Regional Change Prediction of Land Degradation Risks using Cellular Automata-Markov Modeling in Dhi Qar Province, Iraq

Raad Abdulkadhim Abbood
Ministry of Higher Education and Scientific Research, Scientific Research Commission, Space Research and Technology Center, Iraq
raadabbood@gmail.com (corresponding author)

Ali Asghar Jafarzadeh
Department of Soil Science, Faculty of Agriculture, University of Tabriz, Tabriz, Iran
ajafarzadeh@tabrizu.ac.ir

Shahin Oustan
Department of Soil Science, Faculty of Agriculture, University of Tabriz, Tabriz, Iran
oustan@tabrizu.ac.ir

Abdulghafour I. Hamad
Desertification Combat Department Faculty of Agriculture, University of Baghdad, Iraq
abdalghafor.ibrahim@coagri.uobaghdad.edu.iq

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ABSTRACT

Land degradation, followed by desertification, poses a significant threat to countries in arid, semi-arid, and even humid regions. This issue has intensified dramatically since the middle of the last century. In Iraq, land degradation affects 69% of the agricultural land and is exacerbated by the high average temperatures and an annual precipitation of less than 100 mm, impacting over 72% of the country. It is considered one of the three main challenges humanity faces in the 21st century, alongside climate change and freshwater scarcity, both of which diminish land potential and deplete renewable resources. Understanding this phenomenon is particularly crucial for the Nasr region in Dhi Qar Province, southern Iraq, which spans an area of 95,919 ha. This research examines the land cover conversion, land use changes, and land degradation projections for the next 10 to 20 years. Satellite imagery from Landsat 5, 7, 8, and 9, taken at different times (1993, 2003, 2013, and 2024) with a spatial resolution of 30 × 30 m, using Thematic Mapper (TM) and Operational Land Imager [OLI] sensors, was obtained from the United States Geological Survey (USGS). The study area was first analyzed using satellite data and supervised classification. The data were then analyzed deploying a Cellular Automata (CA)-Markov model, revealing a significant increase in the sand dune area, which expanded from 8,128 ha to 18,240 ha during the study period. To predict future trends, the CA-Markov model was applied to classify maps for each Land Use/Land Cover (LU/LC) class through vector-based classification. The model simulated LU/LC changes by projecting the 1993 and 2024 patterns forward to the years 2034 and 2044. The former was calibrated by validating the simulated maps against actual LU/LC maps for the study area, with its accuracy being confirmed by a high kappa coefficient (>76%). The study projects similar land change patterns for 2034 and 2044, with ongoing desertification, declining vegetation cover, and stable agricultural lands throughout the 20-year period.

Keywords-land degradation risks; multi-temporal landsat images; Cellular Automata-Markov model; Dhi Qar province

I. INTRODUCTION

Iraq has recently witnessed severe climate change impacts, marked by rising temperature, decreasing rainfall, and increasing evaporation rates [1]. These climatic changes lead to many challenges, such as land degradation, soil erosion and desertification. Desertification is the result of land degradation in an arid or semi-arid climate, occurring due to human activities and climate change. Recent reports indicate that the rate of Iraq's land desertification has increased to 39%, while an additional 54% is facing the same risk. Regarding Iraq's water, 80% of the latter originates from sources in Turkey. Annually, approximately 100 km² of agricultural land experiences degradation, leading to desertification due to climate change [2].

In the Markov chain, the Cellular Automata (CA) model alone provides a powerful computational technique that can be used to simulate the spatial changes within a system [3]. On the other hand, the CA-Markov model can be used to achieve a better simulation of temporal and spatial patterns of land changes [4]. The Markov process predicts the future state of a system based solely on its immediate previous state. A Markov model describes the change of LU/LC from one period to another, utilizing it as a basis for predicting future changes.

Desertification studies, by their inherent spatial nature, have been directly benefited from the recent advances in remote sensing and Geographic Information Systems (GIS). The CA–Markov model combines the Markov chain with CA techniques. In this model, the Markov chain provides the probabilities of land use change, which are then spatially refined by CA. In addition, several researchers have studied desertification using the CA–Markov model, which has been proven a viable and efficient tool for predicting trends in land degradation processes [5]. Recent studies show that the integration of the Markov chain and CA enables the prediction of land use evolution probabilities, including phenomena such as desertification [6].

