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Spatial Simulation of Future Changes in the LULC for Babil Governorate Using Cellular Automata (CA)−Markov Model

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ABSTRACT

Babil Governorate has witnessed radical changes in land use and land cover (LULC) over the past few decades, driven by rapid population growth and economic development. Despite this, knowledge remains limited regarding land use patterns and the mechanisms of change driven by human activities. Therefore, there is an urgent need to study the transformations of LULC in Babil Governorate to determine the factors influencing these changes, and to predict their future trajectories. This study aims to assess LULC changes during the period 1990-2020 and to predict the expected changes up to 2050 by analyzing land use and land cover data for 1990, 2000, 2010, and 2020. By applying the LULC transition matrix and the Markov model, the study could simulate the expected LULC patterns for the study area in the future. The study results show that the region will experience substantial changes in LULC during the period 2030-2050. Urban areas are expected to increase gradually, while bare land is expected to decline significantly. Water bodies are also expected to grow, and vegetation lands are expected to remain relatively stable. These changes reflect the intertwined effects of urban expansion, climate change, water inflows from neighboring countries, and shifts in land use patterns. The results indicate that current LULC trends will continue over the next three decades. This study can provide decision-makers with the necessary tools to develop sustainable land and water management policies.

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المحاكاة المكانية للتغيرات المستقبلية في استخدام الأراضي والغطاء الأرضي لمحافظة بابل باستخدام نموذج الخلية الآلية لماركوف

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الملخص

شهدت محافظة بابل تغييرات جذرية في استخدامات الأراضي وتغطية الأراضي (LULC) على مدى العقود القليلة الماضية بدافع النمو السكاني السريع والتنمية الاقتصادية. على الرغم من ذلك، لا تزال المعرفة محدودة فيما يتعلق بأنماط استخدام الأراضي وآليات التغيير المدعمة بالأنشطة البشرية. لذلك، هناك حاجة ملحة لدراسة تحولات LULC في محافظة بابل وتحديد العوامل المؤثرة على هذه التغيرات والتنبؤ بمساراتها المستقبلية. يهدف هذا البحث إلى تقييم تغييرات LULC خلال الفترة 1990-2020 والتنبؤ بالتغيرات المتوقعة حتى عام 2050 من خلال تحليل بيانات استخدامات الأراضي وتغطية الأرض لعام 1990 و2000 و2010 و2020. من خلال تطبيق مصفوفة انتقال LULC ونموذج ماركوف، يمكن للدراسة محاكاة أنماط LULC المتوقعة لمنطقة الدراسة في المستقبل. أظهرت نتائج الدراسة أن المنطقة ستشهد تغييرات كبيرة في LULC خلال الفترة 2030-2050. من المتوقع أن تزداد المناطق الحضرية تدريجياً، بينما من المتوقع أن تنخفض الأراضي الجرداء بشكل كبير. ومن المتوقع أيضًا أن تنمو المسطحات المائية، ومن المتوقع أن تظل أراضي الغطاء النباتي مستقرة نسبيًا. تعكس هذه التغييرات الآثار المتداخلة للتوسع الحضري وتغير المناخ وتدفق المياه من البلدان المجاورة وتحولات أنماط استخدام الأراضي. تشير النتائج إلى أن الاتجاهات الحالية لـ LULC ستستمر على مدى العقود الثلاثة المقبلة. يمكن أن توفر هذه الدراسة لصانعي القرار الأدوات اللازمة لتطوير سياسات مستدامة لإدارة الأراضي والمياه.

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Introduction

LULC refers to changes in land use and land cover resulting from human activities (Riggio *et al*., 2020). These modifications have seriously affected the ecological balance at different local (study area) and international levels. As a result, this matter has become a focus of the international community due to its impact on our planet (Anwar *et al*., 2022). As a solution to this issue, geospatial models and open-source geospatial data have proven to be powerful tools for monitoring and tracking the status and changes in land use and land cover. This approach can effectively support efforts to protect the environment and sustainably manage land (Rai *et al*., 2018). Due to the increase in income and population, cities and urban areas have experienced significant expansion, which is natural with increasing human activity.

