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Original Article

Change Detection, Modeling, and Simulation of LCLU Using Multispectral Satellite Images for the Sustainability Development in Najaf City, Iraq

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Abstract *- Sustainability development is the most important and dangerous issue globally, in the present and future. In this study, remote sensing technology represented by multispectral Landsat images is used to find change detection in classes of land cover and land use that are considered part of the sustainable development goals in this city. The adopted duration time are 2000, 2005, 2009, 2015, and 2020 with five multispectral Landsat images. ERDAS Imagine 2015 is the main program used in this study, where the maximum likelihood method is used for the supervised classification. The results are classified images with accuracies 92.13%, 90.91%, 89.74%, 88.39%, and 85.22%, whereas Kappa coefficient 0.8668, 0.8486, 0.8413, 0.8296, and 0.7805 respectively. The change detection of the area for each class during these years has been realized. The results are an increase in the water bodies area by 6.546%, agricultural lands by 2.8%, And urban land area by 7.719%. In contrast, there is a decrease in the bare lands by -17.068%. The results were followed by modeling from the adopted period, then a simulation for all classes of LCLU for period years (2025- 2050). The outcomes of this study gave useful information for sustainability development through providing a benefit to government institutions related to urban planning, water resources, environment, and agriculture in Al-Najaf city, Iraq. The outcomes of this study are considered as part of achievements that related to the 17 goals of 2015 Paris agreement that should be verified in 2030.*

Keywords: *Sustainability development; Remote Sensing; Multispectral; change detection; image Classification.*

I. INTRODUCTION

Sustainability development is considered the most important and the most dangerous problem on our planet, especially in the last years. Land use and land cover (LULC) change is a major issue of global environmental change, which is an important part of sustainability development. Scientific research community called for a substantive study of land-use changes during the 1972 Stockholm Conference on the Human Environment, and again 20 years later, at the 1992 United Nations Conference on Environment and Development (UNCED). There are lots of studies that have proved that LULC and its change had become a key to many diverse applications such as environment [1][2], forestry, hydrology , agriculture ,geology, and ecology[3]. These applications about urban expansion, cropland loss, water quality change, soil degradation, and so on [4]. Satellite data in remote sensing had been widely applied on detecting LULC change [5][6][7], especially urban sprawl [8], urban planning [9], and cropland loss a lot of change detection techniques, that was the process of identifying differences in the state of and object or effect by observing it at different times [10] The most important studies of remotely sensed uses in applying change detection analysis of land cover and land use studies [11][12][13][14] 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 studied change detecting in Kuwait City and its suburbs using multi-temporal land sat thematic mapper data to monitor change in land cover [15] Hussein ZE, et al., they introduced a study about changes in Al-Hawizeh marsh which is the largest marsh in southern Iraq period of (1990 – 2015). The results gave significant changes in the vegetation cover of the study area by approximately 43% [16]. Alkaradaghi K,et al , studied the changing in Sulaymaniyah in Iraq in the period (2001-2017) . They found an increase in both urbanism, water, and plants, and a decrease in the soil, rocks, and forests [17] Sabea AM, and et.al, introduced a study for analysis and monitoring the changes in LULC in Ameriyat al-Fallujah in Anbar province in period of time between (1985 – 2017), were the study gave an increase in water and barren land, while a decrease in salt area. [18] Mustafa YT. Mustafa et al, studied the prediction of the Zakho region in Kurdistan, Iraqi. The prediction for the year 2050 using remote sensing and GIS by Landsat images (OLI, TM) for the period (1989-2014) for 25 years [19]. Fahad et al. studied environmental for Baghdad city for the period (1990-2018) using Landsat satellite (OLI and TM) for (28) years, They concluded that increasing of urban areas and soils while a decreasing in both cultivated and water lands [20], Wang SW, and et.al, Using remote sensing data, socio-economic data, and field observations, simulated spatiotemporal dynamics of land use and land cover changes in the city of Thimphu. Simulation results reveal that the landscape of Thimphu city has changed considerably during the study period and the change trend is predicted to continue into 2050 [21]. In this study we used multispectral Landsat images via especial selection bands to find classification for each image by supervised classification using maximum likelihood by ERDAS is the main image process for each multispectral Landsat image to be classified for four classes that represent Al-Najaf city: water bodies, Agriculture lands, Urban land, and Bare lands. Then finding change detection in the years of adopted period of (2000-2020) in four classes for sustainability development in this city. In addition to try finding equations for the classes and predicting by the found equation.