Studies deploying the CA-Markov model to predict future land use trends have found a continuous increase in built-up areas, a decline in forest areas, and a relative stability in agricultural land over the coming years [7–8]. Moreover, projected land use changes indicate that forest cover will decrease by 16%, while agricultural land will expand in the same year, according to forecast data [9]. According to [10], the Markov model projects that forest cover will have declined from 29% in 2021 to 25% by 2040. Built-up areas have also expanded into arid regions and agricultural lands, and this trend is expected to continue through 2040.

Using the CA-Markov chain method in the TerrSet 2020 program for other areas, based on historical land use trends, the results indicate a trend toward more stable and homogeneous land cover over the next six years [11]. In this context, authors in [12] used a hybrid model combining a neural network, a Markov chain, and a CA model to improve the performance of the standard network model in predicting land use change over a 14-year time period. The results showed that residential and agricultural areas continued to grow, with residential areas increasing at a rate of 2% every fourteen years. Therefore, in recent years, the interest in analyzing LU/LC changes has increased significantly, as well as in the modeling of future LU/LC patterns. Many researchers have focused on studying urban expansion using various techniques [13].

Land cover databases from 1990 and 2018 were employed to highlight land use changes in Hunedoara County, Romania. During this period, pasture areas decreased by 13,071 ha, while 2,763 ha were reclassified as 'high quality agricultural land' [14]. Land cover transformations also indicated that woody savanna areas are expanding, while grasslands and croplands have declined. Finally, forest areas of all types demonstrated moderate gains [15]. Therefore, simulating and monitoring the process of land use change in the future is one of the most important challenges for researchers and decision makers.

When using the CA–Markov model to simulate the land use change map for 2036, irrigated agricultural areas and pastures are projected to have increased at the expense of forestlands in the Kozitparagi watershed [16]. Furthermore, land use maps for 2025 and 2035 were predicted using transition rules and a transition zone matrix. The future trend of desertification was reflected in an increase in critical zones from 31% to 49% over a 20-year period. Sediment retention in Wadi Bisha was also studied using the Revised Universal Soil Loss Equation (RUSLE) and TerrSet models. The results indicated a loss of 58 million tons of soil in the basin [17–19]. The desertification sensitivity of the Mokhtaran Basin in South Khorasan was estimated implementing the MEDALUS model, which was combined with the CA–Markov model to predict desertification risk. Landsat satellite images from 1987, 1998, and 2003 were used, and the desertification trend for 2025 and 2035 was positively predicted [20].

Local-level studies have proven insufficient in addressing desertification and land degradation issues in the southern regions of Iraq, particularly due to the limited use of predictive models. This discrepancy provides strong motivation for the present research, which aims to fill the aforementioned gap using an artificial intelligence-based prediction model to demonstrate how it can provide detailed future insights. This approach can assist decision-makers in assessing environmental risks with better precision and accuracy.

II. STUDY AREA

The current research was conducted in the Al-Nasr area of Dhi Qar Governorate, located in southern Iraq, covering an area of 95,000 ha. As shown in Figure 1, the study area lies between 45° 43′ 00″ to 46° 20′ 00″east longitude, 31°20′00″ to 31°35′00″north latitude, as estimated in March 2025. To study the risks of desertification and land degradation in the selected area with uniform terrain, Landsat 5, 7, 8, and 9 satellite images were utilized for the years 1993, 2003, 2013, and 2024. These images, with a spatial resolution of 30 × 30 m² in TM and OLI formats, were obtained from the USGS. The satellite images used in this study are depicted in Figures 1-3. In addition, Landsat satellite image utilization enabled the calculation of indicators related to vegetation cover, water, and land degradation for the study area.

To ensure high accuracy in remote sensing studies, the proposed approach was based on integrating satellite imagery with available data. Four cloud-free satellite images from Landsat 5 and Landsat 8, corresponding to the years 1993, 2003, 2013, and 2024, were used for the Al-Nasr area.

