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Land Cover Change Detection in Al-Karkh / Baghdad

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Abstract: ***This paper focuses on the environmental change monitoring in all areas of West Tigris (Al_ Karkh), the current study highlights the spatial and temporal changes detection in land cover for Al-Karkh using different analyses methods the supervised maximum likelihood classification method, the normalized difference Vegetation Index (NDVI), Geographic Information Systems (GIS), and Remote Sensing (RS). Techniques spectral indices were used in this study to determine the change of vegetation, urban and water area, through analyses Landsat images for different two years (2000, 2017). Different change detection techniques were applied to monitor the changes. The change analysis based on two dates, spanning over a period of two years using supervised classification, NDVI, NDWI and NDBI, showed a decreasing trend (1.607%) in vegetated areas, increase (2.567%) in water bodies, increase (2.928%) in urban areas.***

Keywords: Classification, Vegetation index, GIS, Remote sensing

1. Introduction

The earth's surface is changing as a result of natural phenomena or human activity, for example, wildfires, lightning, strikes, storms, pests, agroforestry, agricultural expansion, social, economic, technological, historical factors and urban growth and the like [1]. Land cover initially describes the physical state of the land surface, which includes cropland, forests, and wetlands, but it has broadened in subsequent usage to contain human structures such as buildings, pavements and other aspects of the natural environment, including soil type, biodiversity, surface water and groundwater [2]. In contrast, land use refers to the way in which human beings exploit the land and its resources including agriculture, urban development, grazing, logging and mining. However, land cover and land use are often used interchangeably because the two terms are interdependent and closely related [3]. Regardless of that, land use/land cover change (LULCC) is defined as the transformation of the land or replacement of one land-cover type on the earth's surface [4]. Documentation of the spatiotemporal pattern of land use/cover using satellite imagery, which allows scientists the ability to determine the causes and results of change in relation to human activity patterns [5], therefore, studying changes in land use/land cover has become an important research theme in the remote sensing spatial analysis Since the 1970s [6]. The land cover change detection problem studied in this paper is essentially one of taking a data set of vegetation related time series and detecting changes by giving each location a change score based on the extent to which it is considered a change point. There are a number of specific challenges associated with Earth Science data that make this a challenging problem. The spatiotemporal nature of Earth Science data is especially challenging since traditional data mining techniques do not take advantage of the spatial and temporal autocorrelation present in such data. In particular, change detection becomes challenging since changes in vegetation levels are occurring all the time.

2. Related work

Digital change detection aims to detect changes over time. By and large the change detection system relies on difference in radiance value between two or more dates. There is no universally optimal technique; choice depends upon the application. Change map using post classification technique of two images will only be generally as accurate as the product of the accuracies of each individual classification. Review of change detection using multi-temporal remote sensing data has been carried out [7]. Four of the most commonly used change detection techniques were applied to detect the nature and extent of the land-cover changes in New Burg El-Arab city using Landsat multispectral images [8]. These techniques are; (1) post-classification, (2) image differencing, (3) image ratioing, and (4) principal component analysis. Finally, a quantitative evaluation for the results of these techniques indicates better post classification comparison results. Object-based land cover classification and change analysis in the Baltimore metropolitan area using multitemporal high resolution remote sensing data was carried out [9]. The results from analyses indicated that an object based approach provides a better means for change detection than a pixel based method because it provides an effective way to incorporate spatial information and expert knowledge into the change detection process only limitation is its applicability other than high resolution data. A method for change detection in high-resolution remote sensing images by means of Multi resolution level set (MLS) evolution and support vector machine (SVM) classification, which combined both the pixel level method and the object-level method [10]. Radiometric normalization of image is prerequisite for any change detection [11].

3. Change Detection

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times [12]. With increasingly intensifying social and economic development, the local ecological environment has changed dramatically. Change detection is an important process in monitoring and managing natural resources and assessing Environmental impact because it provides quantitative analysis of the spatial distribution of changes. [7] list four aspects of change detection which are important when monitoring natural resources:

a) Detecting the changes that have occurred.
b) Identifying the nature of the change.
c) Measuring the area extent of the change.
d) Assessing the spatial pattern of the change.