II. MATERIALS AND METHODS

A. Study area

AL-Najaf Province is an important and famous spot in Iraq which is located in the south-west part of Iraq, see Fig.1., the location AL-Najaf province is represented by the longitude (42o 50'00" E- 45o 44'00" E) and by latitude (29o 50'00" N- 32o 21'00" N) covering an area of 28202.8847 km2 which is bounded from the north by provinces of Karbala and Babylon and from the east it bounded by Muthna and Qadsia Provinces, from south and south-west, is bounded by Saudi Arabia kingdom, and it bounded by Anbar Province from the west [22] . It has a population of 1,221,248 people, according to 2011 statistics. And the population of the governorate is 1,500,522; according to the 2017 census, it is considered the fifth city in terms of population; its center is the city of Najaf. It is a governorate of a great religious and historical nature due to the presence of many Shiite Islamic shrines, the Wadi al-Salam area, and the Kufa Mosque, And also one of the important cities in Iraq because of the shrine of Ali bin Abi Talib, the first imam among the Shiites and the fourth of the Rightly-Guided Caliphs among the Sunnis, and a center for the Shiite seminary in Iraq. This study area includes: Al-Najaf District Center with Al-Najaf Sea, AL- Kufa district Center with Al-Abbassiya Sub-district ,Al- Huriya Sub-district, Ibn Najm Marsh, and AL-Manathera district Center with Al-Heera Sub-district, and Al- Mishkahab Sub-district. His works have been applied in adopted study areas within the sedimentary plain. The total study area is (1005.41 km^2). Where it is an area that appears in the image as it includes more details in each class, but all these details will be included in the class, where this job belongs to the classification process.

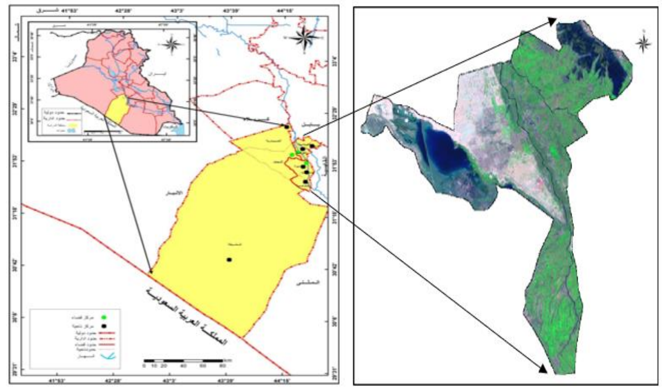

Fig.1. The study area

B. Data Acquisition and Pre-processing

For achieving detecting land use/land cover changes, it is necessary to choose multi-temporal data sets that be acquired at the same time for the same study area [23][24][25]. Therefore, to guarantee the accuracy, all (2000 - 2005 – 2009 - 2015 and 2020) images must be acquired in the spring season during the day and the same hour. In this Study, two multi-temporal Landsat 5 (TM) and Landsat 8 (OLI) images that were acquired respectively, as shown in the table 1, All the images used were picked up during the day. Landsat data have been obtained from the USGS Earth Explorer site (https://earthexplorer.usgs.gov). With path (168) and row (38), with a spatial resolution of 30m. ERDAS IMAGE has been used for pre-processing, including an atmospheric correction to remove cloud pixels.