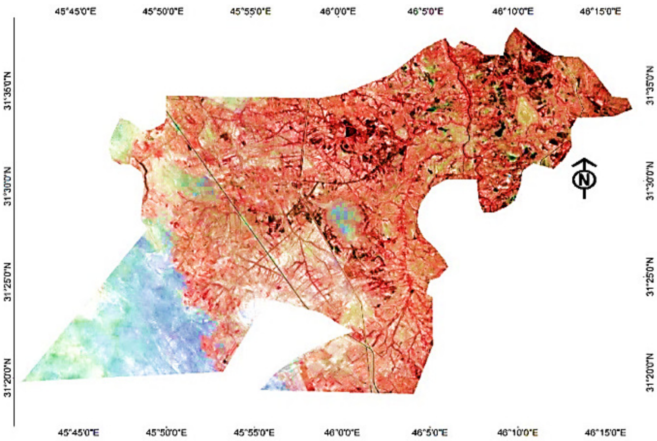


Fig. 1. Satellite image of Al-Nasr district.

III. METHODOLOGY

A. *Maximum Likelihood Classification*

In this study, four satellite images from the years 1993, 2003, 2013, and 2024 were used to predict future land use maps for the next 10 and 20 years. The predictions were carried out employing the CA-Markov model implemented in the TerrSet 2020 program, as illustrated in Figure 2, which presents the methodology for the modeling of desertification and soil degradation in the study area. As a first step, radiometric and geometric corrections were applied to enhance the accuracy and quality of the satellite images, as mentioned in [21]. Secondly, the satellite images were classified using the maximum likelihood method in the ENVI program. Based on the resulting transition matrix from the Markov chain model, the CA-Markov model was applied to estimate the LU/LC map for 2024. Finally, the model was verified by simulating LU/LC changes between 1993 and 2003, and by using them to predict the LU/LC maps for 2013 and 2024. These simulated maps were compared with the classified maps of the same years to assess the model's accuracy. Subsequently, LU/LC maps for 2034 and 2044 were predicted deploying the Markov and CA models.

B. *Image Classification and Accuracy Evaluation*

Satellite image classification provides information about land use, desertification, and soil degradation, creating thematic maps by identifying distinct land covers based on the spectral signature of each feature in the studied area [22]. The maximum likelihood classification, a widely utilized supervised technique, known for its accuracy (ranging from 80% to 90%), was used in this study [23]. The classification of remote sensing images provides satisfactory results in identifying different textures through image processing. For image classification performance, it is necessary to select a type of classification methodology that best aligns with the research objectives. Additionally, it is necessary to choose the best sensor according to its/the spectral, radiometric, spatial, and temporal resolution required for the study. Deploying the maximum likelihood classification method, land use maps for 1993, 2003, 2013, and 2024 were generated for the Al-Nasr area, identifying key land cover classes, such as agricultural areas, water bodies, and soil types, as illustrated in Figure 3. Finally, accuracy evaluation, a critical step after classification, compared the classified images with the reference data. In the Nasr area, the overall accuracy rates were 92%, 82%, 92%, and 90% for the years 1993, 2003, 2013, and 2024, respectively.

