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Dynamics of Land Use and Land Cover Change Using Geospatial Techniques – A Case Study of Baghdad, Iraq

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ABSTRACT

Urban land-cover change is increasing dramatically in most emerging countries. In Iraq and in the capital city (Baghdad). Active socioeconomic progress and political stability have pushed the urban border into the countryside at the cost of natural ecosystems at ever- growing rates. Widely used classifier of Maximum Likelihood was used for classification of 2003 and 2021 Landsat images. This classifier achieved 83.20% and 99.58% overall accuracies for 2003 and 2021 scenes, respectively. This study found that the urban area decreases by 16.4% and the agriculture area decrease by 5.4% over the period. On the other hand, barren land has been expanded up to more than 7% as well as increasing in water land that should probably due to flooding (almost 15% more than 2003). To reduce the undesirable effects of land-cover changes over urban ecosystems in Baghdad and in the municipality in specific, it is suggested that Baghdad develops an urban development policy. The emphasis of policy must be the maintenance an acceptable balance among urban infrastructure development, ecological sustainability and agricultural production.

Keywords: land cover; maximum likelihood (ML); change detection.

INTRODUCTION

The arid and semiarid districts influenced by deterioration processes exceed 60% of the national territory. The most vital deterioration is connected to the loss of biodiversity and of land productivity. Vast deforestation and land degradation because of the urbanization and industrialization, wars, natural disasters like drought, flooding induced by global warming are in common (Ziboon 2015). Another study, studied in the last three ages, roughly 6.8 million km^2 of land which was grassland, forest, and woodlands are the most land uses of it has been converted to other land uses. These changes have substantial impacts on several aspects of the life like the agriculture, resources of the earth, the climate and so on (Acito 2017). Locally, because of the wars that Iraq has been involved in (since 1980), the climate changes and land cover in Iraq have been reformed significantly without being observed. Hence, the study and the understanding of these changes are beneficial for several reasons like controlling the sprawl that has occurred due to the identifying the human impacts, planning of the cities in Iraq, absence of the security and managing the resources. Iraq which is similar to many countries, especially in the middle and in the southern part of it, is showing to the problem of the deterioration in the eco-environment. The area that is susceptible to the deterioration is approximated to be one million hectares (Jabbar 2011).

Due to the ability of GIS and Remote sensing to provide data and tools that can be used to support and differentiate the Land use and land cover change, there is an excellent way of monitoring and analysing this phenomenon (Halefom 2018). Remote Sensing technology and satellite data provide the capability of change detection from time series data from different period of time from the specific Land cover classes (Viana 2019). Remote sensing and GIS applications become an essential to assess the urbanization in cities and its distribution in order to make the decision makers vision's perspicuous to build the cites in future (Mahmoud 2021). Digital image processing aid observation, identification, mapping, assessment, and monitoring of land cover at a range of spatial, temporal, and thematic scales (Cheng 2020). In addition, remotely sensed imagery has positively utilized in the past for monitoring, detecting, and displaying changes on large regions (Ali 2016). This information could be utilized to identify the relationships among biophysical activities. Satellite data offers numerous additional benefits over traditional data sources, like field survey, aerial photography methods, due to it offers the capability for (Mezaal 2017):

1) Including broad geographic regions in their entirety.
2) Assessing dynamic landscape patterns (synoptic).
3) Observing changes and trends across large-scale patterns through time.
4) Providing spatially and temporally comprehensive data.
5) Be objective, consistent and repeatable.

Suitable procedure of the information developed from remote sensing data can aid decision makers for linking science and management by comprehension the natural procedures which affected as a result of the disturbances (Mezaal 2018). Change detection is the procedure of detecting the changes in the state of phenomenon or an object by observing it at various times (Wang 2018, Bruzzone 2012. In 2019). Thyagharajan and Vignesh, stated that change detection is an essential method in managing and monitoring natural resources and urban development, actually it is what is needed these days a lot. The aims of this research are monitor, assess, and map the environmental changes in Baghdad by utilizing Geoinformation technology and change detection techniques, utilizing free satellite images (i.e., Landsat thematic maps in 2003 and 2021).

BACKGROUND

Lately, the health of the environment in relationship to the rate at which resource extraction activities happen has been a rising concern. This changing, land use might change the environment (in a potentially negative manner) and dynamic relationship of the environment therefore, involves intensive understanding and monitoring over-time (Mimura 2017). The significant fundamentals comprised in the global monitoring of environmental change are the accurate, reliable mapping, quantifying of physical changes such land cover across large- and small-scale natural environments (Gómez 2016).

