ISSN: 0974-5823 Vol. 7 No. 2 February, 2022

International Journal of Mechanical Engineering

Simulating and Predicting Land Cover Changes in Al Najaf Province Utilizing a CA-Markov Model

Fatima Abdul Al-Aali[1,] ; Ebtihal T AL-Khakani[2]*

[1,2] Department of Physics, College of Education for Girls, University of Kufa

al Najaf, Iraq

Abstract

Land Use/Land Cover (LULC) is a serious phenomenon that can affect human activities. Spatial-temporal land-use change (LULC) analysis and monitoring and modeling of urban expansion are critical to urban environmental planning and management. Land cover change (LULC) is recognized worldwide as one of the main drivers of environmental change that can affect human activities. A LULC change assessment is the most accurate way to understand past land use, the types of change that need to be assessed, and their critical effect on urban environmental planning and management. This paper aims to assess and determine changes in the temporal and spatial LULC using satellite imagery data and Land Change Modeler (LCM) and predict the future of LCLU for the year 2030. The research was carried out in part of Najaf Province which was identified as a study area. Landsat images from 2000, 2015, and 2021 were used to assessment and expect the spatiotemporal distribution of LULC differences. Future projections of the LULC map were made depending on the historical trend of changing LULC for 2030. For all classified pictures; total accuracy (OA) ranged from 90% - 92%, with a kappa index measurement (K) of 0.87 to 0.9. The results discovered that the almanac population growth along with socio-economic development is considered to be the main driver of land transformation in the region. The forecast map shows a important trend of desert class reduction by 2030, equivalent to 93 Km^2. However, urban region and farmed land class are expected to rise to 14 Km^2 and 58 Km^2, respectively. Finally, this kind of study output is very important to environmental scientists, land managers, decision-makers, and urban planners in Al Najaf province.

Keywords: Land cover, CA-Markov, Landsat-8 , Change detection, kappa index

1. Introduction

The land-Use Cover change LULC indicates a change in physical land kinds such as water bodies, bare soil, forests, vegetation, etc., while land use variation refers to a change in a specific area of land that is used or managed by People to provide it **(Liu , Shi; 2019)**. Land use and land cover change (LULC) is the result of People activities and following developments around the world **(Bai et al., 2008)**. Land use models are driven by population dynamics, which are directly responsible for land cover change **(IPBES, 2018; Verma plus Raghubanshi, 2019)**. Land use land cover dynamics is critical to environmental and sustainable built-up development, understood in various methods. Both of these are more related to sustainable urban economic growth **(Liping, et al., 2018)**. The evolution of modern technologies, such as Geographic Information systems, remote sensing, has used high-resolve imagery to monitor and assess LULC dynamics in recent ages. These technologies are combined with spatial replicas that allow users to simulate land use transformation **(Kumar et al., 2014)**.

The applications of remote sensing technology in monitoring the land cover changes have grown in recent decades as a result of the rapid advancement of remote sensing technology through integration with the Geographical Information System (GIS) **(Al-khakani and Yousuf, 2021; Al-khakani and Al-Ruwashdi, 2021)**. The scarcity of data sources and technology in RS and GIS can forecast the changes in future land use. The Markov chain examination is a frequently used model to predict and simulate future land cover changes **(Weng., 2002)**. The Markov model is a theory that represents the creation of a system with an arbitrary Markov prediction method **(Iacono et al., 2015)**. This model can be used to construct a transition probability matrix in two dissimilar periods using the LULC map. This matrix lets estimating the probability of transitioning the land cover classes from one to another class or staying in the same class **(Huang., 2020)**.

The main objective of this research is to propose a methodology for monitoring and analyzing the urbanization process in order to better understand it and support effective urban planning towards urban sustainable development. The focus is on detecting Spatio-temporal changes of land cover patterns from 2000 to 2021 and projects into the future (2030) based on multi-temporal visuals for remote sensing and urban growth simulation.

2. Methodology

2.1 Study area and data sources

Al-Najaf Governorate is located in the Middle Euphrates region in Iraq, about 161 km southwest of the capital, Baghdad. Geographically, located within the latitudes of 32°15'- 29°50' and the longitudes of 44°44'-42°50' in the southwest side of Iraq, as shown the Fig.1. The average elevation of Al-Najaf city is about 70 m above sea level. According to the 2021 census, the Governorate had a population of approximately 1,589,961. In this research, a part of Najaf Governorate was extracted as a study area with an area of 2,194 Km2 within the latitudes of 32°20'30"- 31°35'54" and the longitudes of 44°35' 22"- 43°58' 11". The study area covered various types of land cover, including urban, desert, bare soil, water (lake and river), and agricultural land.

Landsat images have been collected between 2000 and 2021 to find out land cover changes. Images of 2000 were acquired from Landsat 5 Thematic Mapper (TM), and of 2015 and 2021 from Landsat 8 Operational Land Imager (OLI), (Table 1). All images have been captured on the satellite path/row:168/38 and expected in UTM using the WGS84 datum of 38 N. All these imageries were downloaded from the United States Geological Survey (USGS) ((http:/earthexpolorer.usgs.gov//)).