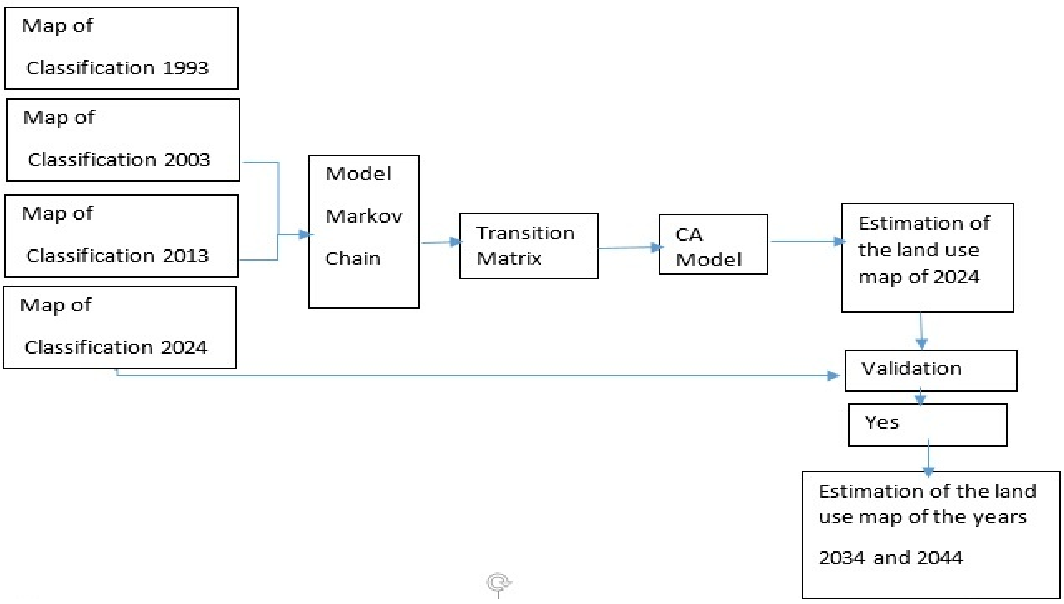
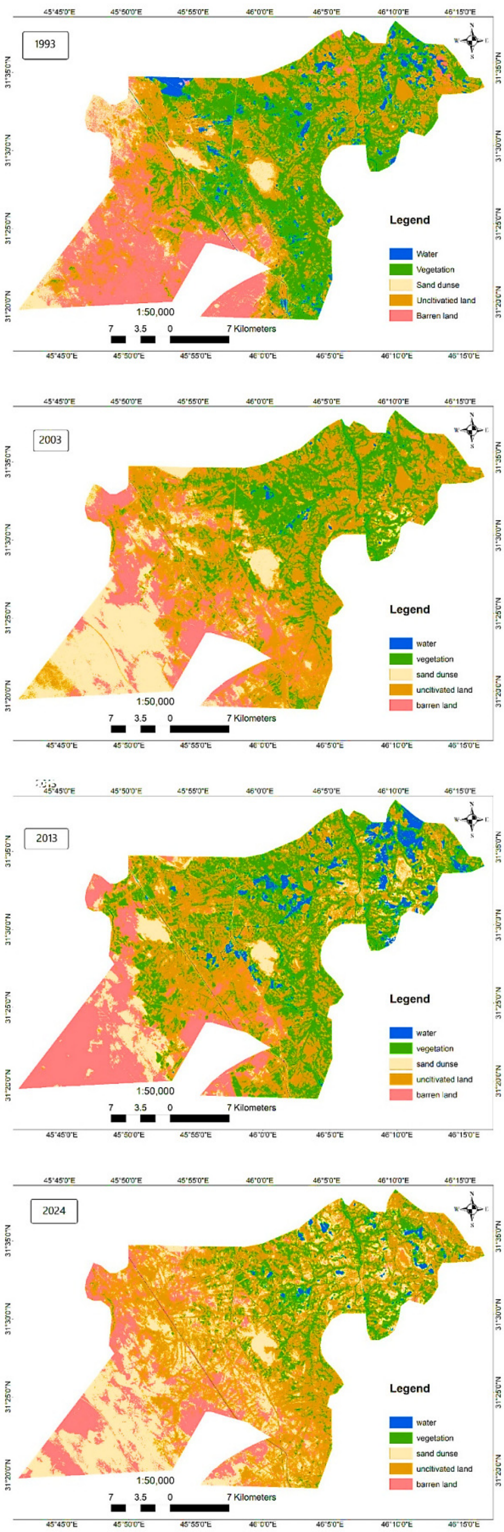


Fig. 2. Implementation steps of CA-Markov model.



(a) (b) (c) (d)

Fig. 3. Satellite image classification of LU/LC for: (a) 1993, (b) 2003, (c) 2013, and (d) 2024.

A widely used post-classification comparison method in this context involves the analysis of two classified images. To assess changes in land use and land ownership categories for the AL-Nasr area (1993-2024), transition matrices were calculated for different years in the study area by comparing thematic maps.