The most significant step in understanding the change in land cover is change detection. "Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different time"(KHORRAMI 2019). For comprehension the interactions and relationships among natural phenomena and human, it is very valuable to have timely and accurate information about change detection of the ground. Information about the changes is interesting for manufactures, military, and civilians. The idea behind change detection is the information obtained after subtracting two images from each other. All of the information ((image pixels)) that is similar will repeal each other out, and all of the information that will stay showing the area changes. These images are best when photographed from as similar a situation as possible. In recent decades, Remote sensing data are essential sources extensively utilized in change detection (Skidmore 2017). The procedure of determining that variances are important. It has become known as 'change detection'. The information obtained via analysed remote sensing change detection may offer a superior comprehension of the biophysical relationships in an ecosystem, then is possible with field survey collection alone (Wang 2018). With this comprehension, administrators can be utilized remote sensing as a vital tool for supportable environmental controlling (Dibs 2018).

Generally, remote sensing-based change detection analysis includes the application of multitemporal datasets for quantitatively analysing the temporal impacts of the natural phenomenon. Remote sensing data, like thematic mapper (TM), Satellite Probatoire d'Observation de la Terre (SPOT), Advanced very high-resolution radiometer (AVHRR) and radar, are the key data sources for various change detection applications during the past decades, due to the benefits of repetitive data collection, its synoptic sight and digital format that appropriate for computer processing (Chipman 2019). In the most urban land-cover/land-use change researches Landsat image utilized due to the distinction of the data as the comparatively consistent spectral and radiometric resolution and\only long-term digital archive with a medium resolution (Kim 2016).

From remotely sensed data, there are several change detections approaches have utilized for detecting and observing changes in land use/cover such as image differencing, image regression principal component analysis (PCA), Change vector analysis (CVA), image rationing, and post-classification comparison (PCC) (Rahmes 2014). Every technique has its own advantages and disadvantages because of the effects of spectral, spatial, thematic, and temporal constraints. In addition to the aforementioned constraints, there are other factors affecting the digital change detection: atmospheric condition, differences in the degree of illumination and sun angle, and differences in soil moisture (S Bhagat 2012; Daide 2022).

The approaches of Change-detection have distinctive merits and demerits. For example, the post-classification (map-to-map comparison) approach determines transformation from one land-cover/land-use type to another with less information on the intensity of such changes. The method often involves intensive manual interpretation and required very good skills for applying the interpretation. The spectrally based (image-to-image) approach of change detection introduced quantitative information on spectral change over time. However, interpretation of the spectral variance images with reference to the category of land-cover/land-use change is not continuously clearly (Samal 2015). The most of urban change researches utilizing remotely sensed data assumed homogeneity within a single pixel, producing in no quantifiable changes at the sub-pixel level. Actually, most of the Landsat pixels in urban regions are mixed and comprised of abundant land-cover/land-use types. Ignoring the sub-pixel difference of Landsat image can conduct to a biased guess in urban change study (YANG 2021).

METHODOLOGY

Study area

The study area situated at a latitude range of N 33°11' 38" to N 33°31' 28" longitude E 44°14' 24 " to E 44°35' 26" with 168 Path and 37 Raw. It encompasses an area of 2,260.2 km^2. The study region is placed in the Alluvial plain which the hot desert climate dominates in the sedimentary plain and the western plateau as shown in Figure 1. Annual average rainfall in the area ranges between 50–200 mm, most of the rain occurs between

Figure 1. Location map of the study area

month of October and April. It is distinguished by great temperature variant among the daytime and night time, summer and winter, the maximum of which extents approximately 45–50 °C.

Data acquisition and pre-processing

The images of the study area were obtained from the Web site of the U.S. Geological Survey (i.e., USGS) (available online at http://glovis.usgs.gov/) namely Landsat. In this study, two Landsat images from 2003 and 2021 were used for change detection analysis; these images were chosen from Landsat (ETM+) and Landsat 8, respectively. The Six reflective spectral bands (without thermal bands) were stacking and utilizing in an image-to-image geometric projection. ENVI 5.2 software was utilized to the process and analysis. Image geometric rectification, radiometric calibration, image clipping, noise removal, classification approach, manual enhancement and statistical yield were executed to achieved the objectives of the study. In addition, Arc GIS 10.1 software was utilized to produce the final map involved the title, legend and scale bar. Figure 2 shows the experiment structure to achieve the thematic maps from the Landsat imageries using supervised classification technique. All the images were automatically georeferenced by the website with WGS84 projected coordinate. All the processing for images and subsequent image analyses were executing with the ENVI 5.2 platform. The platform has utilized to conduct the analysis of land cover mapping in the study area including urban expansion studies.