Land use patterns in these areas are influenced by various factors (industrial, technological, globalization, economic, and administrative) (Fei *et al*., 2021). It is important to know that rapid urban expansion significantly impacts the economic conditions of cities. This widespread phenomenon, often resulting from poor urban planning, causes negative side effects such as deforestation, decreased agricultural land, and the conversion of pastures into built-up areas (Feng *et al*., 2021). The forthcoming years will witness multiple and interconnected challenges in land use due to the expected increase in demand for goods and services, which will lead to the depletion of limited land resources (Popp *et al*., 2017). Therefore, making the right decisions about the environment and long-term sustainable development is conditional on the availability of accurate data on land use and land cover change. Consequently, this data is essential for evaluating studies and discussions on current global changes. Given the expected increase in demand for products and services, which puts increasing pressure on limited land resources, the world will face new and intertwined challenges in land use in the near future (Cuevas *et al*., 2016).

This study aims to analyze the spatial distribution of land use and land cover types in Babil Governorate and to provide detailed information to support decision-making related to natural resource management. Additionally, the study aims to evaluate the efficiency of the Cellular Automata-Markov model in predicting future changes in land use.

Related work

A variety of spatial simulation models have been employed, including the conversion of land use and its effects on a model developed by Das *et al*. (2019) and the future land use simulation model proposed by Lin *et al*. (2020), to predict dynamic changes in land surface cover over time and space.

Among the most prominent models that have received widespread attention in this field is the CA-Markov model, which combines the power of Markov chains in representing temporal changes with the flexibility of cellular automata in simulating spatial interactions, making it a powerful tool for understanding the dynamics of complex spatial changes (Wang *et al*. 2021). Furthermore, studies have shown that the CA-Markov model provides a powerful tool for analyzing the complex spatial changes and offers valuable insights to support decision-making in the field of spatial planning. For example, Ruben *et al*. (2020) and Kisamba and Li (2023) successfully used this model to predict land cover changes, and they proposed sustainable land use policies.

In a previous study, Matlhodi *et al*. (2021) compared the performance of the Cellular Automata-Markov and GEOMOD models in predicting future land use changes in the Nepalese Fewa Lake watershed. Their results showed that the Cellular Automata-Markov model outperformed in simulating future scenarios.

Liu *et al.* (2017) proposed a novel Future Land Use Simulation (FLUS) model to forecast changes in land use and land cover in the future. The model integrates top-down and bottom-up approaches to accurately simulate the complex interactions between human activities and climate change. The FLUS model was tested on a Chinese case study and outperformed existing models in predicting future land use patterns under various scenarios. This innovative model provides valuable insights for sustainable urban planning and policymaking.

Based on the promising results shown by the CA-Markov model in previous studies, we applied this model for the first time in Babil Governorate to assess current land use change patterns and to predict its future distribution until 2050. Thus, this study introduces a new scientific contribution in this field at the level of Babil Governorate. A comprehensive study is conducted on historical LULC change data in Babil Governorate. Changes in LULC were assessed over different periods, and their causes were identified. Future land use in the study area is also projected. The results of this study are expected to enhance the sustainable use of natural resources in the study area.

Study Area

Babil Governorate is situated in the center of Iraq, south of the capital Baghdad, and is the cradle of ancient civilizations. It is the fifth-largest governorate in Iraq in terms of population, with approximately two million inhabitants as of 2018 (Hashim *et al.*, 2022). Geographically, it extends between longitudes 43° 58' 10" and 44° 38' 35" East, and latitudes 32° 7' 25" and 33° 0' 35" North, covering an area of approximately 5119 km^2 (Talib and Laffta, 2024). It is bordered by Baghdad Governorate to the north, Wasit Governorate to the east, Karbala and Anbar Governorates to the west, and Najaf and Qadisiyah Governorates to the south (Talib and Laffta, 2024) (Fig. 1).

Babil Governorate experiences a hot and arid continental climate with summer temperatures exceeding 50 °C. Despite these harsh climatic conditions, Babylon has managed to develop a thriving agricultural economy through an extensive network of irrigation canals that supply agricultural lands. This network contributes to the production of a variety of crops, including grains, vegetables, and fruits, making agriculture a cornerstone of the local economy (Hashim *et al.*, 2022).