C. Application of Markov Model in Land Use/Land Cover Change

Markov model application is achieved by creating a LU/LC transition probability matrix from the first time to the second time, which describes the nature of LU/LC changes. The prediction of LU/LC changes in the Markov model was carried out using [24]:

$$S(t+1) = P_{ij} \times S(t) \quad (1)$$

where S (t) and S ($t+1$) are the states of the system at times t and $t+1$ and P_{ij} is the transition probability matrix in a state calculated through:

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix}$$

$$\left(0 \le P_{ij} < 1 \text{ and } \sum_{j=1}^{N} P_{ij} = 1,\ (i,j = 1,2,\ldots,n)\right)$$

where P_{ij} expresses the probability of change from time i to time j. In addition to the transition probability matrix, a transition area matrix was also generated. This matrix specifies the area expected to change from one LU/LC type to another one in a future period. This matrix, which was the area corresponding to an LU/LC at time j, was created by multiplying each column of the transition probability matrix by the area corresponding to time i. The transition area matrix expresses the probability that a specific LU/LC type will occur at a given location in the future. First, the area of barren land, covered by vegetation, water bodies, pastures, urban land, and agricultural land was extracted from satellite images for the years 2013-2024 and converted into a transfer probability matrix. Then, the probability of converting a given LU/LC type in 2013 to the same LU/LC type in 2024 was calculated.

IV. CELLULAR AUTOMATA MODEL

In the automatic cell model, which is a dynamic process model, the transfer of a cell from one LU/LC to another LU/LC depends on the status of the adjacent cells. A cell is assumed to have a higher probability of switching to LU/LC type A than LU/LC type B if the cell is closer to LU/LC type A. The CA model can be obtained using:

$$S(t, t+2) = f\{S(t), N\} \quad (2)$$

where S is the set of finite and discrete cell states, N is the cell field, t and $t+1$ represent different times, and f is the rule of cell state deformation in the local space.

A. Cellular Automata -Markov Model

The combined Markov chain and auto cell (CA-Markov) model is a combination of auto cells and an auto transfer matrix to predict land use changes. In fact, the combination of these two gives the model a spatial character. This model was implemented in a software environment (IDRISI TerrSet 2020 Geospatial Monitoring and Modeling Software), and the steps included:

- Converting vector data to point data.
- Defining the transfer rules, which can be fed into the CA-Markov model by calculating the transfer probability matrix.
- Defining the auto cell filters, which determine the spatial weighting factor and change with the change of the current neighboring cell state (in this research, the 5 × 5 proximity filter was used).
- Defining the starting point and number of iterations.

In this research, the starting point was 2024, and 10 iterations were utilized to predict desertification and land use changes in 2034 and 2044.

B. Model Validation

To assess the model's simulation ability, the simulated map was compared to a reference map using *K*-indices (*K* no, *K* Location, *K* Location Strata, and *K* Standard), to assess overall and location-specific accuracy [25]. Kappa values, ranging from 0 to 1, indicate the level of agreement, with values less than 0.4 indicating low accuracy, values between 0.4 and 0.75 indicating moderate accuracy, and values greater than 0.75 indicating high agreement. This study defined a kappa value of at least 0.77 as an acceptable level of agreement.

V. RESULTS

A. Model Results

In the Al-Nasr area of Dhi Qar Governorate, southern Iraq, land use and land need analysis was carried out for the years 1993, 2003, 2013, and 2024, and then forecasted for the next 10 and 20 years (2034 and 2044). Various land use changes occurred across the land use classes for the aforementioned periods. The gain and loss graphs for the five land use classes are illustrated in Figure 4.

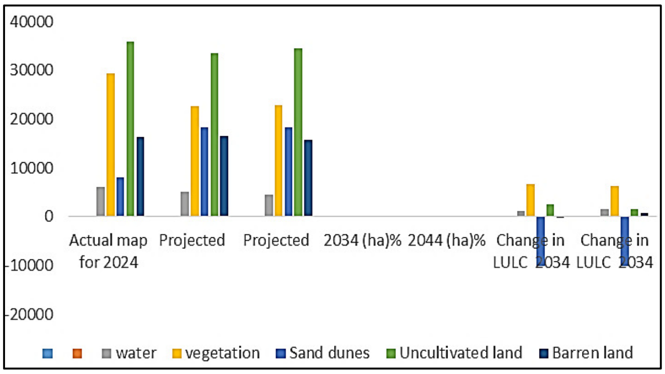


Fig. 4. Actual map for 2024 and future predictions for 2034 and 2044.