Radiometric correction

When the electromagnetic energy released or reflected is identified by a sensor, the energy measured will not match with the energy emitted or reflected by the same object observed from a short time (Dibs 2018). This is because of the atmospheric conditions such as fog or aerosols, sun’s azimuth and elevation, sensor’s response etc. which effect the detected energy. Therefore, to achieve the real reflectance or irradiance, those radiometric distortions should be rectified.

Atmospheric correction

Remote sensing includes the passage of solar radiation over the atmosphere before the system is collected by the advice. Due to this, remotely

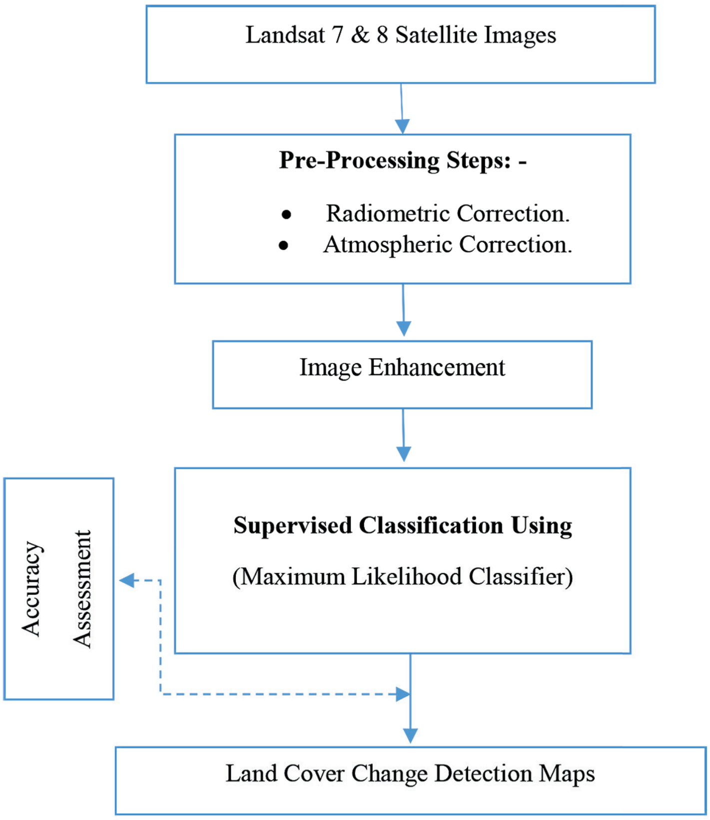

Figure 2. Proposed methodology of the current study

sensed images contain information about the atmosphere and the earth's surface. Therefore, a quantitative analysis of surface reflectance, eliminating the impact of the atmosphere is a critical pre-processing step. To compensate for atmospheric influences, characteristic like the distribution of aerosols, amount of water vapor, and scene visibility should be well-known. Since direct measurements of these atmospheric properties are seldom obtainable. These characteristics are then utilized to compel vastly accurate models of atmospheric radiation transfer to yield an estimation of the true surface reflectance. Utilize the atmospheric correction workflow to correct imagery for atmospheric influences (Doxani 2018). Atmospheric correction is crucial for image processing for identifying the existence of objects utilizing a reference spectral library. In this study, the dark object subtraction atmospheric correction method was used to remove some atmospheric attenuation from Landsat images.

Image enhancement

Enhancements are utilized to produce it easier for comprehension of imagery and visual interpretation (Rani 2016). The advantage of digital imagery is that it agrees us to handle the digital pixel values in an image. Although radiometric corrections for atmospheric impacts, illumination and sensor characteristics might be prepared former for distribution of data to the handler, the image might still not be improved for visual interpretation. Remote sensing instruments, mostly those functioned from satellite platforms, should be designed to deal with levels of target/background energy which are typical of all situations possible to be faced in routine utilize. With large differences in spectral response from a various range of targets (e.g., snowfields, forest, deserts, water, etc.) no standard radiometric correction could optimally description for and show the ideal contrast and brightness range for all objects. Therefore, for each image and application, distribution of brightness values and a custom modification of the range is usually crucial.