Administratively, the governorate is divided into six districts: Hilla (the governorate center), Al-Mahawil, Al-Musayyib, Al-Hashimiyah, Al-Hamza Al-Gharbi, and Kothi (Hashim *et al.*, 2022).

Babil is renowned for its ancient historical sites dating back to the Sumerian and Babylonian civilizations, making it the most important tourist destinations in Iraq for tourists from all over the world. It is the place where visitors come to enjoy the beauty of its archaeological sites and to learn more about its ancient history. https://en.wikipedia.org/wiki/Babylon_Governorate).

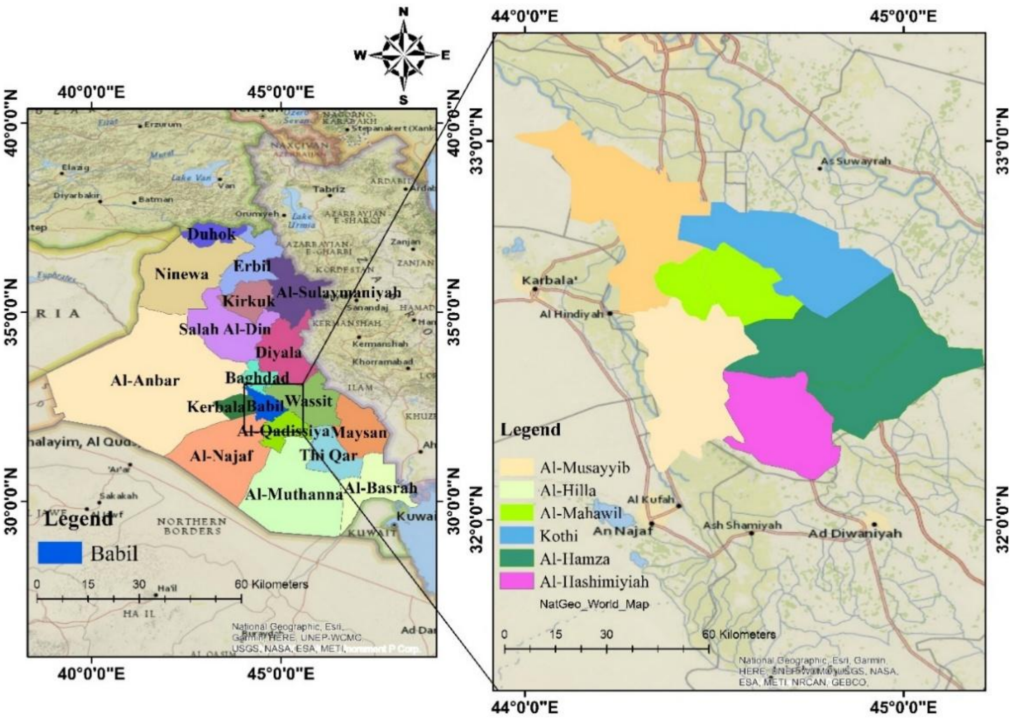

Fig. 1. Geographical map illustrating the location of Babylon Governorate and its administrative divisions in the central part of Iraq

Materials and Methods

Opted method

A comprehensive methodology integrating satellite image processing, land use classification, and Markov modeling is employed to predict future land use changes as illustrated in Fig. 2.