Table 1. Characteristics of used satellite data

Year	Satellite	Sensor	Spatial Resolution	Date
2000	Landsat 5	TM	30 m	16/3/2000
2005	Landsat 5	TM	30 m	14/3/2005
2009	Landsat 5	TM	30 m	25/3/2009
2015	Landsat 8	OLI	30 m	10/3/2015
2020	Landsat 8	OLI	30 m	23/3/2020

C. Image Classification

Classification is the process of grouping pixels or regions of the image into classes representing different ground-cover types. There are two main types of image classification techniques method used in land use and land cover classification. First is supervision classification, which is used for classifying land cover types using sample polygons (ground truth points) from known land cover types. Second is unsupervised classification, which is used for classifying land cover classification from satellite image data when the user does not know the number of types of land cover in the field [26]. For this study, the Maximum Likelihood Super Classification type is used for Landsat images classification. The study area images were classified into four classes (water bodies, agriculture lands, Urban land, and bare lands) using the supervised classification technique.

D. Mathematical Modeling

Mathematical modeling is a mathematical process that finds the relationship between variables, and it is measured by the coefficient of determination which is a measure used in statistical analysis that evaluates the quality of a model in explaining and predicting future results, and its value ranges from zero to one. The coefficient of determination makes the interpretation of correlation coefficients easier [27]. The coefficient of determination is simply the squared value of the correlation coefficient. The coefficient of determination R^2 describes the relationship between the area of LCLU class and year, and determines how much the variable variation area of the LCLU class is dependent on the independent variable year.

E. Methodology of Research

The comprehensive methodological framework and data analysis are shown in Fig.2, where the parts of the methodology for the study are as follows.

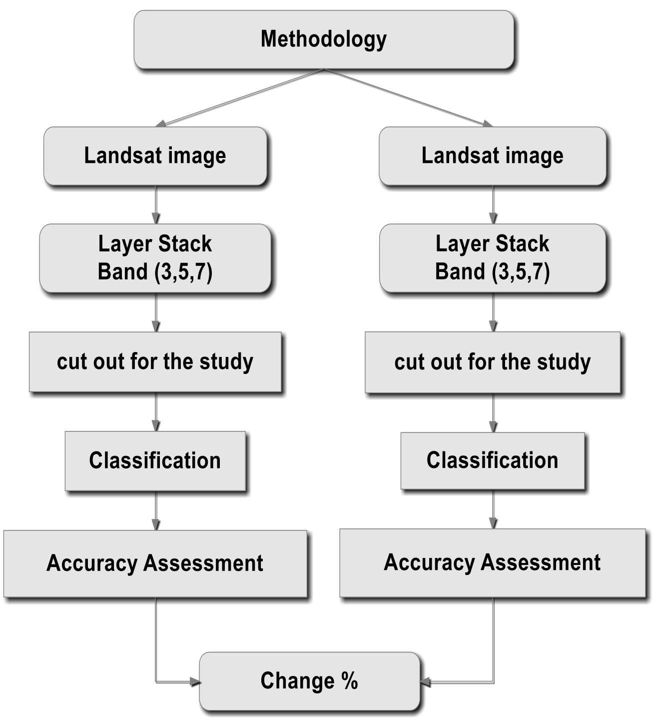

Fig.2. Methodological workflow and data analysis

In this study, we used multispectral Landsat images via especial selection bands to find classification for each image by supervised classification using maximum likelihood by Erdas is the main image process for each multispectral Landsat image to be classified for four classes that represent Al-Najaf city: water bodies, Agriculture lands, urban lands, and Bare lands. The accuracy assessment of the image classification is a very crucial part. For accuracy assessment, overall accuracy, and kappa coefficient were computed for the final land cover maps produced. The results are classified images (maps) with accuracies (92.13%, 90.91%, 89.74%, 88.39%, and 85.22%) and Kappa coefficient (0.8668, 0.8486, 0.8413, 0.8296, and 0.7805) for the adopted five images of the period years respectively.