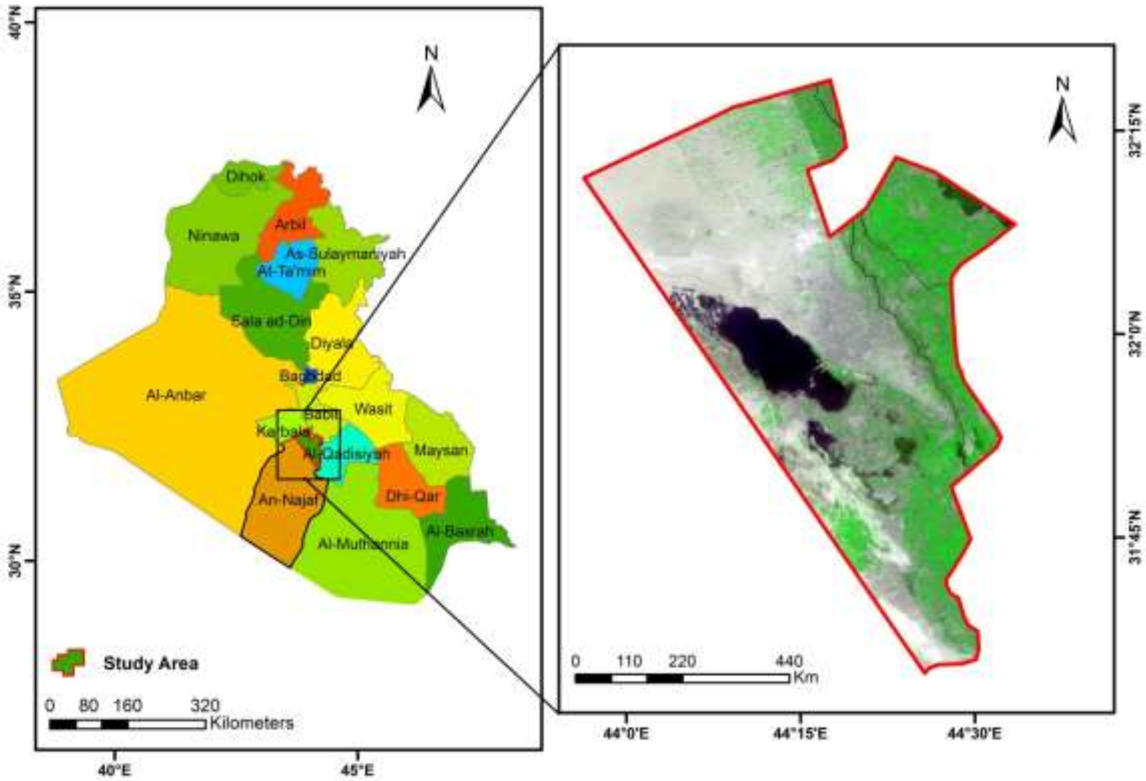


Figure 1: Location map of the study area

2.2 Dataset Pre-Processing and Classification

The Landsat images are the main data used in this research. Three Landsat images were used in this study: 2000, 2015, and 2021 (Table 1); Landsat 5 Thematic Mapper (TM) and two Landsat 8 from the United States Geological Survey (USGS) were downloaded. The image classification processing was done using Arc-GIS10.8.

Table 1: Landsat images with their collection resolution and dates.

type of Satellite sensor	Path/Row	Collection date	Resolution
Landsat 5 TM	168/038	February 29, 2000	30 m
Landsat 8 OLI	168/038	February 6, 2015	30 m & 15 m
Landsat 8 OLI	168/038	March 17, 2021	30 m & 15 m

Landsat images for the years 2000, 2015, and 2021 were cut using the study area frontier layer. These pictures were classified in a GIS environment based on the wide algorithm of the Supervised Maximum Likelihood classification MLC, method to produce the land-use changes. Based on the training samples, these areas were categorized into five classes, namely: water body, agriculture land, desert area, bare soil, and urban area.

2.3 Accuracy Assessment and Change Analysis

Accuracy assessment or validation is a main part of any scheme that uses spatial data. Classification truth is the mark to which the classification of the image corresponds to the reference data (ground truth data) **(Anand. 2017).** Classification inaccuracy results when there is a difference between the classified data and the reference data **(Foody., 2008).** For 2000, and 2015, the reference points were collected from original Landsat images, Google Earth, discussions, previous reports, and maps. For the 2021 image, original Landsat images, Google Earth, field observation, interviews, and collection deliberations of random reference points in different LULC kinds were documented from the field review conducted by using GPS. About 200 check samples were taken randomly throughout the study area for each classified image covered all types of land use for each year. To measure the accuracy of each classified map, the error/confusion matrix method was used. This method is the most effective and widely method employed in the image classification field. The confusion matrix provides user accuracy, producer accuracy, overall accuracy, and kappa statistics **(Congalton and Green., 1999)**

After measuring the accuracy of each classified LULC map between 2000 and 2021, the quantification of the dynamic of transformations over period was examined by computing the area of an exact class group per period (i.e., for each target year 2000, 2015, and 2021) (**Butt et al. 2015).** Utilizing the LCM to obtain various temporal maps and LULC maps to reveal changes in the LULC categories. This allows us to know the trend and contribution of revolution between LULC classes over time. Two LULC charts were used to study the primary conversions, which were modeled individually as partial models at a later stage **(Nguyen et al., 2020).**

2.4 Land Use Prediction Modeling

In this study, Markov Chain and Cellular Automata CA-Markov models were utilized to simulate the future variations in land use in Najaf city. Changes in LULC classes can be analyzed and summarized through the number of possibilities of transitional areas from one case to other different cases during a certain period using the Markov chain processing. To expect LULC change, the Markov matrix model depends on the Bayes equation (Eq.2) that predicts the change by comparing the first LULC map (T1) and the second LULC map (T2) **(Eastman., 2016).**

$$\mathbf{S_{(t+1)} = \boldsymbol{P_{ij}} * S_{(t)}} \qquad (1)$$

$$Pij = \begin{bmatrix} P11 & P12 & \cdots & P1n \\ P21 & P22 & \vdots & P2n \\ \cdots & \cdots & \cdots & \cdots \\ Pm1 & Pm2 & \cdots & Pnm \end{bmatrix} \qquad (2)$$

P is the conversion probability; *Pij* exemplifies the probability of translating from the present event *i* to extra event *j* in next time; *Pn* is the state's possibility for any time period. The lowest conversion has a probability near to ‘0’, and the highest transition has possibilities near to ‘1’ **(Ahmed et al., 2012; Nouri et al., 2014).** The transition probability matrix was calculated for the period 2000–2015 to forecast the land-use patterns for 2021, and for 2015– 2021 to project future land use patterns through 2030.