Image classification

The key purpose of satellite and other imagery classification is the recognition of objects on the Earth's surface and their presentation in the form of thematic maps. Image Classification is one of the most imperative steps in management remote sensing imagery and signifies significant input data for Geographic Information Systems (GIS) (Robertson 2018).

Numerous causes to utilize Landsat satellite images in this study. They have a tremendous price-quality ratio, spatial characteristics (30 m resolution) and worthy spectral (seven bands from visible to the infrared spectra). Two multi-spectral images have utilized, one from Landsat 8 (2021) and the another from Landsat 7 (2003). The images are shown in Figure 3. all Images were georeferencing to World Geodetic System (WGS-1984) datum. Both cover the whole study area and are somehow cloudless, which allows simple analyzing (i.e., processing) and accurate image classification.

The classification of satellite image and another image are separated into techniques namely supervised and unsupervised. The key variance among the two is in the way the spectral signatures are generated. With supervised approach the operator defines the regions, where a separate specific class of land cover is existing and then the computer calculates the spectral signatures. Instead, in the unsupervised approach the computer generates the spectral signatures utilizing mathematical data clustering in the multi-dimensional feature space.

In this study, supervised approach based on maximum likelihood classifier was utilized. it suggests that the statistics for each feature in each band are typically spread and calculates the probability that a certain pixel fits to a specific class. Unless choice a probability threshold, all the group of pixels are classified. Pixel is specified to the land cover class that has the highest probability (i.e., the maximum likelihood classifier) individually. In this study, four classes were identified based on the various land cover of desire area: urban area, barren land, agriculture, and water.

The most significant step in supervised approach is the collection of training datasets. Training sites are selected within the image that is representative of the land cover of interest after the classification scheme is adopted. Maximum likelihood classification supposes that the statistics for each land cover/ use class in each band are typically spread and analyses the probability that a given pixel belongs to a particular class. The combination of Blue (Band 1), green (Band 2) and red (Band 3) offers a good spectral information for extraction of land cover classes such as Bare land and water bodies, and the vegetation class.