III. RESULT AND DISCUSSION

A. LULC change in a different period (2000 - 2020)

Results from the classified maps indicated that in 2000 were occupied by different classes, water bodies covered 11.189%, agricultural lands were about 37.816%, urban land was about 6.504 %, and bare lands most part of Al-Najaf city were about 44.489%. On the other hand, these classes cover about 15.257%, 32.505%, 7.489%, and 44.747% respectively of the study area were covered by in 2005, change detection analysis presented water bodies, urban land, and bare lands showed have been increased by 4.068%, 0.985%, and 0.258% respectively. Agriculture lands were reduced by - 5.311% during the time from 2000 to 2005. On the other hand, about, water bodies covered 10.97%, agricultural lands were about 37.02 %, urban land was about 9.548%, and bare lands most part of Al-Najaf city were about 42.451% of the study area were covered by in 2009. Change detection analysis presented agricultural lands; urban land showed have been increased by 4.515% and 2.059%, respectively. Whereas water bodies and bare lands were reduced by - 4.28% and -2.296 respectively during the time from 2005 to 2009. On the other hand, about water bodies covered 13.357%, agricultural lands were covered 33.8%, urban land was covered 13.299%, and bare lands about 39.536% of the study area in 2015. Change detection analysis presented water bodies, and urban land showed have been increased by 2.387% and 3.751%, respectively. Agriculture lands and bare lands were reduced by - 3.22% and 2.915% during the time from 2009 to 2015. On the other hand, about water bodies covered 17.735%, agricultural lands most part of the al-Najaf city were covered 40.62%, urban land was covered 14.223%, and bare lands covered 27.421% of the study area were covered in 2020. Change detection analysis presented water bodies, agriculture lands, and urban land showed have been increased by 4.378%, 6.82%, and 0.924%, respectively. Bare lands were reduced by - 12.115% during the time from 2015 to 2020. The biggest change detection analysis in this study presented water bodies, agriculture lands, and urban land showed have been increased by 6.546%, 2.8%, and 7.719%, respectively. Bare lands were reduced by -17.068% during the time from 2000 to 2020. LULC maps of these adopted years are illustrated in Fig.3., the data are drawn in Fig.4., and data is registered in Table 2.

Table 2: LULC Change between the different time intervals (2000 to 2020)

		Water bodies	Agriculture lands	Urban land	Bare lands	Total
2000	Area in(km^2)	112.5	380.21	65.4	447.3	1005.41
	Area (%)	11.189	37.816	6.504	44.489	100
2005	Area in (km^2)	153.4	326.81	75.3	449.9	1005.41
	Area (%)	15.257	32.505	7.489	44.747	100
Change in Area (%) (2000-2005)		4.068	-5.311	0.985	0.258	0.00
2009	Area in(km^2)	110.3	372.3	96	426.81	1005.41
	Area (%)	10.97	37.02	9.548	42.451	100
Change in Area (%) (2005-2009)		-4.28	4.515	2.059	-2.296	0.00
2015	Area in(km^2)	134.3	339.9	133.71	397.5	1005.41
	Area (%)	13.357	33.8	13.299	39.536	100
Change in Area (%) (2009-2015)		2.387	-3.22	3.751	-2.915	0.00
2020	Area in(km^2)	178.31	408.4	143	275.7	1005.41
	Area (%)	17.735	40.62	14.223	27.421	100
Change in Area (%) (2015-2020)		4.378	6.82	0.924	-12.115	0.00
Change in Area (%) (2000-2020)		6.546	2.8	7.719	-17.068	0.00