2.5 Model Validation

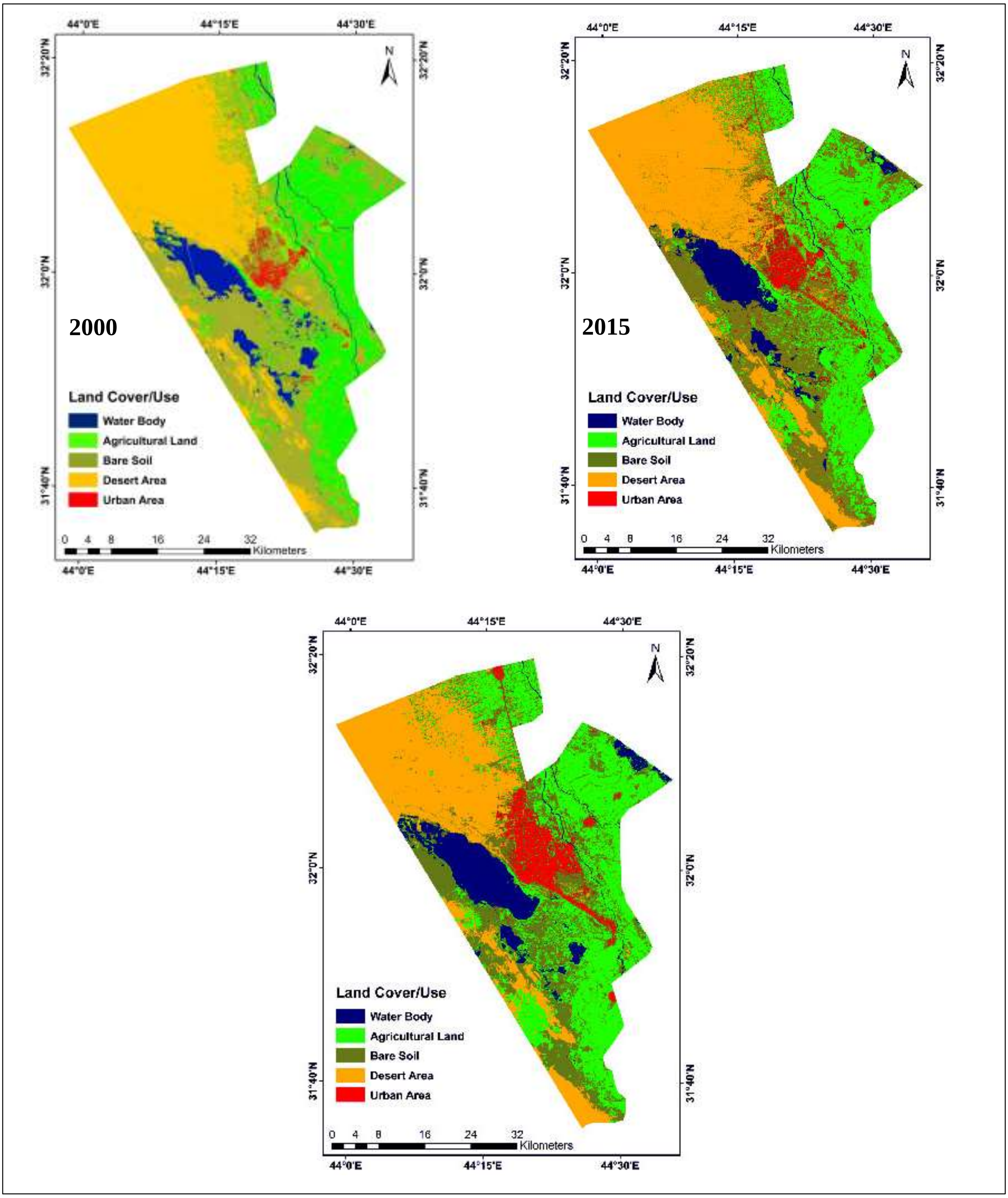
Validation is simply the process of evaluating the quality of a projected LULC map compared to a reference map (Wang et al., 2016). The LULC images for 2021 were simulated using Landsat images from 2000 and 2015, and the simulated LULC was compared to the actual map. The 2000 and 2015 images were provided for LCM calibration and the model was confirmed by simulating the prevailing 2021 LULC map. The LCM confirmation procedure contains a cross-tabulation three-part comparison between successive land cover maps (2015), the projected land cover map (2021), and the current (real) map (2021). A unit test of the LCM module was secondhand to statistically evaluate the quality of the 2021 LULC predictive image compared to the 2021 reference picture(Wang et al 2016).

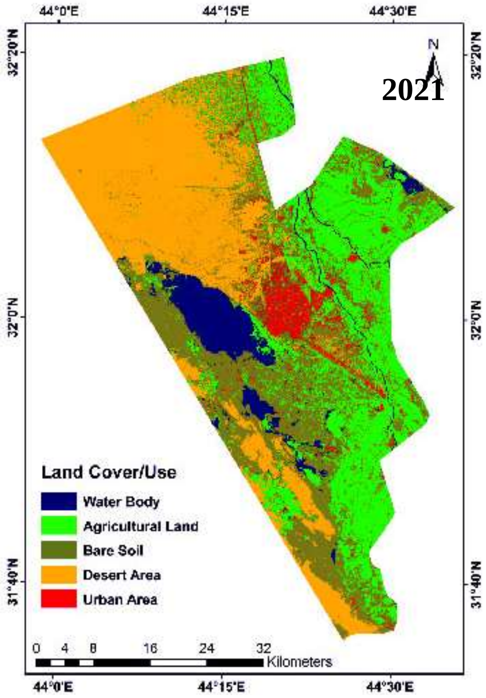
Three parameters, Kno, Kstandard, and Klocation are highly suggested for evaluating a simulated map. Values like 1 satisfy the simulation, while 0 is unsatisfactory (Hamamd et al., 2018). Kappa for no ability (kno), Kappa for standard (Kstandard) and Kappa for location (Klocation) were used to confirm the forecast LULC pictures. The overall simulation accuracy was achieved using Kappa for no capability (kno), and the quantity and location between the existing image and predicted image were obtained by Kappa for standard (Kstandard) and Kappa for location (Klocation).