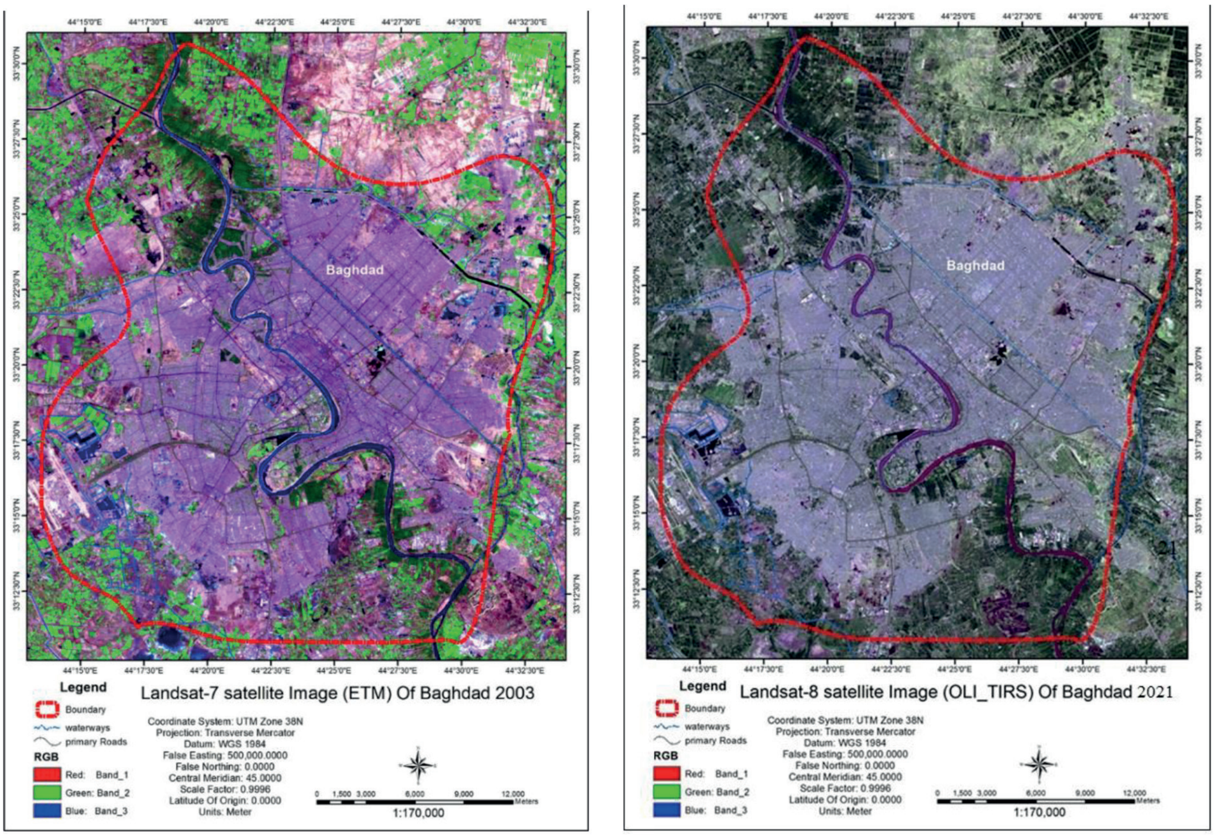

Figure 3. The original scenes for Landsat images for (2003 and 2021)

Change detection

It is essential for studying change on the earth's surface. The change detection approaches are gathered into seven categories: namely (1) visual analysis, (2) algebraic, (3) transformation, (4) classification (5) advanced models, (6) Geographical Information System (GIS) techniques, and (7) other techniques [19]. After the image classification step, the post classification change detection was utilized to measure the changes in land cover classes with "from-to" change information (Bianco 2017). In order to find the extent for the changes between two scenes, the percentage of each land cover classes were calculated based on the classified images. Finally, these areas were compared between corresponding classes.

A significant characteristic of change detection approach is to identified what is really varying to what i.e., which land use class is altering to the another. This information detects both the undesirable and desirable changes and features that are "relatively" stable overtime. This information aid as a useful tool in management decisions. This method includes a pixel-to-pixel evaluation of the study year images via overlap.

RESULTS AND DISCUSSION

Once the probabilities allocated for all features sampled in the input signature file are proportionate to the number of cells collected in each signature. Therefore, those with more cells obtain greater weights and features that have less cells than the average in the sample obtains lower weights than the average. Consequently, the respective features have fewer or more cells specified to them.

After doing classification for both images the distribution of different classes can be shown in Figure 4. The result of the 2003 Baghdad image classification was 79% for urban area which is the greatest percentage of all classes in images, followed by vegetation 19% and barren land 0%. Finally, the percentage of water bodies of Baghdad 2003 was 2% as illustrated in Figure 5. Essentially, the image classification report of Landsat 7 imagery for 2003 is clarified in Table 1.

The level of precision for the results of image classification was calculated by accuracy assessment via confusion matrix [6–31]. Error matrixes which signify the relation among the features which mapped by scheme and reference data