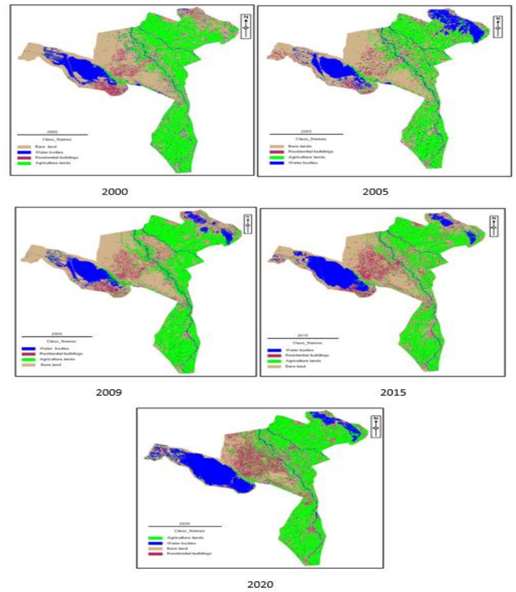

Fig.3. LULC maps for 2000, 2005, 2009, 2015, and 2020 years

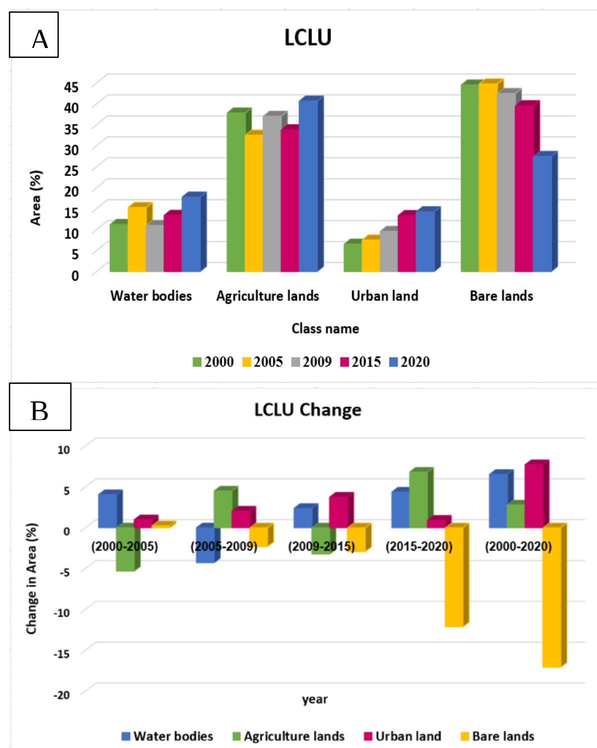

Fig. 4. (A) The LCLU trend of years (2000 to 2020) (B) The LCLU change detection of years (2000 to 2020)

Fig.5. illustrates the result of mathematical modeling for each class.