3. Results and Conversation

3.1 LULC Change Discovery and Classification Assessment

To evaluate the changes in the LULC in Al Najaf city, land cover patterns were categorized for 2000, 2015, and 2021 into five categories are urban area, agricultural land, desert area, water bodies, and bare soil (Figure 2). The classification results in 2021 showed that agricultural land was dominated, occupying the highest proportion (32.86%) of the LULC. The next dominant class is the desert area with a proportion of 27.93%, while the urban land which occupied 3% of the total area in 2000, increased to 9.4 % in 2021, whereas, desert territory declined from 36.27% in 2000 to 27.93% in 2021, also, bare land decreased sharply during this period, at the expense of increasing agricultural and urban areas (Table 2).


44°0'E
44°15'E
44°30'E
32°20'N
32°0'N
31°40'N
N
2000
Land Cover/Use
Water Body
Agricultural Land
Bare Soil
Desert Area
Urban Area
0 4 8 16 24 32
Kilometers
44°0'E
44°15'E
44°30'E
32°20'N
32°0'N
31°40'N
N
2015
Land Cover/Use
Water Body
Agricultural Land
Bare Soil
Desert Area
Urban Area
0 4 8 16 24 32
Kilometers
44°0'E
44°15'E
44°30'E
32°20'N
32°0'N
31°40'N
N
Land Cover/Use
Water Body
Agricultural Land
Bare Soil
Desert Area
Urban Area
0 4 8 16 24 32
Kilometers



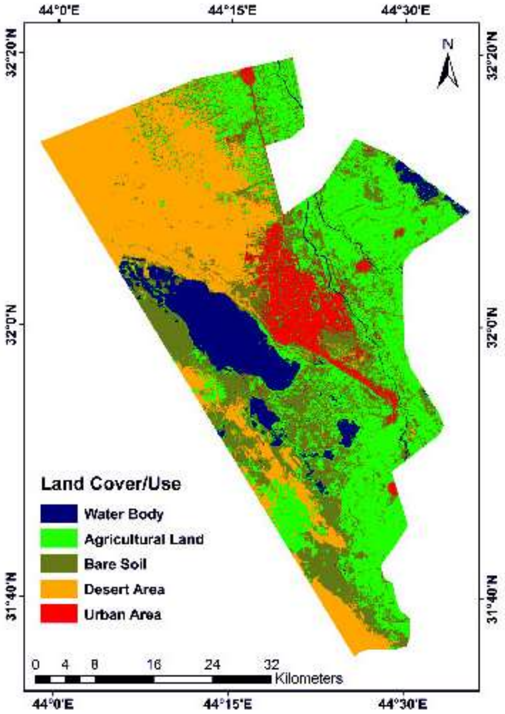


Figure 2. The LULC of the AN Najaf city in 2000, 2015 and 2021

Classification	2000		2015		2021	
	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)
Water bodies	128.86	5.87	136.63	6.23	192.62	8.78
Agricultural land	551.71	25.15	593.08	27.04	720.95	32.86
Bare soil	650.98	29.67	750.45	34.21	461.25	21.03
Desert	795.71	36.27	590.74	26.92	612.89	27.93
Urban areas	66.49	3.04	122.85	5.6	206.04	9.40
Total	2193.75	100	2193.75	100	2193.75	100

Table 2: LULC area from 2000 to 2021 (in Km^2) and percentage

In addition, utilizing LCM change analysis, LULC change analysis was performed to estimate the gain-loss and net change sustained by various groups. The gain, loss, and net change area of the LULC classes in each period time was calculated to examine evaluations of spatial and temporal variations across different classes in the years 2000, 2015, and 2021, as shown in two figures 3 and 4.

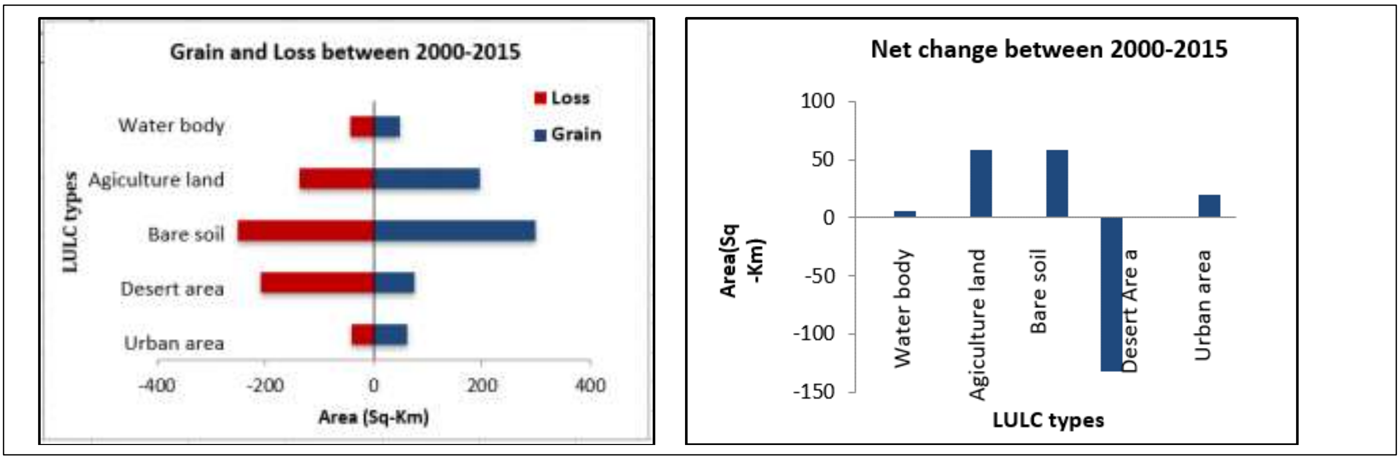


Figure 3. Gain-loss area and Net change area of LULC class in 2000-2015.