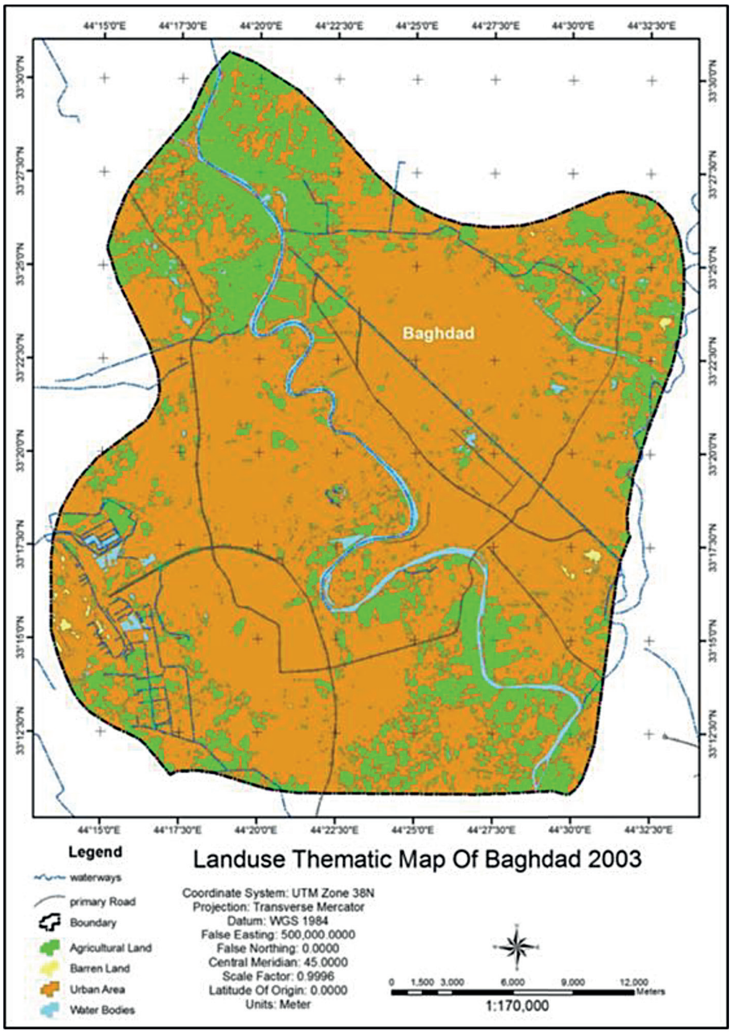

Figure 4. Classification map result for the year of 2003

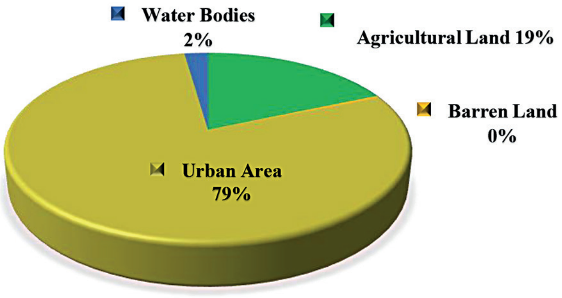

Figure 5. Percentage of the classification result 2003

Table 1. Maximum likelihood classification for 2003

Land use type	Area (km^2)	Percentage
Agricultural land	151.38	18.5
Barren land	2.89	0.4
Urban area	647.43	78.9
Water bodies	18.43	2.2
Total	820.13	100.0
Overall accuracy = 84.70	Kappa coefficient = 0.79	

were prepared and it could generate the producer, user and Kappa coefficient and overall accuracy.

In this study, Kappa coefficient and overall accuracy for image classification in 2003 was acceptable (0.79 and 83.20% respectively). The land use map was compared to the reference data to calculate the accuracy of the classification. Using post classification techniques, the reference data was arranged by considering random sample points with use of stratified random point sampling technique. Therefore, the ground truth data which prepared from Google Earth were used to verify the classification accuracy. The Maximum Likelihood (ML) method requires a short training time by a coarse grid-search approach.

It can be obviously understood from classified image in Figure 6 utilizing two parameters, based the user accuracy vegetation and water

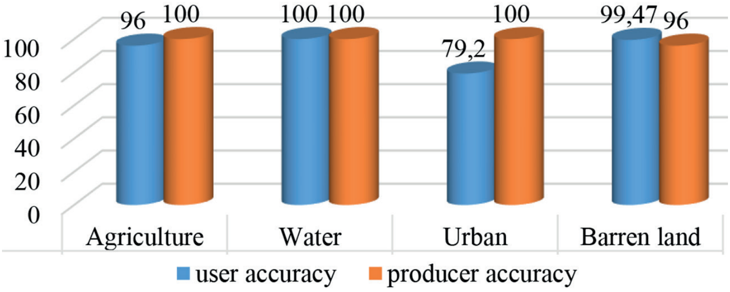

Figure 6. Comparison of producer and user accuracy 2003

bodies are well recognized while, build up is not as precise as others, still acceptable more than 66 percent. On the other hand, for producer accuracy, all derived features show high range 100% accuracy, but unclassified class consider as an error for produces. Producer's error tells the producer of the map how well a certain class can be classified, while user's error gives information to the user of the map that how accurate the classification is. From Figure 7 and 8, It can be obviously realized that urban area has the best percentage of all classes in images (more than 50%), followed by bare land 11% and water land 13%. While, the percentage for the green land of Baghdad 2021 is 24%. Moreover, the result for classifying 2021 images was explained in Table 2.

Kappa Coefficient and overall accuracy in 2021 was very suitable and actually more precise rather than 2003 ETM7 (0.99 and 99.58% respectively).