The gains and losses over the 1993–2003 time period show a slower transition between the land use classes compared to those between 2003 and 2013, while only the vegetation and sand dune classes experienced significant changes in the years 2024, 2034, and 2044. Table I presents the 2024 transition area data, which were used as input parameters for the CA-Markov model simulation. The obtained results of the change rates in the land use groups, and their comparison with the baseline scenario across the entire landscape, showed an increase in desertified lands, a decrease in vegetation cover, and an increase in bare lands that are likely to occur in 2034 and 2044, as portrayed in Figure 4.

B. Predicting The Future Desertification Map

The future desertification map was prepared using the future land cover map, having assigned new points to the relevant indicators, as displayed in Figure 5.

(a)

(b)

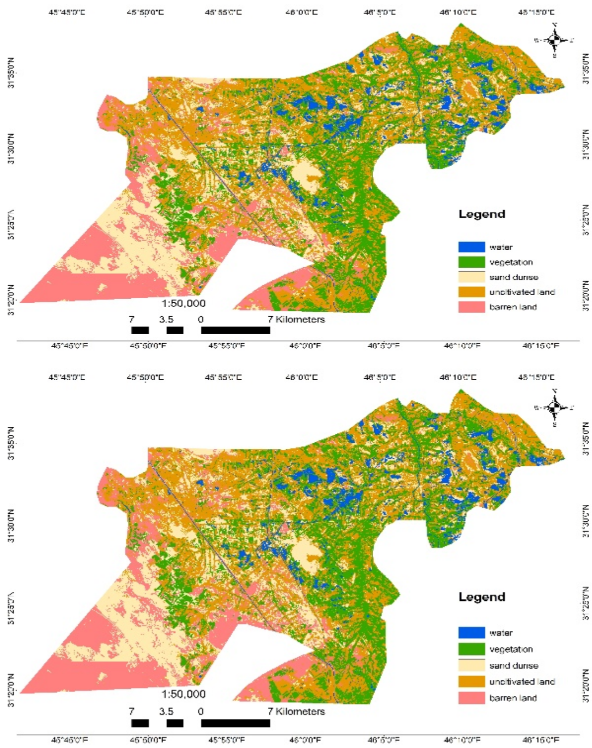


Fig. 5. Prediction of future desertification: (a) desertification projection for the year 2034, (b) desertification projection for the year 2044.

TABLE I. AL-NASR DISTRICT LU/LC STATISTICS (2024 AND PROJECTIONS FOR 2034 AND 2044)

LU/LC classes	(1)	(2)	(3)	(4)	(5)
Water	6126	5013	4585	1113	1542
Vegetation	29306	22672	22920	6634	6386
Sand dunes	8128	18240	18240	10112	10112
Uncultivated land	35927	33444	34449	2483	1478
Barren land	16401	16521	15697	-120	705

(1) Actual land use area extension map for 2024 (ha).
(2) Projected land use area extension map for 2034 (ha).
(3) Projected land use area extension map for 2044 (ha).
(4) Change in land use area extension for the year 2034 (ha).
(5) Change in land use area extension for the year 2044 (ha).

According to the prepared maps, the desertification classes in the region have changed, indicating an expansion of desertification—an important indicator of the worsening desertification situation, particularly in poor areas [26]. The expansion of the desertification status categories in the present and future were calculated and presented in Table I.

C. Transition Area Matrix From Markov Chain Model

To create transition area matrices that depict the expected changes between land classes within the study area, Markov chain analysis was performed using two images (initial *t-1* image and subsequent *t* image). For the land use change simulation of Nasr district in 2013, the 1993 land use map served as the initial image (*t-1*), and the 2003 land use map served as the subsequent image (t). For the second simulation map for 2024, the 2003 land use map served as the first image (*t-1*), and the 2013 land use map served as the subsequent image (*t*). For the prediction maps of 2034 and 2044, the 2013 land use map served as the initial image (*t-1*), and the land use map of 2024 served as the second image (*t*). As observed in Table I, the largest transition in Nasr district was from water areas to dry soil areas and from agricultural areas to dry soil areas. The most significant change happened in dry soil areas of agricultural land and sand dunes between 1993 and 2024.