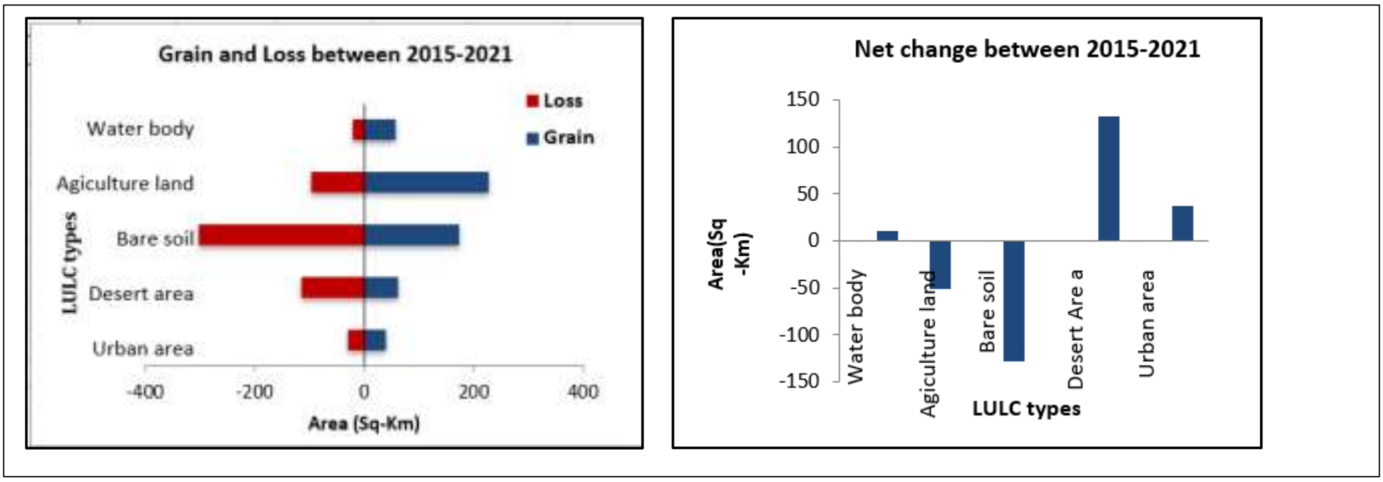


Figure 4. Gain-loss area and Net change area of LULC class in 2015-2021

Accuracy assessment was carried out to analyze LULC changes by creating confusion/error matrices in each LULC group from classified maps from 2000, 2015, and 2021. Overall accuracy, kappa data, producer's and user's accuracy were secondhand for evaluation. Kappa coefficients (K) and the total accuracy (OA) of the classified maps show 90.1%, 92%, 92%, and 0.90, 089 and 0.90 for 2000, 2015 and 2021, respectively (Table 3). The latest LULC map accuracy values are higher and may be related to the higher spatial resolution of the satellite imagery.

Table3: Accuracy assessment of classified LULC maps for 2000, 2015, and 2021.

LULC Class	Producer's Accuracy%			User's Accuracy%		
	2000	2015	2021	2000	2015	2021
Water	100	100	100	90	97.1	90
Agriculture	100	97.7	96.0	93.3	93.5	98
Bare soil	75	81.8	80.4	90	85.7	90.2
Desert	91.7	89.1	93.9	93.6	98	93.9
Urban	96	93.8	92.9	80	83.3	83.9
	OA%			K		
	90.1	92.0	92.0	0.90	0.89	0.90

It was found that the overall accuracy for each period is more than 90%, which indicates a very good analytical accuracy. According to **(Anderson, 1976)**, kappa index accuracy must not be less than 85%, so the kappa index also showed very good value, meaning that the accuracy evaluation values of the classified images are reliable.

3.2 Transition Probability Matrix

To predict the 2021 and 2030 map, a transition probability matrix was created for the period 2000-2015 and 2015-2021, respectively, through the IDRISI Selva program by going to the Molding list and then the Markov tool and after setting the interval between the two visuals to predict land cover patterns for the year 2021.

Tables 4, 5 provide a summary of the probability matrix for major land use transfers for all categories that occurred for the periods 2000-2015 and 2015-2021. According to the below results, the probability of future movement from bare areas to urban areas increased from 4% during the period 2000-2015 to 6% during the period 2015-2021, which indicates urban expansion and exploitation of bare spaces. The results also indicate an increase in the probability of the future transition from desert areas to agricultural areas from 3% during the period 2000-2015 to about 12% during the period 2015-2021, which indicates that the desert areas are well exploited for agriculture in the northeastern part of the study area. The tables display the decreasing and increasing possibilities of transition during two time periods, from 2000-2015 to predict land cover patterns for the year 2021 and from 2015-2021 to predict land cover patterns for the year 2030.

Table 4: Transition probabilities matrix for the periods 2000-2015.

LULC Category	Water bodies	Vegetation	Bare soil	Desert areas	Urban areas
Water bodies	0.7141	0.0905	0.1913	0.0023	0.0018
Vegetation	0.0416	0.5820	0.3477	0.0118	0.0170
Bare soil	0.1280	0.1772	0.5417	0.1111	0.0420
Desert areas	0.0341	0.0341	0.2757	0.6870	0.0025
Urban areas	0.0023	0.0370	0.3961	0.0024	0.5621

Table 5: Transition probabilities matrix for the periods 2015-2021

LULC Category	Water bodies	Vegetation	Bare soil	Desert areas	Urban areas
Water bodies	0.7575	0.1376	0.0984	0.0050	0.0015
Vegetation	0.0701	0.6814	0.2137	0.0244	0.0104
Bare soil	0.0956	0.3366	0.3948	0.1109	0.0621
Desert areas	0.0138	0.1193	0.1743	0.6804	0.0122
Urban areas	0.0227	0.0881	0.3723	0.0254	0.4915

3.3 Model validation

Before starting to apply the spatial simulation of the map of expected changes for the year 2030, the model accuracy must be evaluated. By comparing the predicted LULC maps for 2021 to the actual LULC map for 2021 (figure 5), the accuracy of simulation and model validation were evaluated.