4. Change Detections Techniques

Many techniques have been developed which can be organized into algebraic/statistical, change vector/ transformation, classification or combinations of them. Different change detection algorithms that were documented in the literature include:

a) Mono-temporal change delineation.
b) Delta or post classification comparisons.
c) Multidimensional temporal feature space analysis.
d) Composite analysis.
e) Image differencing.
f) Multi-temporal linear data transformation.
g) Change vector analysis.
h) Image regression.
i) Multi-temporal biomass index
j) Background subtraction.
k) Image ratioing

The basic premise of "Everything is related to everything but near things are more related than distant things". Spatiotemporal interpolation to generate voxel-field data in a spacetime domain from observational data is indispensable to many spatiotemporal reconstruction and visualization of dynamic spatial phenomena [13].

5. Study Area

The study area located between Latitude: 33°19′ and 33.317°N and Longitude: 44°24′ and 44.400°E. It covers an area of 201 km², Divided into three areas (Al - Karkh district center, Al - Mansour sub district, Al - Mamoon sub district).

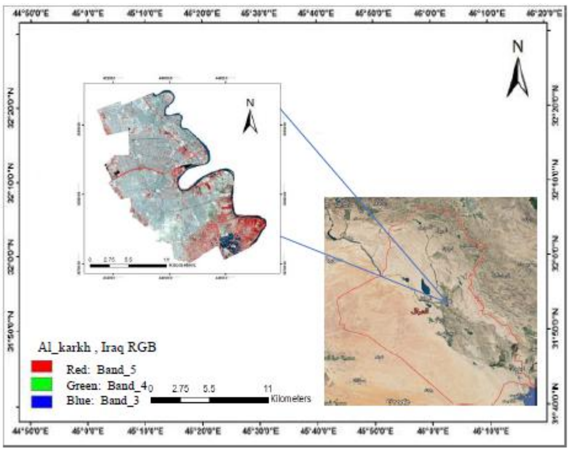

Figure 1: Location of study area in Iraq and location of Al_Karkh

6. Materials and Methods

The studied area is covered by the Landsat image for selected two years (2000, 2017) from Landsat 7 and Landsat 8 (OLI-TIRS) respectively with different sensor is being downloaded from the USGS Earth Explorer for (18) year for the purpose of coverage during the drying period and the consequences on the environment in Al-Karkh, the imagery is free of clouds, haze, and dust (distortions of interfering atmospheric) [14]. Processing the images and imagery interpretation for the development of cover maps and land use were achieved by using imagine software (Arc GIS 10.5). The collected data were obtained and analyzed and calculated to detect the change in land cover. Prospect prediction is done based on past data.

6.1 Image preprocessing

Digital image processing was manipulated using Arc GIS. The geometric is corrected and calibrated. Data were classified according to the type of cover land into 'zones', each zone has similar spectral properties. The data of ground truth were classified according to every single classifier collected by its signatures spectral for two years (2000, 2017).

6.2 Classification of images

In this study, the supervised land use/cover classification was applied. Maximum likelihood method was to analyze the image by using Arc GIS, this method is considered most sophisticated and achieves good separation of classes [15]. Each point had specific color tone and the pixel value which was recognized by the software itself when the datasets were trained during supervised land use cover classification [16]. All the randomly generated points were then identified by the user and assigned to different classes. The supervised classification was done for two years (2000 and 2017). The correctly identified points were considered as classified values.

6.3 Estimation Land Cover

The equation below shows the Normalized Difference Vegetation Index (NDVI), [17]:

$$NDVI = (NIR\text{-}Red) / (NIR+Red) \quad (1)$$

For (landsat7)

$$NDVI = (Band\ 4 - Band\ 3) / (Band\ 4 + Band\ 3) \quad (2)$$

For (landsat8)

$$NDVI = (Band\ 5 - Band\ 4) / (Band\ 5 + Band\ 4) \quad (3)$$

In which, NIR represents the nearby infrared reflectance in a section of the band. Red is the reflectance in the red portion of the band. NDVI value ranged between -1.0 and +1.0, where distributed between positive values which indicated green vegetation and not vegetated land covers represented by negative or near zero value such as deserts, water bodies, and urban area. Snow has larger visible reflectance than NIR reflected, these features yield negative values. Rock and bare soil areas have a similar reflectance in the two bands and result in NDVI near zero Dalezios, 2002.