To analyze and detect changes in the years 1993, 2034, and 2044, satellite images from 1993, 2003, 2013, and 2024 were used. To verify model validity, a simulation map for the years 2013 and 2024 was compared with a real classification map of the satellite image for the same years. This simulation, performed for validation by the available observed LU/LC 2024 and the overall validation with Kappa 0.775 was in high agreement [11]. After data validation, LU/LC for 2034 and 2044 were successfully predicted using the same CA-Markov model. The resulting Kappa coefficient (77%) showed the high ability of the CA-Markov model to simulate the change in land use in Nasr City. Prepared land use prediction maps for the years 2034 and 2044, revealed a decrease in agricultural land and an increase in bare lands, respectively. In these maps, the water bodies are shown in blue, the agricultural lands in green, and the dunes in yellow, while uncultivated land is represented in walnut color and barren land in pink. The change in the number of points from one land use category over another in a given period of time was measured by the transfer area matrix, which provides an explanation for the large transfer area in agricultural uses. The results exhibited that the most likely use changes for the period 1993-2024 were a decrease of water bodies, an increase of dunes, and a decrease of pastures and agricultural lands. In the region, decreased rainfall can lead to a reduction in agricultural lands, since they do not receive sufficient water for irrigating crops or pastures. Additionally, the area experiences a sharp rise in temperatures and an increased evaporation rate.

In the area, factors such as rising temperatures, increased evaporation due to more sunshine hours, harsh environmental conditions, inappropriate land management, urban expansion, and unsustainable use of natural resources, all impact the availability of resources and services. Therefore, predicting the future of land use and ownership in the Nasr region of Dhi Qar province in southern Iraq is important for planning purposes. Accordingly, projections were made for the years 2034 and 2044, assuming that the rate of change in the study area continues to follow the same historical pattern over the next 10 and 20 years. It is expected that the area of barren lands, sand dunes, and water recession will increase. A decrease in green areas is also predicted, according to the results. These changes in land use area may be due to severe climate change and decreased rainfall, which have made the land unusable due to high soil salinity and the decline in agricultural activity. Based on the obtained results, the cultivated land and water bodies in the region are expected to have decreased by 6634.06 ha and 1113.35 ha, respectively, in 2034. The sand dune area will have increased by 10111.85 ha and 10111.71 ha in 2034 and 2044, as can be seen in Table I, which may be due to the climate change represented by higher temperatures and less rainfall.

VI. CONCLUSION

In the present research, Land Use/Land Cover (LU/LC) data for 2024, derived from spectral-based modeling of Landsat satellite images along with data from 1993, 2003, and 2013, were used for model calibration and validation. These spectrally defined land cover classes also served as a base map for future simulations. The CA-Markov model was applied to simulate LU/LC for 2024 in the Nasr district, using transition zones generated from a machine learning process. The simulation was validated by comparing it to the available observed LU/LC for 2024, demonstrating a high level of agreement with an overall Kappa coefficient of 0.775. Following data validation, LU/LC predictions for 2034 and 2044 were successfully generated using the same CA-Markov model. The simulations for 2034 and 2044 predict a decrease in vegetation cover and water bodies, while the area of sand dunes is expected to increase significantly due to higher temperatures, reduced rainfall, increased evaporation, and decreased cultivation. The decrease in cultivated land may indicate a shift in the local population towards government and other formal jobs, rather than agricultural work. The results reveal various losses and gains in LU/LC categories by 2044 and 2034: water bodies (1.2% and 1.3% loss), vegetation cover (1.29% and 1.27% loss), sand dunes (44% increase for both years), uncultivated areas (1.1% and 1% increase), and barren lands (1.1% and 0.9% increase), respectively, attributed to the aforementioned factors.

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