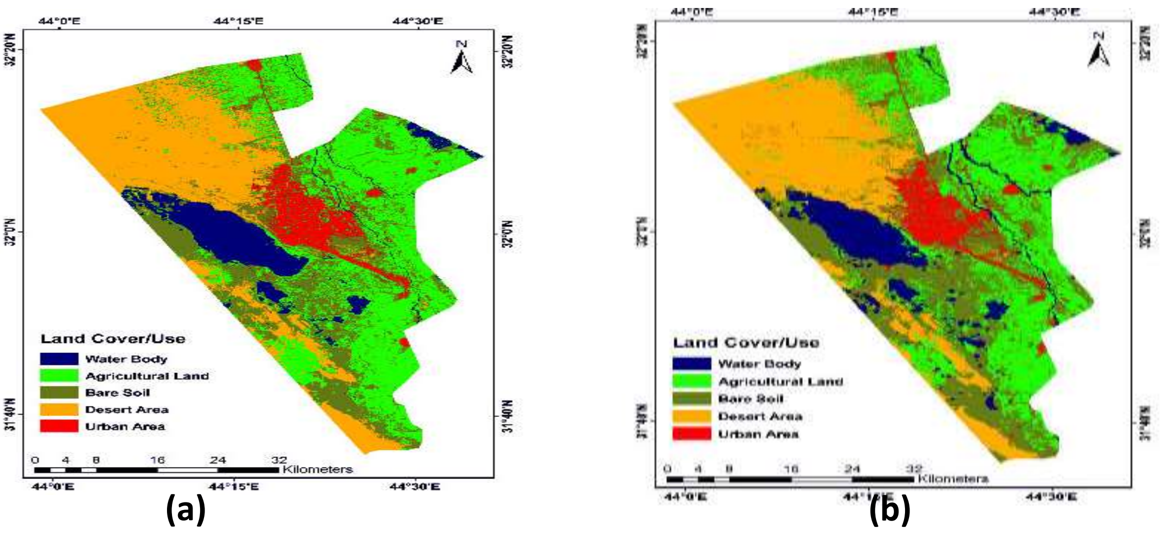


Fig.5: Map of land cover patterns of 2021, (a) actual and (b) projected.

Kappa statistics represent the most widely accepted method for determining the simulation model's power and applicability. The Kappa index of Agreement is reported in figure6, Kappa for no data (kno), Kappa for standard (Kstandard), Kappa for location (Klocation), and kappa for stratum-level location (KlocationStrata) were calculated using the GIS Analysis submodule in Idrisi. The statistics of location revealeds that Kno is 0.8862, Klocation and Klocation Strata are 0.8821, and Kstandard is 0.8326, as in figure 6. This demonstrates a high level of agreement between predicted and actual LULC maps, indicating that the CA-Markov Chain model has been successfully validated. According to **(Fleiss et al 2003)**, if the value of the Kappa is greater than (0.75), the agreement is excellent, . This means that this model can predict the future map for the year 2030.

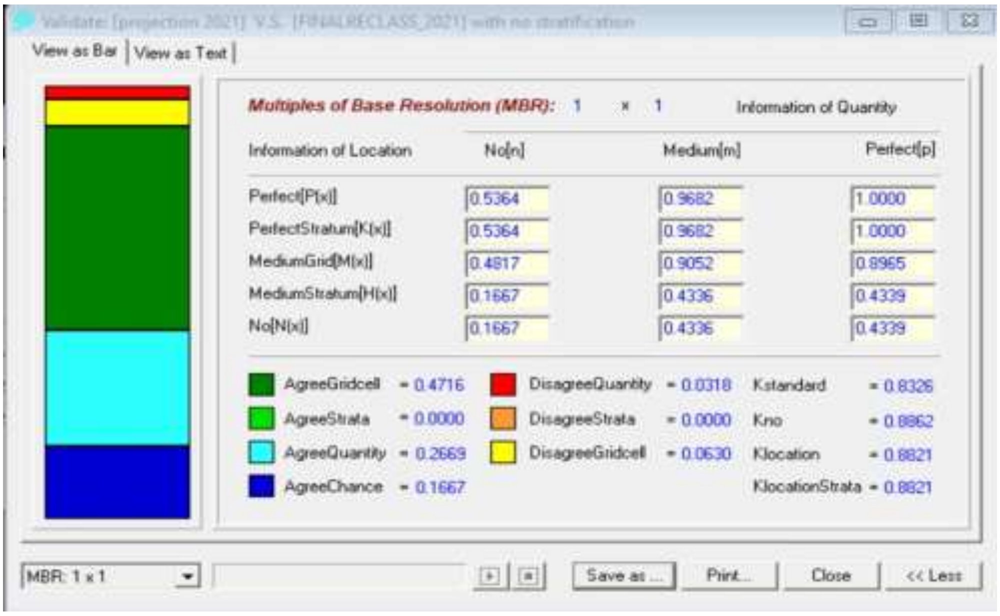


Fig. 6: LULC change prediction validation based on the actual and projected 2021

3.5 Future LULC Prediction

To forecast the future scenario, the CA-Markov Chain simulation model uses previous and subsequent LULC maps **(Sang et al., 2011).** Changes in the previous period can be used to forecast variations in the later period, according to the Markov Chain concept **(Ghosh et al. 2017, Wang et al. 2021).** The simulations of future LULC were predicted for 2030, with a 9-year time interval between 2021 and 2030. Built on the idea of conversion probability, the Markov model calculates the probability of a change from a specific land cover class to another through a dimensioned matrix for LULC categories **(Nadoushan et al, 2015).** Figure 7 shows the simulation findings as a projected LULC map for 2021. Similarly, the coverage area, percentage, and rate of variation are given in Table 6. Also figure 8 shows the increase or decrease that expect in LULC classes for the period 2021-2030.