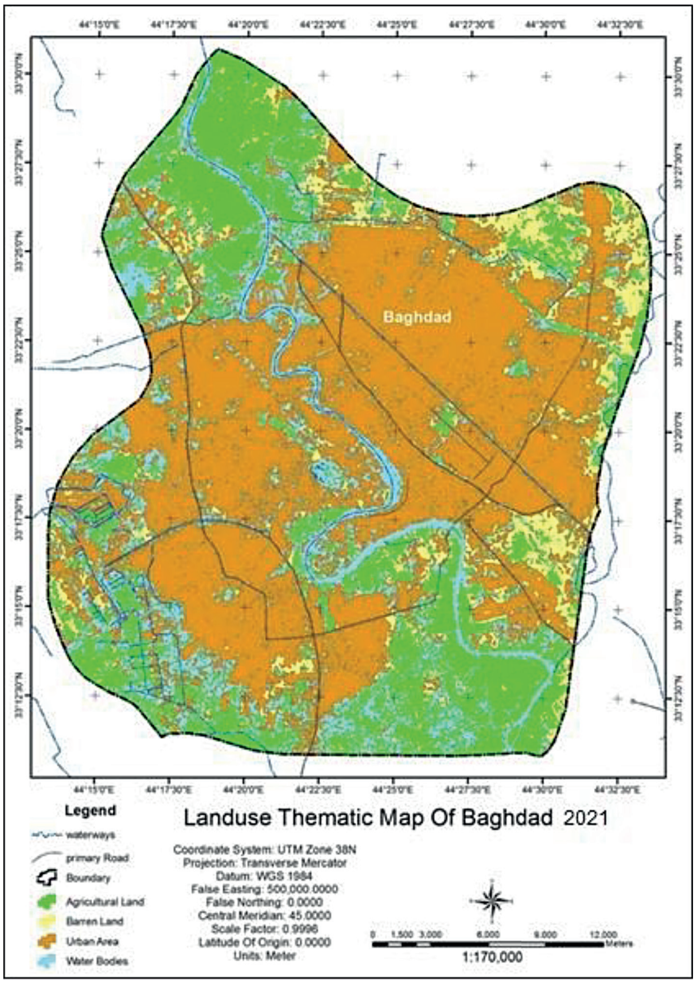

Figure 7. Classification map result for 2021

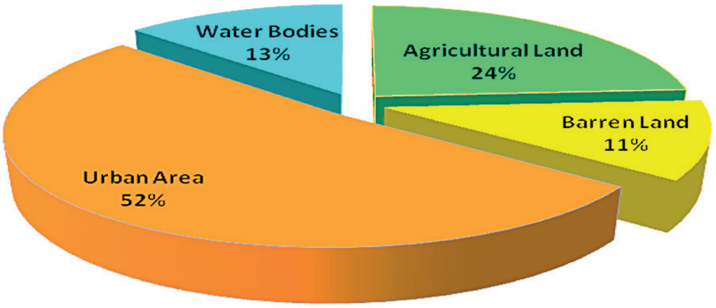

Figure 8. The percentage of the classification result 2021

As it could be obviously shown from sample region of classified image in Figure 9 utilizing two parameters. According to the user accuracy vegetation and water bodies are well recognized (100%) as well as urban and barren land which are existing a high accurate rate as 98.3% and 99.47% respectively. On the other hand, for producer accuracy all resultant features show great range of accuracy almost 99 to 100 percent which indicated there was no considerable error in image classification approach. The change detection percentage (Table 3) of various land cover types were utilized is to compare among the two yields of the image classification by using the ENVI 5.2 software and discover the area that has altered in both term of increasing or decreasing and the resulted in a valid thematic map shown in Figure 10. The changed that happened was a decreasing in the urban area about 16.5%; however, the research could find an increasing in both of Barren land (7%) & water area (15%). It can be found out

Table 2. Maximum likelihood classification input channels: 1, 4, 7 for 2021

Land use type	Area (km²)	Percentage
Agricultural land	196.58	24.0
Barren land	91.87	11.2
Urban area	424.16	51.7
Water bodies	107.52	13.1
Total	820.13	100.0
Overall accuracy = 99.58%	Kappa coefficient = 0.99	