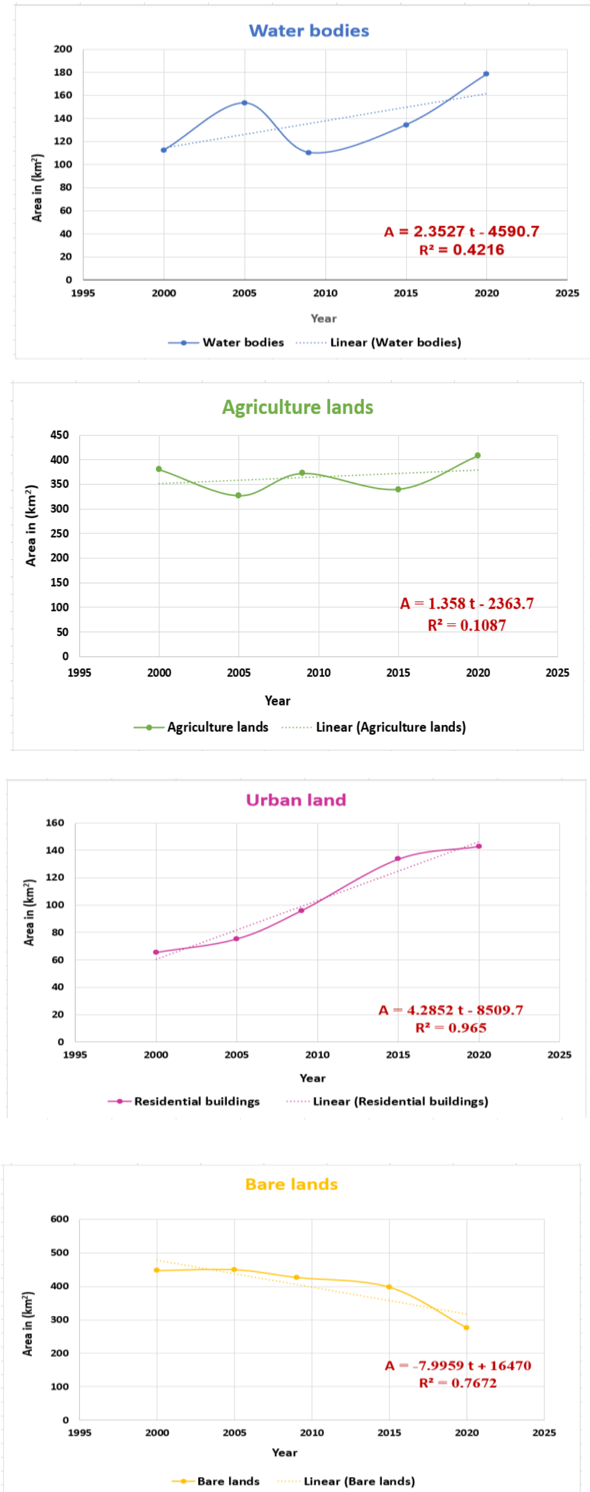

Fig.5. The curves of the mathematical model between the area of LCLU and the years (2000 to 2020)

We find that the highest value of the coefficient of determination (R^2) is for the urban land during the study period, where the value of the coefficient of determination (R^2=96%), followed by bare lands where the value of the coefficient of determination (R^2=76%), and then the water bodies where the value of the coefficient of determination (R^2=42%), and the lowest value that is found for agriculture lands where the value of the coefficient of determination (R^2=10%) Table 3, Therefore, we find the two best equations: the first for the urban land , and the second for the bare lands, whereas, there are not good equations for each of the water bodies and agriculture lands. The irregular changes of most of the class of LCLU in the study area have an impact on the fluctuation of the value of the coefficient of determination (R^2), due to its direct impact on climate change and the amount of rain that greatly affects agricultural land and water bodies, and the other factor that affects LCLU change is human activities Where agricultural land has been transformed into urban land in most areas of Al-Najaf city.

Table 3: The regression equation for LCLU Class and Coefficient of Determination (R^2)

LCLU Class	Regression Equation	Coefficient of Determination (R^2)
Water bodies	A = 2.3527 t – 4590.7	0.4216
Agriculture lands	A = 1.358 t - 2363.7	0.1087
Urban land	A = 4.2852 t - 8509.7	0.9650
Bare lands	A = -7.9959 t + 16470	0.7672

B. Simulation of future changes in years 2025-2050

The regression equations predicted the changes for the future through the calculation area of each class of LCLU for every five years as an interval between the adopted year (2025 to 2050). Data registered in table 4, where Fig.6. reveals that both positive and negative changes, results in 2025 will be occupied by different classes, water bodies will be covered 17.26%, agricultural lands most part of Al-Najaf city will be about 38.41%, urban land will be about 16.68%, and bare lands will be about 27.65%, change detection analysis presented urban land and bare lands showed that will be increased by 2.45%, 0.229% respectively. Water bodies and agricultural lands will be reduced by -0.475%, -2.21 respectively during the time from 2020 to 2025. On the other hand, about water bodies will be covered 18.42%, agricultural lands most part of the al-Najaf city will be about 39.09%, urban land will be about 18.82%, and bare lands will be about 23.67% of the area will be covered in 2030. Change detection analysis presented water bodies, agricultural lands, and urban land showed that will be increased by 1.16%,0.68%, and 2.14%, respectively. Bare lands will be reduced by -3.98% during the time from 2025 to 2030. On the other hand, water bodies covered 19.59%, agricultural lands will be covered 39.77%, urban land will be covered 20.93%, and bare lands will be covered 19.7% of the area will be covered in 2035. Change detection analysis presented water bodies, agricultural lands, and urban land showed that will be increased by 1.17%, 0.68%, and 2.11%, respectively. Bare lands will be reduced by -3.97% during the time from 2030 to 2035. On the other hand, about water bodies will be covered 20.77%, agricultural lands most part of the al-Najaf city will be about 40.44%, urban land will be about 23.08%, and bare lands will be about 15.71% of the area will be covered in 2040. Change detection analysis presented water bodies, agricultural lands, and urban land will be increased by 1.18%, 0.67%, and 2.15%, respectively. Bare lands will be reduced by -3.99% during the time from 2035 to 2040. On the other hand, about water bodies will be covered 21.93%, agricultural lands most part of the al-Najaf city will be about 41.12%, urban land will be about 25.2%, and bare lands will be about 11.75% of the area that will be covered by in 2045. Change detection analysis presented water bodies, agricultural lands, and urban land showed that will be increased by 1.16%, 0.68%, and 2.12%, respectively. Bare lands will be reduced by -3.96 % during the time from 2040 to 2045. On the other hand, about water bodies covered 23.11%, agricultural lands most part of Al-Najaf city were about 41.772%, urban land that will be about 27.32%, and bare lands will be about 7.798% of the area that will be covered in 2050. Change detection analysis presented water bodies, agriculture lands, and urban land showed will be increased by 1.18%, 0.652%, and 2.12%, respectively. Bare lands will be reduced by -3.952% during the time from 2045 to 2050. On the other hand, change detection analysis presented water bodies, agriculture lands, and urban land showed that will be increased by 5.375%, 1.152%, and 13.09%, respectively. Bare lands will be reduced by -19.623% during the time from 2020 to 2050.