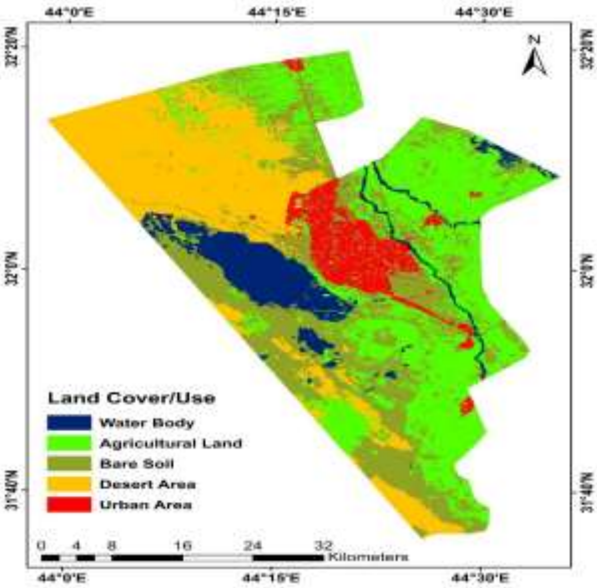


Fig. 7: The predicted 2030 LULC of the study area.

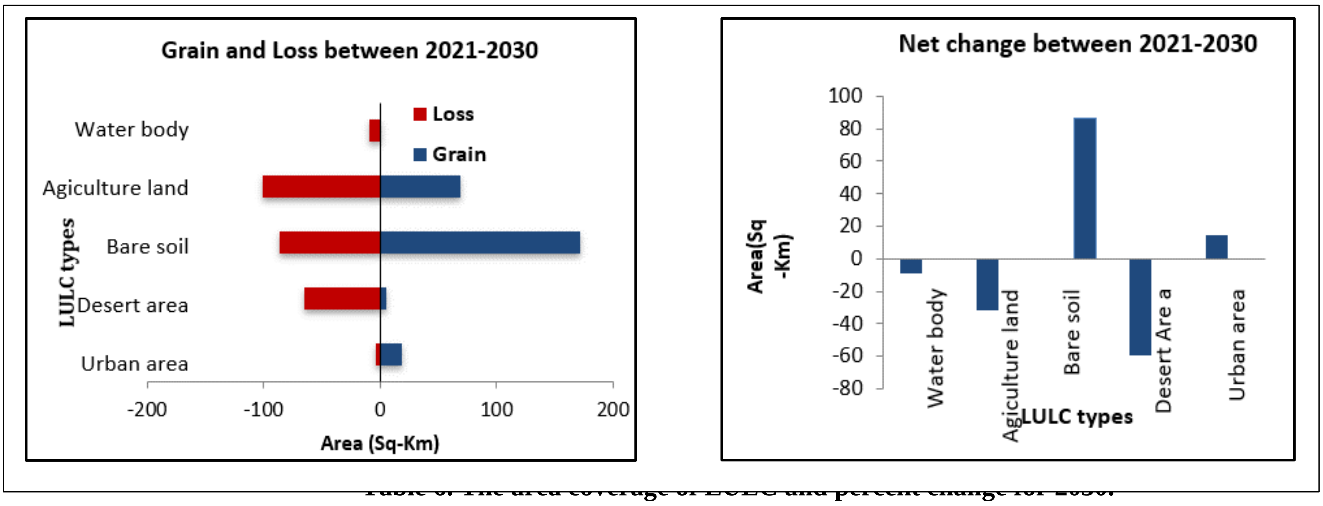


Table 6: The area coverage of LULC and percent change for 2030.

Classes LULC	Area(km^2)	Area %
Waterbody	197.34	9.0
Agriculture land	778.49	35.5
Bare soil	478.53	21.8
Desert Area	519.41	23.7
Urban Area	219.98	10.0
Total	2193.75	100

Table (6) represents the expected area and percentage for each land cover type in 2030, where agricultural areas occupy an area of 778.49 km^2, equivalent to 35.5%, followed by Desert areas, which occupy an area of 519.41 km^{2}or 23.67%, and the percentage of water is about 9%, and bare soil by 21.81%, while urban areas are 10%.

4. Conclusions

The classification results of the LULC analysis obtained for 2000, 2015, and 2021 in Al Najaf, showed that the overall accuracy of the LULC map was between 90.1 and 92.0% with a kappa between 0.87 and 0.90. In this study, most of the land conversion of the study area were agricultural land, urban area, and water body because the province has experienced population growth and socio-economic growth.

The 2021 and 2030 LULC simulations using the Markov Chain integration caused in high accuracy. The results show that the projected LULC map in 2021 shows reliable results with significant agreement compared to the original LULC map. The simulation clarifies that the forecast map for 2030 shows the observed trend from 2000 to 2021 and indicates that the area of the desert area will continue to reduction by more than 93 km2. On the other hand, water, urban and agricultural land are expected to increase by about 5 km2, 14 km2, and 58 km2 respectively. This projected 2030 map will help develop a model of adaptability to the sharp increase in development activities from 2000 to 2021. Therefore, proper planning should be carried out in the region, which can reduce future impacts.

