

# LAND USE AND LAND COVER CHANGE DETECTION USING SATELLITE IMAGES FOR THE KUFA DISTRICT, NAJAF, IRAQ

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**Abstract-** Remote sensing technology is the widely applied technology used for land use/ land cover change detection analysis. In this study, two Landsat 8 OLI imagery (2013-2019) have been used to extract change detection analysis with five classes (i.e.: residential buildings, water bodies, orchards, agriculture lands and bare lands) achieved by ERDAS imagery 2015. Supervised classification maximum likelihood classifier method was utilized to prepare land use land cover maps of the study area. The accuracy of the classified LULC map was assessed using A Google earth linked with ERDAS imagery. Results shows, agriculture lands, water bodies and orchards have increased by 5.43%, 0.22% and 1.56% while residential buildings and bare lands have decreased by -3.56% and -3.57% respectively.

**Keywords –** Remote sensing, land use and land cover, ERDAS imagery and Kufa

## I. INTRODUCTION

Remote sensing data supports researchers and decision makers for monitoring and changes in the field of long-term interest without on-site monitoring in the field. As a result, the work is less expensive and less costly to collect data and analyze change detections, and it explains the reasons for these changes. Remote sensing was used to implement a large-scale change detection. The most important studies of remotely sensed uses in applying change detection analysis of land cover and land use studies (Rawat and Kumar; 2015; Hegazy and Kaloo; 2015; Butt et al.; 2015). Some studies were conducted by observing changes in the land cover only in the region while others linked these changes in the land with social data as secondary data. For example, (Kwarteng and Chavez, 1998) studied change detecting in Kuwait City and its suburbs using multi-temporal land sat thematic mapper data to monitor change in land cover. (Jensen and Toll, 1982) also explore the development of residential land use on the urban edge. Another study was conducted by (Sexton et al., 2013) to discover urban land change. The authors have been monitored the urban growing of urban areas in Washington and Baltimore over a long period. Several other studies on the urban change detection and land cover changes can be found in the literature (Yin et al.; 2005; Lu et al.; 2009; Griffiths et al.; 2010; Wakode et al.; 2014; Mihai et al., 2015; Zhang, 2001; Zhang et al., 2013). The literature has various technology to detect change where presented in review articles by (Minu and Shetty, 2015), (Ridd and Liu, 1998) and (Lu et al., 2004). In this study, a supervised classification technique was selected and applied for two-year images using ERDAS imagery software. There are different algorithms for supervised classification. One of the most common algorithms in supervised classification is the maximum probability classifier (Benedictsson et al., 1990). In this current study, the maximum likelihood classifier algorithm was chosen because it usually provides the highest accuracy (Natural Resources Canada, 2010). This algorithm checks the probability function of pixels for each of the categories and assigns pixels to the category with the highest probability. The algorithm is mainly based on the assumption that cells are usually distributed in a multi-dimensional space. The algorithm then calculates the probability of a specific pixel belonging to a specific class (Park; 2016). Five classifications of LULC were

performed in the study: residential buildings, water bodies, orchards, agriculture lands and bare land. For each imagery, 256 random points were chosen to evaluate the accuracy of the LULC classification for the study area.

## II DESCRIPTION OF THE STUDY AREA

The KUFA district is located about (8.99) km eastern of AL-Najaf province see Fig. 1, is geographically located 44020'0"- 44037'30"E and 31058'30"- 32012'30" N. AL-Najaf province is located in south-west part of Iraq, covering an area of (28537) km<sup>2</sup>, the sub districts are located within of the KUFA district center are Al-Abbassiya sub district and Al-Huriya sub district (Municipality Najaf province).

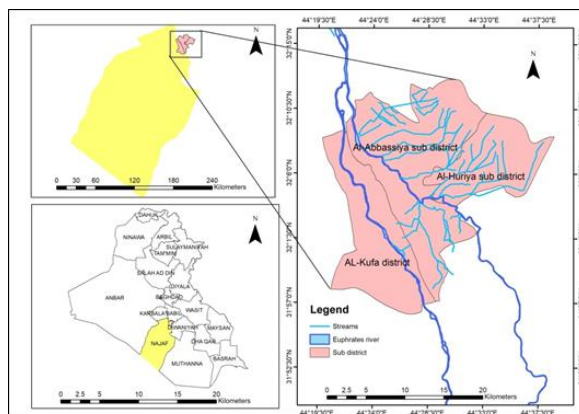


Figure 1. Study area location

## III. METHODOLOGY OF RESEARCH

The comprehensive methodological framework and data analysis are shown in Fig. 2. The itemized methodology for the study is as follows.