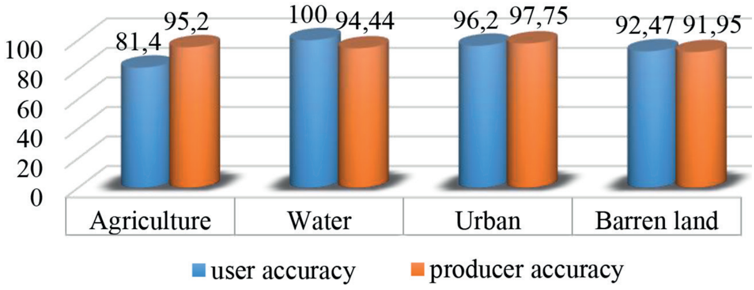

Figure 9. Comparison of producer and user accuracy 2021

Table 3. Change detection analysis table

Year	Area (km²)	2003					
		Urban	Agriculture	Water bodies	Barren land	Row total	Class total
2021	Urban	442.37	18.1	0.59	0.86	461.92	461.92
	Agriculture	128.85	86.16	4.66	0.12	219.79	219.79
	Barren land	57.3	7.37	0.33	1.5	66.5	66.5
	Water bodies	45.21	14.68	12.19	0.02	72.1	72.1
	Class total	673.73	126.3	17.77	2.51	0	0
	Class changes	231.36	40.14	5.58	1.01	0	0
	Image difference	-211.81	93.49	54.33	63.99	0	0

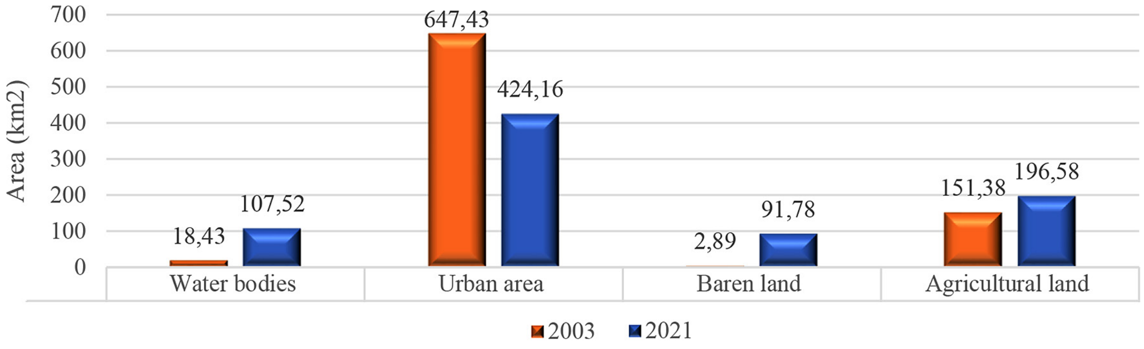

Figure 10. Comparison the percentage of the classification result between 2003 vs 2021

that one of the reasons of water bodies expansion is might be because of heavy raining on the time that image was captured as a result flooding came over the low elevation area. Actual Rapid increase of open area (soil and bare lands) probably due to decreased of agriculture or vegetation lands over the time as well as destroying the buildup area during the war.

CONCLUSION AND RECOMMENDATIONS

This research assessed and monitored the changes in land cover pattern in Baghdad province using multi-temporal Landsat 7, 8 TM imagery from 2003 to 2021 within a time interval of 19 years. The Maximum Likelihood (ML) classifier achieved 83.20% and 99.58% overall accuracies for 2003 and 2021 scenes, respectively. This study provides empirical evidence that urbanization of the Baghdad decreased dramatically for the time interval mentioned above. The main reason of this problem is many people emigrate from Baghdad to other destinations due to the invasion of U.S.A to Iraq between the same period of this study time. Rapid increase of open area (soil and bare lands). While natural vegetative cover (natural vegetation and current croplands) declined, water bodies expanded enormously within the period and might be because of heavy raining and flooding low elevation area.

The land cover changes in the municipality of Baghdad; that is characterized degradation of the ecosystem, produced socioeconomic and environmental consequences which compromised the ability of the biological systems to support human needs and the ability of people to cope with the climatic, economic and socio-political changes. The same conclusions were deduced in other places of Baghdad including the north of Baghdad. It is recommended to develop an urban development policy especially in the municipality of Bagdad in order to decrease the unwanted impact of land-cover changes on urban ecosystems. The policy requires establishment of a balance between agricultural production, urban infrastructure development and ecological sustainability. Furthermore, a single management authority is required to develop the government institutions capacity that is responsible for the public land administration and development.

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