We conclude that the area of water, agricultural and urban land will tend to increase during the coming years and at different rates, while the vacant lands tend to decrease during the coming years (2025 -2050) shown in Fig.7.

Table 4: The projected area of LCLU in (2020 to 2050) in the Al-Najaf city

land cover /land use		Water bodies	Agriculture lands	Urban land	Bare lands	Total
2020	Area in km^2	178.31	408.4	143	275.7	1005.41
	Area (%)	17.735	40.62	14.223	27.421	100
2025	Area in (km^2)	173.51	386.2	167.7	278	1005.41
	Area (%)	17.26	38.41	16.68	27.65	100
Change in Area (%) (2020-2025)		-0.475	-2.21	2.45	0.229	0.00
2030	Area in km^2	185.2	393.01	189.2	238	1005.41
	Area (%)	18.42	39.09	18.82	23.67	100
Change in Area (%) (2025-2030)		1.16	0.68	2.14	-3.98	0.00
2035	Area in km^2	197.04	399.83	210.47	198.07	1005.41
	Area (%)	19.59	39.77	20.93	19.7	100
Change in Area (%) (2030-2035)		1.17	0.68	2.11	-3.97	0.00
2040	Area in km^2	208.8	406.61	232	158	1005.41
	Area (%)	20.77	40.44	23.08	15.71	100
Change in Area (%) (2035-2040)		1.18	0.67	2.15	-3.99	0.00
2045	Area in km^2	220.5	413.41	253.4	118.1	1005.41
	Area (%)	21.93	41.12	25.2	11.75	100
Change in Area (%) (2040-2045)		1.16	0.68	2.12	-3.96	0.00
2050	Area in km^2	232.3	420.01	274.7	78.4	1005.41
	Area (%)	23.11	41.772	27.32	7.798	100
Change in Area (%) (2045-2050)		1.18	0.652	2.12	-3.952	0.00
Change in Area (%) (2020-2050)		5.375	1.152	13.09	-19.623	0.00

