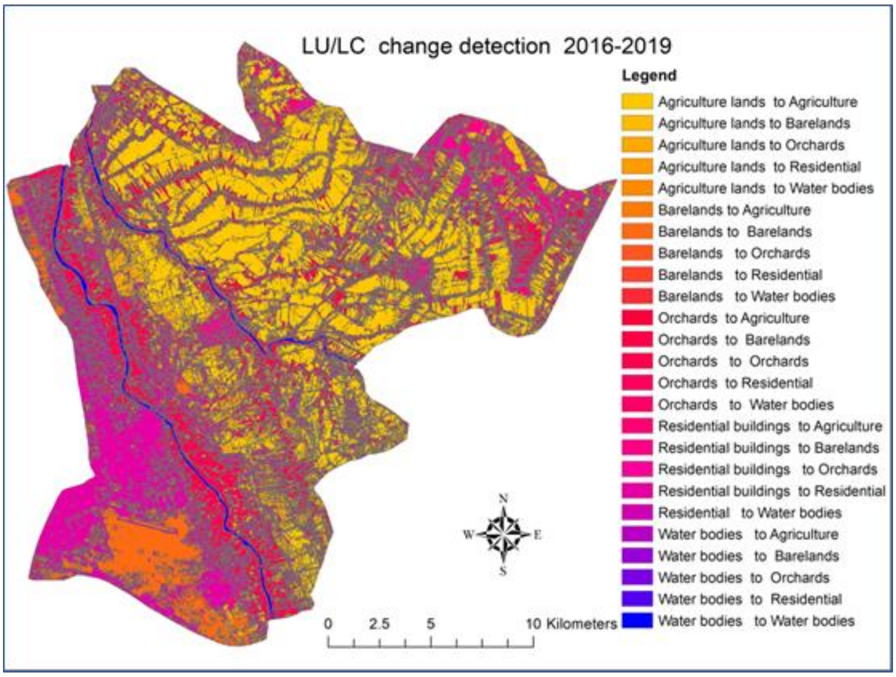

Figure 7: LULC map of change detection during 2016-2019

Tables 1 and **2** are the land use/land cover post-classification matrix. The introductory stage and the last state of variations were 2013 and 2016, 2016 and 2019, respectively, with a 3-year interval. **Tables 1** and **2** show that in 2013-2016, 17.4 km^2 of barren lands were converted into agricultural land, while 31.09 km^2 was converted into residential buildings. At the same time, 44.45 km^2 of orchards had been transferred into agricultural lands, and 15.73 km^2 was transferred into residential buildings.

A change of dissimilar LULC into an alternative for the interval from 2016 to 2019 was observed. The total area of agricultural land in 2016 was 194.37 km^2, 8.55 km^2, and 50.41 was converted to bare lands and orchards, respectively. At the same time, 17.75 km^2 of residential buildings were transferred into the orchard area.

Table 1: Post-classification matrix from 2013 to 2016

	2013						
	LU/LC classes	**Agriculture lands**	**Bare lands**	**Orchards**	**Residential buildings**	**Water bodies**	**Total**
2016	Agriculture lands	100.08	17.4	44.45	32.29	0.15	194.37
	Bare lands	0.48	29.37	0.94	5.13	0	35.92
	Orchards	18.85	4.93	64.07	14.43	0.91	103.19
	Residential buildings	8.37	31.09	15.73	68.31	0.11	123.61
	Water bodies	0.01	0.01	0.8	0.01	4.34	5.17
	Total	127.79	82.8	125.99	120.17	5.51	462.25

Table 2: Post-classification matrix from 2016 to 2019

	2016						
	LU/LC classes	**Agriculture lands**	**Bare lands**	**Orchards**	**Residential buildings**	**Water bodies**	**Total**
2019	**Agriculture lands**	117.82	0.87	21.24	12.54	0	152.46
	Bare lands	8.55	26.46	2.68	28.83	0.01	66.53
	Orchards	50.41	1.49	63.32	17.75	0.43	133.41
	Residential buildings	17.3	7.09	14.78	64.14	0.04	103.34
	Water bodies	0.29	0.01	1.17	0.36	4.69	6.51
	Total	194.37	35.92	103.19	123.61	5.17	462.25

Table 3: Area and percentage of LULC in the study area

LU/LC classes	**(2013-2016)**				**(2016-2019)**			
	Area/ km^2		**Percentage**		**Area/ km^2**		**Percentage**	
	2013	2016	2013	2016	2016	2019	2016	2019
Residential buildings	120.74	124.77	26.00	26.77	124.77	103.85	26.77	22.36
Bare lands	83.46	36.37	17.97	7.80	36.37	67.03	7.80	14.43
Water bodies	5.52	5.19	1.19	1.11	5.19	6.52	1.11	1.40
Orchards	126.49	104.20	27.24	22.35	104.20	133.86	22.35	28.82
Agriculture lands	128.20	195.61	27.61	41.96	195.61	153.14	41.96	32.98

Table 4: Change detection in Kufa

LU/LC classes	**(2013-2016)**		**(2016-2019)**	
	Change area km^2	**Change (%)**	**Change area km^2**	**Change (%)**
Residential buildings	-4.04	-0.77	20.93	4.41
Bare lands	47.08	10.17	-30.66	-6.63
Water bodies	0.32	0.07	-1.33	-0.29
Orchards	22.29	4.88	-29.67	-6.47
Agriculture lands	-67.40	-14.36	42.47	8.99

Conclusion

The LULC analysis conducted in Kufa for 2013, 2015, and 2016 yielded categorization results indicating the presence of five distinct classes: residential buildings, water bodies, orchards, bare fields, and agricultural land. In the study area, the analyses of LULC changes during 2013 and 2016 are shown in Figure (6) and Table (4) as follows.

- Residential buildings increased by 4.04 km^2, 0.77% of the total area.
- Bare lands decreased by 47.08 km^2, and 10.17% of the total area was converted into agricultural lands.
- The orchard's area decreased by 22.29 km^2 with a percentage of 4.88%, which transferred into agricultural lands. The latter increased by 67.40 km, 14.36% of the total area, due to the lack of water bodies.
- Water bodies decreased by 0.32 km^2, 0.07 % of the total area.

LULC changes during 2016 and 2019, as shown in Figure (7) and Table (4), are the following.

- The bare lands increased by 30.66 km^2 to 6.63% of the total area.
- The orchards increased by 29.67 km^2, with 6.47% of the total area due to agricultural land being converted into orchards due to the availability of water bodies.
- The residential buildings decreased by 20.93 km^2, with 4.41% of the total area transferred into agricultural lands.
- Water bodies increased by 1.33 km^2, 0.29% of the total area.

Remote sensing data can be utilized to analyze changes in land use and land cover (LULC). Satellite remote sensing data can provide valuable insights into land cover dynamics and land use changes, including spatial distribution and potential future trends. The rapid expansion of urban areas, often surpassing population growth rates, is causing significant concerns among citizens and public agencies responsible for growth and development. This expansion leads to the loss of agricultural lands and wetlands, rising infrastructure costs, increased traffic congestion, and environmental degradation. Remote sensing data is valuable for detecting changes in places, such as population increase and vegetation, spatially and quantitatively over the years. Accurate data is crucial for strategic development and conserving our natural resources and environment. It is indispensable for urban planners and residents alike. Satellite remote sensing methods offer a cost-efficient option for obtaining additional information, particularly when financial resources are diminishing.

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