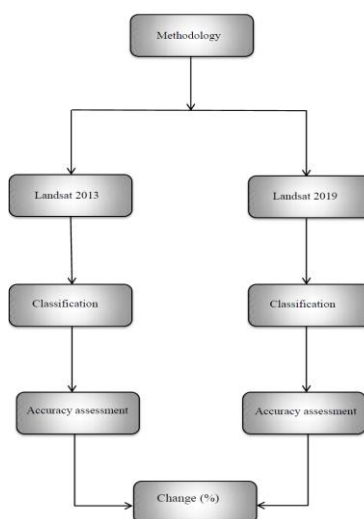


Figure 2. Methodological workflow and data analysis

## IV. DATASET SOURCE AND METHOD

Land use and land cover map satellite imagery of study area obtained from USGS Earth explorer (<https://earthexplorer.usgs.gov>). Landsat 8 OLI images in path (168) and row (38), spatial resolution of 30m x 30m, acquisition date (26-07-2013 and 27-07-2019). Satellite imagery categorizes based on ground truth points and Google Earth connectivity with ERDAS Imagine 2015.

## V. LAND USE/LAND COVERS CLASSIFICATION

The objectives of land cover land use for understanding the general procedures for classifying the land cover from satellite images, to conduct the land cover classification from Landsat 8 OLI imagery using supervised classification,

to understand how the image classification is accurate in assessing the quality of the classification success and understanding how to interpret the benefit of a person's classification. Essentially, there are two types of image classification techniques method used in land use and land cover classification. Supervision classification is one of; a for classifying land cover type using sample polygons (ground truth points) from known land cover types. Another type of classification is; unsupervised classification; it is a type of land cover classification from satellite image data when the user does not know the number of types of land cover in the field (Andualem et al, 2018 ). For this study a supervised classification type was used using known ground truth points by linking ERDAS Imagine to Google Earth and image sync. In supervised classification, the classification operation is planned by creating, managing, evaluating, and editing signatures with the signature editor. Signatures are specific areas where names are assigned to the supervised classification. Signatures are used to break various categories such as classes of residential buildings, water bodies, orchards, agriculture lands into many subcategories according to classification requirements. Some tools like signature editor were developed using the AOI layer created in the create layer option. In this study, after pre-processing data, a training sample was chosen according to the spectrum features. In contrast to traditional land use / coverage classifications, the maximum probability classification was used to map the land use / cover of the KUFA. After classifying the image using a supervised classification, the classification accuracy was verified using ground control points.

## VI. RESULTS AND DISCUSSION

### 5.1 Image classification and accuracy assessment

The supervised maximum likelihood classification have been used in this study is a wide range method of analyzing remote sensing image data (Richards, 1995). It identifies earlier known types of land cover through a mixture of analysis of personal practice of aerial photography; map analysis and fieldwork ( Jensen, 2005 ). Uses training data methods and differences to guess of probability that a pixel is the class member. The pixel is assigning in the category with the maximum probability of membership (Ozesmi and Bauer, 2002). A supervised classification method has been used in order to quantitative analysis of Landsat 8 images datasets. The LULC maps of the KUFA region produced were assessed using a conventional error array of user and product accuracy developed by comparing randomly and independently selected test pixels with those used for classification. The overall accuracy and Kappa coefficients are shown in Table 1-2 for the Landsat 8 (2013-2019) classifications. Accuracy results for land sat 8 imagery of 2019 show that, overall accuracy is 89.57% and kappa coefficient is 0.8582, while land sat 8 imagery of 2013, the overall accuracy is 92.19% and the kappa coefficient is 0.8966. Since the Kappa coefficient is considered stronger than the others (Jensen, 2005), the results are evaluated according to the Kappa coefficient. As shown in Table 1-2, Landsat 8 classification of 2013, it showed a slightly higher accuracy than Landsat 8 of 2019. The classification accuracy assessment was performed based on 256 random points identified and located using a stratified random method in the ERDAS software to represent the LULC classes different from the region. To properly evaluate accuracy, the number of random generated points must be 250 or more ( Andualem et al, 2018 ). The 256 points have used in this study to represent field checkpoints (ground truth data). The ground point data and classification results were compared and statistically analyzed using error matrices. Fig.3 of the LULC timeline shows five main categories: residential buildings, water bodies, orchards, agriculture lands and bare lands of 2013 and 2019.

Table -1 Accuracy assessment of image classification results of 2019.

Class name	Residential buildings	Water bodies	Orchards	Agriculture lands	Bare lands	Row Total	Produces accuracy	Users accuracy
Residential buildings	29	0	0	0	3	32	100.00%	90.63%
Water bodies	0	6	0	0	0	6	100.00%	100.00%
Orchards	0	0	39	6	5	50	97.50%	78.00%
Agriculture lands	0	0	0	57	1	58	90.48%	98.28%
Bare lands	0	0	1	0	15	16	62.50%	88.24%
Column Total	29	6	40	63	24	162		
Overall Classification Accuracy =						89.57%		
Overall Kappa Statistics =						0.8582		

Table -2 Accuracy assessment of image classification results of 2013.