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6.4 Land use covers change detection

Two satellite images were collected to detect the spatial and temporal changes in land cover for the same area. All images from each individual year have been classified according to a various-date, post classification, change-detection in order to detect the changes during one interval periods (2000–2017). The post-classification approach provides changes data from - to. Classified pairs of two different decade data have been compared using the cross-table in order to determine qualitative of the changes for the periods of 2000–2017.

7. Proposed System Implementation and Results

7.1 Steps of work

Figure 2 show the flow chart of data analyses and manipulations. Acquisition dates of the studied Landsat images given in Table 1, while, the digital image of the study area for two years (2000 and 2017) show in Figure 3.

Table 1: Acquisition dates of the studied Landsat images.

Image year	*Sensor type*
2000	Landsat 7
2017	Landsat 8 (OLI-TIRS)

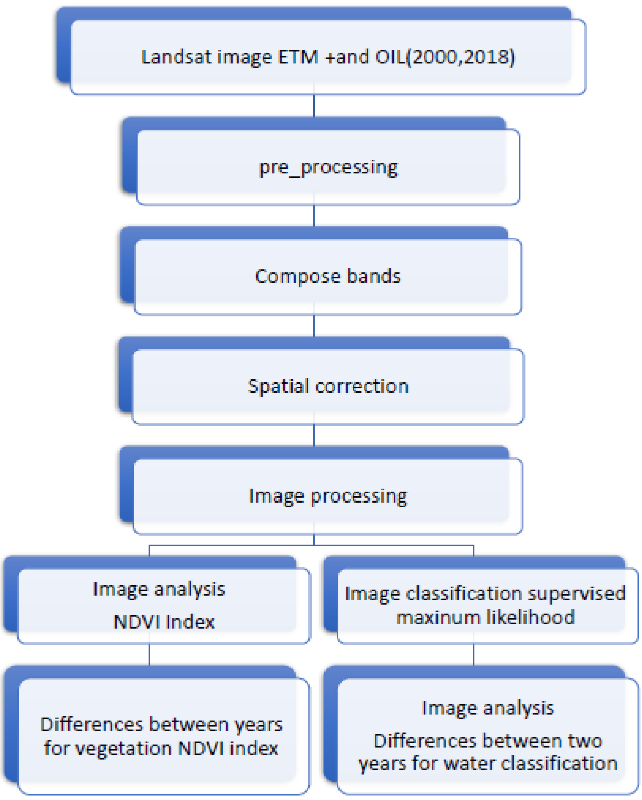

Figure 2: Flow chart of data analyses and manipulations.

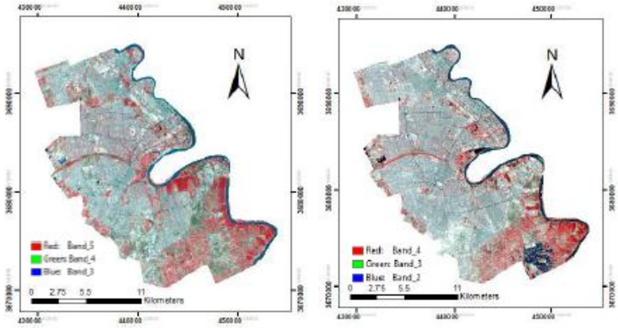

Figure 3: Digital image of the study area for two years (2000 and 2017)

7.2 Classification of images

Table 2 shows the areas of supervised classification Maximum likelihood method of Al-Karkh (2000 and 2017), while Figure 4 shows the supervised classification analysis Maximum likelihood method for the same area.