5. References

1. AL-Khakan, E. T., & Al-Ruwashdi M. A. Spatiotemporal Monitoring of Urban Expansion Utilizing Remote Sensing Data: The Case Study of An Najaf Governorate 2021;15(8): 33-41.
2. Anderson, J.R., A land use and land cover classification system for use with remote sensor data. Vol. 964. 1976: US Government Printing Office.
3. Yousuf, R. T., & AL-Khakan, E. T. Assessing Degree of Desertification Using Tasselled Cap Transformation and Spectral Indicators Techniques: Iraq. Scientific Journal of King Faisal University: Basic and Applied Sciences 2021; 22(1): 48-53.
4. Liu Q, Shi T. Spatiotemporal differentiation and the factors of ecological vulnerability in the Toutun River Basin based on remote sensing data. Sustainability 2019;11(15):4160.
5. Bai ZG, Dent DL, Olsson L, Schaepman ME. Proxy global assessment of land degradation. Soil Use and Management 2008;24(3):223-34.
6. Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES). Summary for policymakers of the assessment report on land degradation and restoration [Internet]. 2018 [cited 2021 Mar 10]. Available from: https://www.ipbes.net/system/tdf/spm_3bi_ldr_digital.pdf?fil e=1&type=node&id=28335.
7. Verma P, Raghubanshi A. Rural development and land use land cover change in a rapidly developing agrarian South Asian landscape. Remote Sensing Applications: Society and Environment 2019; 14:138-47.

8. Liping, C., Yujun, S., Saeed, S., 2018. Monitoring and predicting land use and land cove changes using remote sensing and GIS techniques - A case study of a hilly area. Jian gle, China. Plosone 13, 1-23.
9. S. Kumar, N. Radhakrishnan and S. Mathew, “Land use change modelling using a Markov model and remote sensing,” Geomatics Natural Hazards and Risk 5(2), pp. 145-156, 2014.
10. Y. Huan, H. Zhebgwei, P. Xin, Wetland shrink simulation using cellular automata: A case study in Sanjiang, China, Procedia Environmental Science, 2, 2010, pp. 225–233.
11. F. Ridwan, M. Ardiansyah, K. Gandasasmita, Pemodelan perubahan penutupan/penggunaan lahan dengan pendekatan artificial neural network dan logistic regression: Studi kasus DAS Citarum, Jawa Barat. Buletin Tanah dan Lahan, 2017, pp. 30–36.
12. D.T. Nguyen, I. Iskandar, S. Ho, Land cover change and CO2 stock in the Palembang City, Indonesia: A case study using remote sensing, GIS technique and LUMENs. The Egyptian Journal of Remote Sensing and Space Science, 2016, pp. 313–321.
13. M. Iacono, D. Levinson, A. El-Geneidy and R. Wasfi, “A Markov chain model of land use change,” TeMA Journal of Land Use Mobility and Environment 8(3), pp. 263-276, 2015.
14. Y. Huang, B. Yang, M. Wang, B. Liu and X. Yang, “Analysis of the future land cover change in Beijing using CA–Markov chain model,” Environmental Earth Sciences 79(2) 60, pp. 1-12, 2020.
15. Anand, Anupam. "Unit-14 Accuracy Assessment." IGNOU, 2017.
16. . Foody, G. M. (2008) 'Harshness in Image Classification Accuracy Assessment'. International Journal of Remote Sensing 29 (11), 3137-3158.
17. Butt A,Shabbir R,Ahmad SS, Aziz N (2015) Land use change mapping and analysis using remote sensing and GIS: a case study of Simly watershed,Islamabad,Pakistan.EgyptJRemoteSensSpaceSci18: 251–259.
18. Nguyen, H. T. T., Pham, T. A., Doan, M. T., & Tran, P. T. X. (2020). LAND USE/LAND COVER CHANGE PREDICTION USING MULTI-TEMPORAL SATELLITE IMAGERY AND MULTI-LAYER PERCEPTRON MARKOV MODEL. International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences.
19. Eastman, J.R. TerrSet Geospatial Monitoring and Modeling System—Manual. Available online: www.clarklabs.org (accessed on 2 January 2016).
20. Ahmed, B., Ahmed, R., 2012: Modeling urban land cover growth dynamics using multi-temporal satellite images. A case study of Dhaka, Bangladesh. ISPRS International Journal of GeoInformation, 1(1), 3-31.
21. ouri, J., Gharagozlou, A., Arjmandi, R., Faryadi, S., Adl, M., 2014: Predicting Urban Land Use Changes Using a CA–Markov Model. Arabian Journal for Science and Engineering, 39(7), 5565-5573. doi:10.1007/s13369-014-1119-2.
22. Wang, W.; Zhang, C.; Allen, J.M.; Li, W.; Boyer, M.A.; Segerson, K.; Silander, J.A. Analysis and prediction of land use changes related to invasive species and major driving forces in the state of Connecticut. Land 2016, 5, 25. [Google Scholar] [CrossRef].
23. Fleiss, L.; Levin, B.; Paik, C. (2003). Statistical Methods for Rates and Proportions. US, New Jersey: John Wiley & Sons, Ltd. 768 PP.
24. Nadoushan MA, Soffianian A, Alebrahim A. Modeling land use/cover changes by the combination of markov chain and cellular automata markov (CA-Markov) models. Journal of Earth, Environment and Health Sciences 2015;1(1):16.
25. Sang L, Zhang C, Yang J, Zhu D, Yun W. Simulation of land use spatial pattern of towns and villages based on CA-markov model. Mathematical and Computer Modelling 2011;54(3-4):938-43.
26. Ghosh P, Mukhopadhyay A, Chanda A, Mondal P, Akhand A, Mukherjee S, et al. Application of cellular automata and markov-chain model in geospatial environmental modeling: A review. Remote Sensing Applications: Society and Environment 2017; 5:64-77.
27. Wang SW, Munkhnasan L, Lee WK. Land use and land cover change detection and prediction in Bhutan's high-altitude city of Thimphu, using cellular automata and Markov chain. Environmental Challenges 2021; 2:100017.