Class name	Residential buildings	Water bodies	Orchards	Agriculture lands	Bare lands	Row Total	Producers accuracy	Users accuracy
Residential buildings	54	0	1	0	9	64	98.18%	83.08%
Water bodies	0	8	0	0	0	8	100.00%	100.00%
Orchards	0	0	53	4	3	60	96.36%	88.33%
Agriculture lands	0	0	1	81		82	95.29%	98.78%
Bare lands	1	0	0	0	40	41	76.92%	97.56%
Column Total	55	8	55	85	52	255		
Overall Classification Accuracy =						92.19%		
Overall Kappa Statistics =						0.8966		

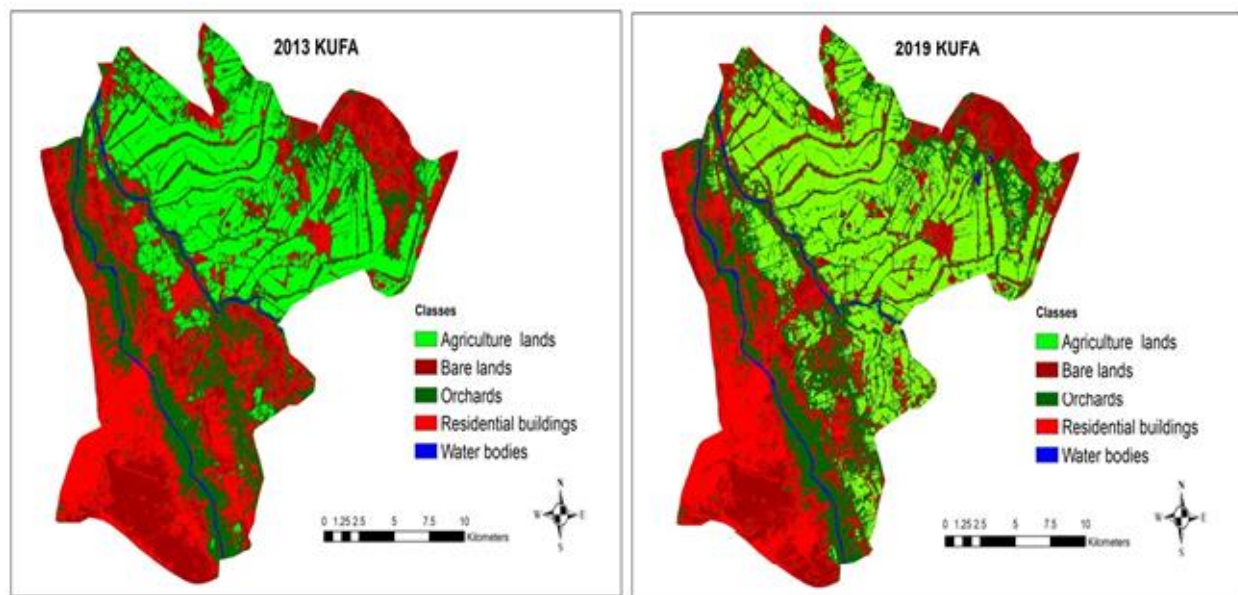


Figure 3. The five classes in 2013 and 2019 satellite images of the KUFA

### 5.2 Change detection analysis

In change detection analysis, remote sensed data are useful for monitoring land use/ land cover changes ( Singh, 1989 ). Results from the classified maps indicated that in 2013 were occupied by different classes, residential buildings were about 26.05%, bare land was 18.15%, water bodies covered 1.19%, and agricultural lands and orchards covered most part of KUFA and occupied about 27.47% and 27.15% respectively. On the other hand, in 2019, about 32.81% and 28.70% of the area were covered by agricultural land and orchards compared to 27.47% and 27.15% in 2013 showed a decrease in cultivated land in 2013. Bare lands, residential buildings and water bodies were covered by 14.58%, 22.50% and 1.41%, respectively. The areas covered by residential buildings bare lands decreased by -3.56% and -3.57% of the total geographical area for the 2013-2019 period (Table 3).

TABLE -3 LULC distribution in the KUFA

LULC Class	2013		2019		Change(%)
	Area(km <sup>2</sup> )	Area(%)	Area(km <sup>2</sup> )	Area(%)	
Residential buildings	121.01	26.05	104.49	22.50	-3.56
Bare lands	84.30	18.15	67.74	14.58	-3.57
Water bodies	5.51	1.19	6.54	1.41	0.22
Orchards	126.09	27.15	133.33	28.70	1.56
Agriculture lands	127.59	27.47	152.40	32.81	5.34
Total	464.50	100.00	464.50	100.00	0.00

#### IV.CONCLUSION

This study evaluated and monitored changes in LULC pattern in KUFA using Landsat 8 OLI image data from 2013 to 2019. During the study period (2013-2019), the bare lands decreased significantly as a result of the conversion in agricultural land and orchards. The supervised maximum classification was used to classify images into different LULC categories. Five LULC classes were identified as residential buildings, water bodies, orchards, agriculture land and bare lands. Classification accuracy is also estimated using field knowledge obtained from Google Earth association with ERDAS imagery. Results accuracy ranges from 89.57% to 92.19% for all the classes. Change detection analysis presented agriculture lands, water bodies and orchards have been increased by 5.34%, 0.22% and 1.56% respectively. Bare lands has been decreased by -3.57% and residential buildings was reduced by -3.56% during time from 2013 to 2019.

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