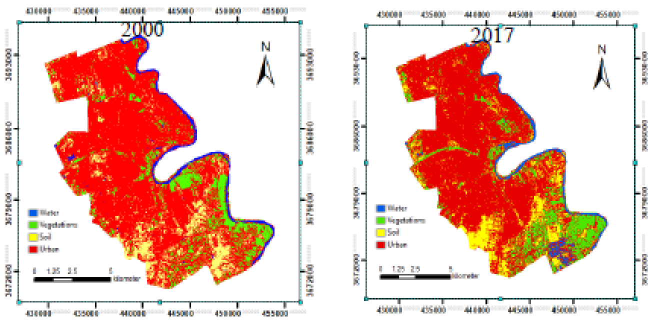

Figure 4: Supervised classification analysis Maximum likelihood method of Al-Karkh (2000 and 2017)

Table 2: Areas of supervised classification Maximum likelihood method of Al-Karkh (2000 and 2017)

Supervised Classification				
	2000		2017	
Class	Area km²	Area%	Area km²	Area%
Water	12.702	4.223	16.656	5.537
Vegetation	72.389	24.069	70.785	23.535
Urban	167.08	55.553	191.536	63.685
Soil	50.186	16.689	20.172	6.709
Sum	300.753	100%	300.753	100%

7.3 NDVI

NDVI was implemented using Equations 1, 2 and 3. The obtained results show in the following tables and figures:

Table 3: Areas of vegetation and no vegetation lands and their percentage in Al-Karkh based on the NDVI index (2000 and 2017)

NDVI Index				
	2000		2017	
Class	Area km²	Area%	Area km²	Area%
No Vegetation	228.364	75.930	229.968	76.465
Vegetation	72.389	24.069	70.785	23.535
Sum	300.753	100%	300.753	100%

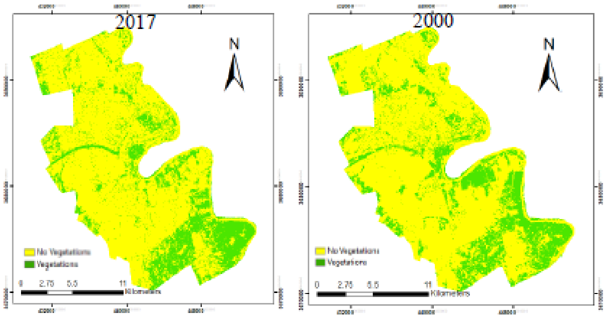

Figure 5: Spatial distribution of land use obtained from the NDVI index in Al-Karkh (2000 and 2017)

Table 4: Change Vegetation by NDVI Index analysis of Al-Karkh (2000 and 2017)

Change Vegetation by NDVI Index		
2000-2017		
Class	Area km²	Area%
Increase of Veg.	26.016	8.650362%
Decrease of Veg.	27.621	9.183921%

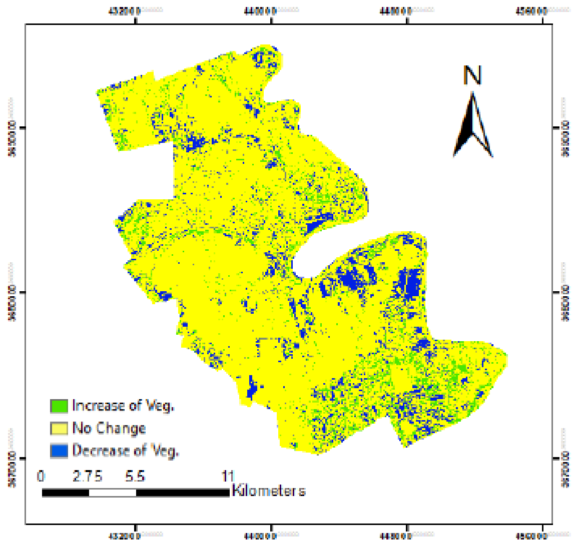

Figure 6: Areas of vegetation differentiating (NDVI) analysis of Al-Karkh between 2000 and 2017