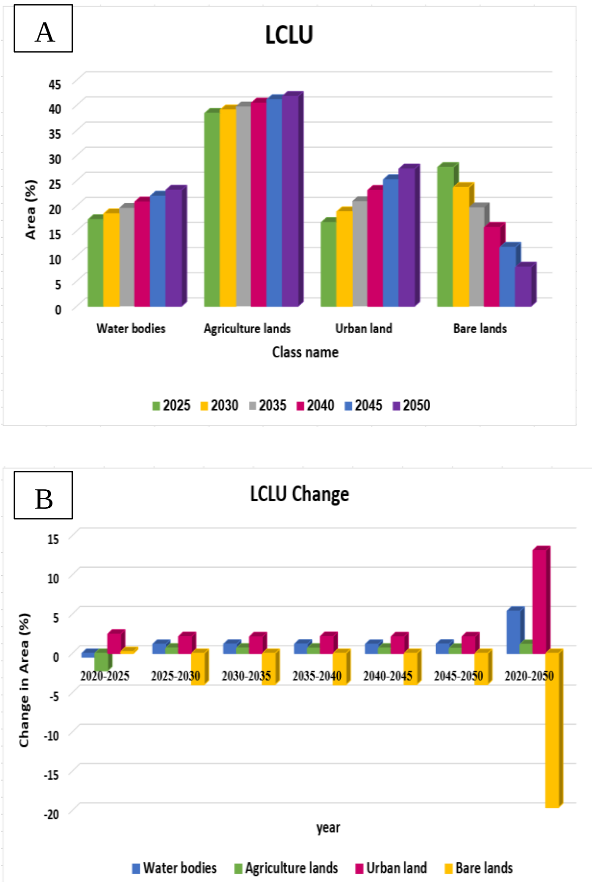

Figure 6: (A) The LCLU trend of years (2020 to 2050) (B) The LCLU Change Detection of years (2020 to 2050)

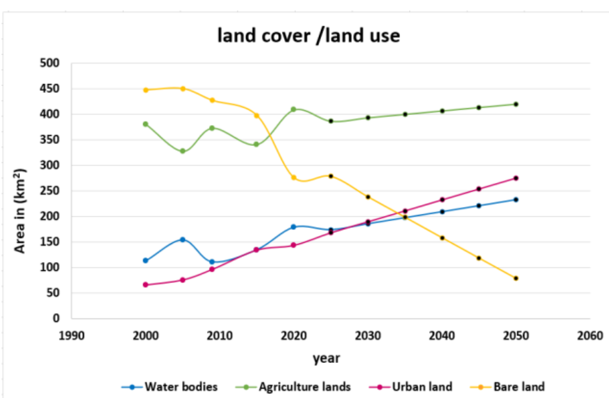

Fig.7. The trends of LCLU from (2000 to 2050) in the study area (Al-Najaf city).

IV. CONCLUSIONS

A achieve the main purpose of this work which is the change detection in major components area that is strongly related to the sustainable development in Al-Najaf city in the period (2000-2020) with the modern technology represented by remote sensing. Achieving the classification of all multispectral Landsat images of all adopted five years 2000, 2005, 2009, 2015, and 2020 with acceptable accuracy 92.13%, 90.91%, 89.74%, 88.39%, and 85.22%. With Kappa coefficient (0.8668, 0.8486, 0.8413, 0.8296, and 0.7805), for Al-Najaf city based on four classes: water bodies, agriculture area, urban land area, and bare area respectively. The results of change detection in (2000-2020) an increase in the water bodies area by 6.546 %, agriculture land area by 2.8%, and urban land area by 7.719%. In contrast, there is a decrease in the bare land area by -17.068%. Finding equation by mathematical modeling of each area of each class, we found two equations with high acceptance: the first for urban land class, with $R^2 = 0.965$ and the second for bare area class, with $R^2 = 0.7672$. Also, finding equations with low acceptance for both of water bodies and agriculture area classes, where $R^2 = 0.4216$ and $R^2 = 0.1087$ respectively. The main reason for this is no constancy in these two classes changes. Predicting the area of classes through simulation step that has used the obtained equations through the mathematical modeling of each class. Simulation results give the future case of the area of each class until the year 2050. As a result of simulation, there is an increase in the water bodies by 5.375, urban area by 1.152, agriculture area by 13.09, and a decrease in the bare area by -19.623. The change detection results give useful information for sustainability development through providing a benefit to government institutions related to urban planning, water resources, environment, and agriculture in Al-Najaf city, the outcomes of this study is considered as part of achievements that related to the 17 goals of 2015 Paris agreement that should be verified in 2030.

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