7.4 NDWI

The equation below shows the Normalized Difference Water Index (NDWI):

$$NDWI = (GREEN - SWIR) / (GREEN + SWIR) \quad (4)$$

For (landsat7)

$$NDWI = (Band\ 2 - Band\ 4) / (Band\ 2 + Band\ 4) \quad (5)$$

For (landsat8)

$$NDWI = (Band\ 3 - Band\ 5) / (Band\ 3 + Band\ 5) \quad (6)$$

Table 5: Areas of water and no water lands and their percentage in Al-Karkh based on the NDVI index (2000 and 2017)

NDWI Index				
	2000		2017	
Class	Area km²	Area%	Area km²	Area%
No Water	288.051	95.78%	284.097	94.46%
Water	12.702	4.22%	16.656	5.54%
Sum	300.753	100%	300.753	100%

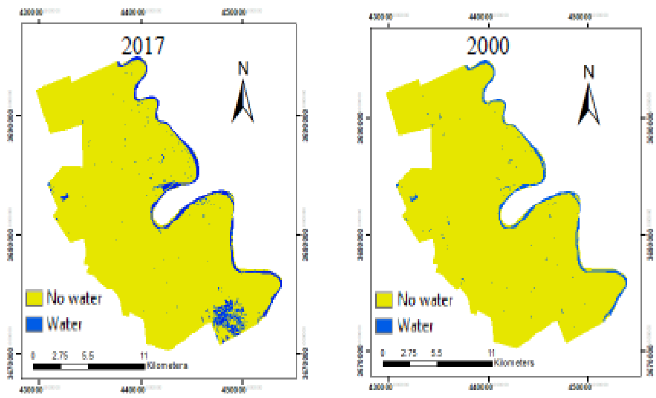

Figure 7: Spatial distribution of land use obtained from the NDWI index in Al-Karkh (2000 and 2017)

Table 6: Change Water by NDWI index of Al-Karkh (2000 and 2017)

Change Water by NDWI Index		
2000-2017		
Class	Area km²	Area%
Increase of Water	15.259	5.650%
Decrease of Water	9.435	3.183%

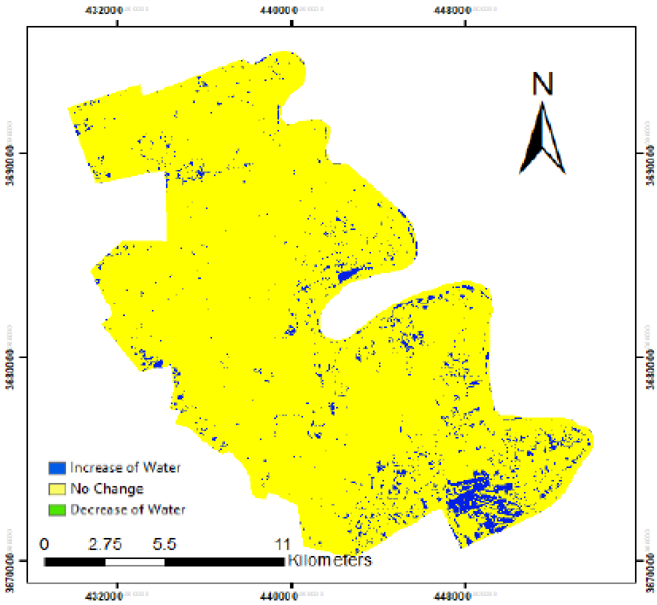

Figure 8: Differences water areas between two years of Al-Karkh (2000 and 2017)

7.5 NDBI

The equation below shows the Normalized Difference Urban Index (NDBI):

$$NDBI = (SWIR - NIR) / (SWIR + NIR) \quad (7)$$

For (landsat7):

$$NDBI = (Band\ 5 - Band\ 4) / (Band\ 5 + Band\ 4) \quad (8)$$

For (landsat8)

$$NDBI = (Band\ 6 - Band\ 5) / (Band\ 6 + Band\ 5) \quad (9)$$

The obtained results from using NDBI were showed in the following tables and figures:

Table 7: Areas of Urban and no urban lands and their percentage in Al-Karkh based on the NDVI index (2000 and 2017)

NDBI Index				
	2000		2017	
Class	Area km²	Area%	Area km²	Area%
No Urban	59.949	19.9%	71.457	23.8%
Urban	240.804	80.1%	229.296	76.2%
Sum	300.753	100%	300.753	100%

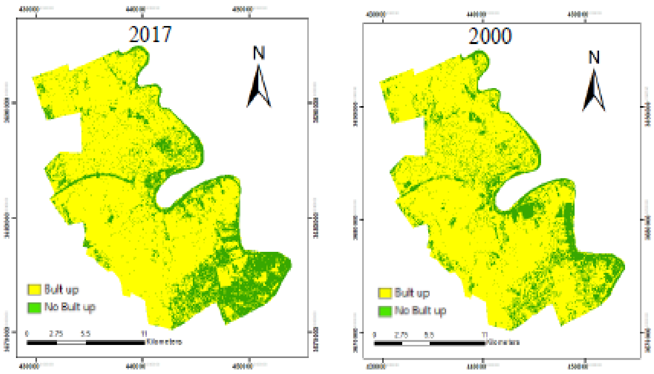

Figure 9: Spatial distribution of land use obtained from the NDBI index in Al-Karkh (2000 and 2017)

Table 8: Change Urban by NDBI index of Al-Karkh (2000 and 2017)

Change Urban by NDWI Index		
2000-2017		
Class	Area km²	Area%
Increase of Urban	38.898	12.934%
Decrease of Urban	30.094	10.006%

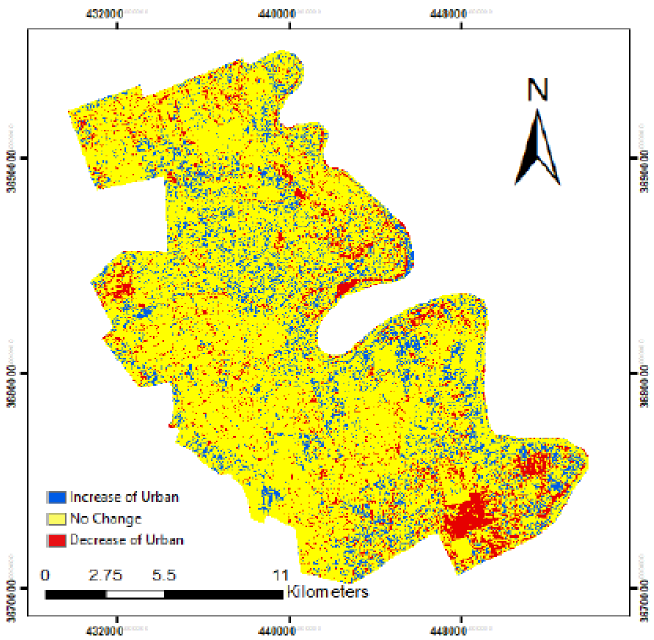

Figure 10: Differences urban areas between two years of Al-Karkh (2000 and 2017)

8. Conclusion

One of the most important uses of remote sensing is the production of Land Use and Land Cover maps. Land Use: refers to the purpose the land surveys, for example, recreation, wild life habitat, or agriculture, urban development, and most areas impacted by human activity. Knowledge of land use helps us to develop strategies to balance conservation, conflicting uses, and developmental pressures. Some of the issues which are of concern include the removal or disturbance of productive land, urban encroachment, and depletion of forests. Land Cover: refers to the surface cover whether vegetation, water, bare soil, urban development or other. Identifying, delineating and mapping land cover are important for global monitoring studies, resource management, and planning activities, change detection techniques using temporal remote sensing data provide detailed information for detecting and assessing land cover and land use dynamics. Different change detection techniques were applied to monitor the changes. The change analysis based on two dates, spanning over a period of two years using supervised classification, NDVI, NDWI and NDBI, showed a decreasing trend (1.607%) in vegetated areas, increase (2.567%) in water bodies, increase (2.928%) in urban areas.

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