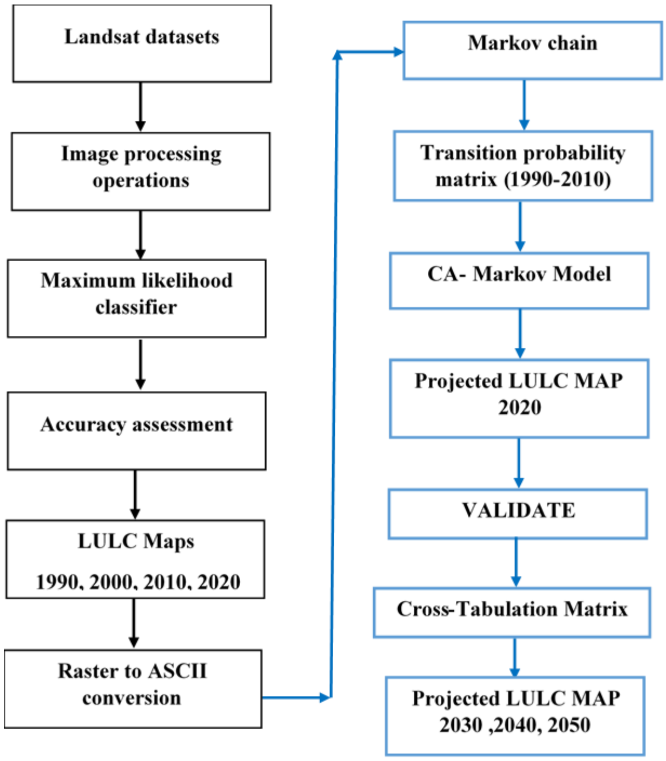

Fig. 2. Flow chart of the correction procedures.

Landsat datasets

A precise methodological framework is employed to analyze satellite imagery spanning multiple temporal periods. Key considerations encompassed the selection of cloud-free images, the assurance of high spatial resolution, and the maintenance of consistent acquisition dates (Marti *et al*., 2016). Subsequently, the images are projected using the Universal Transverse Mercator projection (UTM). Their geographic location is accurately determined using the World Geodetic System 1984 (WGS84) and the ellipsoid (Okiemute *et al*., 2018).

Landsat 7 (+ETM) and Landsat 8 (OLI) datasets (Table 1) are carefully selected for the study, considering the criteria above, pertinent scientific references, and the common use of Landsat imagery in LULC studies. Land cover and land use dynamics are investigated using four Landsat satellite images with a 10-year time interval (Table 1). The Landsat scenes are obtained from the United States Geological Survey (USGS) Earth Explorer website (http://earthexplorer.usgs.gov/).

Table 1: Remote sensing imagery used in this study.

Path	Row	Landsat 7 (+ETM)			Landsat 8 (OLI)
168	37	12 / July / 1990	1 / July / 2000	10 / July / 2010	13 / July / 2020
168	38	12 / July / 1990	1 / July / 2000	10 / July / 2010	13 / July / 2020
169	37				20 / July / 2020

Image processing operations

Initial image processing is carried out using ENVI 5.6 and ArcGIS desktop software (Nath et al., 2022). This includes radiometric and atmospheric correction, as well as repairing distortions caused by the Landsat 7 scan line corrector failure. To address missing data (approximately 22% in the 2010 image), the Nearest Neighbor Interpolation technique is employed. Spatially consistent spectral bands from Landsat 7 and 8 are merged to enhance spectral information. Subsequently, the images are mosaicked and clipped to the study area.

Google Earth imagery is used as a reference to establish ground control points for accurate georeferencing of the Landsat images. To ensure accurate classification, a comprehensive training dataset is created. For the years 1990, 2000, 2010, and 2020, training sites are identified using on-screen digitization techniques on Landsat imagery and Google Earth Pro. To minimize the impact of mixed pixels, homogeneous polygons are chosen as training sites. A stratified random sampling technique is employed to generate 250 sample points per class from these polygons. Additionally, independent validation samples (approximately 25 points per class) are collected to assess classification accuracy.

A maximum likelihood classifier is employed to categorize the pixels into various LULC classes. The unique spectral signatures of each LULC class are compared on the maps to identify the specific land cover types in different areas of Babil Governorate. The classified LULC classes are then compared to the corresponding types observed in Google Earth Pro imagery. The classified images are converted from TIF to ASCII format using the “Raster to ASCII” command for input into IDRISI Selva. The CA-Markov model is applied to analyze historical LULC changes and to predict future trends.

Assessment of the accuracy of classification

Evaluating the accuracy and reliability of image classification methodologies is a crucial stage in the research process (Lu and Lu, 2023). To guarantee reliability and discrimination, it is advised that the accuracy level for LULC classification exceeds 90% as per previous studies (Junaid *et al*., 2023). Studies have emphasized the importance of validating the model and its accuracy in conducting a reliable LULC survey (Ruuska *et al*., 2018). This study relied on Kappa statistics and total accuracy to evaluate the effectiveness of classification maps. Google Earth images and satellite images are used to verify the results. An error matrix combined the land use map, classified land cover, and ground reference information. Several metrics were identified, such as product accuracy, user accuracy, overall accuracy, and Kappa coefficient (Foody, 2020). The proportion of correctly classified pixels in the confusion matrix determined overall accuracy, and the Kappa index indicated the degree of agreement between the classified map and the reference data used (Twele *et al*., 2016). The following equations are used to calculate these two measures:

$$\textit{Overall accuracy} = \frac{\boldsymbol{D}}{\boldsymbol{T}} *100\% \qquad (1)$$

where: D represents the total number of correct calls as summed along the major diagonal, and T represents the total number of correct calls in the error matrix. While the Kappa index ($\widehat{\boldsymbol{k}}$) is calculated as follows:

$$\widehat{\boldsymbol{k}} = \frac{\boldsymbol{T}\sum_{n=1}^{r}\boldsymbol{Y}_{nn} - \sum_{n=1}^{r}(\boldsymbol{Y}_{n+} * \boldsymbol{Y}_{+n})}{\boldsymbol{T}^2 - \sum_{n=1}^{r}(\boldsymbol{Y}_{n+} * \boldsymbol{Y}_{+n})} \qquad (2)$$

where: T represents the total number of cells in the error matrix, r represents the number of rows in the matrix, Y_{nn} represents the total number of correct cells in a class (i.e., value in row n and column n), Y_{n+} represents the total for row n, Y_{+n} represents the total for column n.

Kappa indices are an essential tool for evaluating the accuracy of maps as they provide information about how closely the results match. If the kappa value is greater than or equal to 75%, the maps are highly consistent; if it is between 50% and 75%, the agreement is average; if it is less than or equal to 50%, it is poor (El Baroudy, 2016; Wan *et al*., 2015). As a result, to assess the CA-Markov model's ability to accurately simulate future land use and land cover conditions, Wang and Zheng (2023), after simulating land use and land cover for 2020 using classified images from 1990 and 2020, validated the CA-Markov model. Two map agreements (actual and simulated for 2020) were evaluated using the Kappa index of agreement (K_{IA}) (Mathanraj *et al*., 2021), such as no information Kappa (K_{no}), location Kappa ($K_{location}$), and standard Kappa ($K_{standard}$), using the CROSSTAB module in IDRISI Selva software.

Additionally, the simulated and actual areas of each land use and land cover class are compared using the validate module. Therefore, the Kappa index is a suitable indicator; thus, land use and land cover can be predicted for 2030, 2040, and 2050.

Methods

Land use and land cover change detection

Analyzing Land Use and Land Cover Change (LULCC) is essential to identify the particular changes in different land use categories (Spruce *et al.*, 2020). The land cover change detection map is used to assess and examine the temporal changes in land use and land cover within the defined area. The equation mentioned below is applied to estimate the size of the changes that occurred in each category:

$$C_i = R_i - B_i \qquad (3)$$

where: C_i represents the change in extent for the class i, B_i denotes the base image, and R_i is the most recent image.

The percentage change for each LULC class is calculated using the following equation:

$$P_i = \frac{R_i - B_i}{B_i} \qquad (4)$$

where: P_i denotes the percentage shift for the class i, and B_i denotes the base image, and R_i is the most recent image.

Land Use and Land Cover (LULC) Change Prediction Using Cellular Automata-Markov Model

The Cellular Automata-Markov (CA-Markov) model is a methodology that combines cellular automata and Markov chains. This approach aims to predict future trends and characteristics of LULC change. The cellular automata model looks at the uncertainty that comes from several sources, such as the relationships between model components, the design of the model, and the quality of the data used as input (Palmate *et al.*, 2022). On the other hand, the CA-Markov approach concentrates on the local interactions of cells, considering their behavior in space and time. This method benefits from suitable computational capabilities for dynamic simulation and visualization.

One of the most critical applications of the CA-Markov model involves analyzing the transition probabilities among different LULC classes across various periods (Nouri *et al.*, 2019). By examining these transition probabilities, insights can be gained into the driving forces behind land use changes and their potential future trajectories. This knowledge facilitates predicting LULC characteristics and their potential environmental, natural resource, and landscape implications (Deafalla, 2022). Leveraging the strengths of both Markov models and cellular automata, the CA-Markov model has proven effective in simulating land use change in previous studies (Abdelkarim, 2023). This model identifies potential spatial distributions of transitions (Wang *et al.*, 2021; Rimal *et al.*, 2018).

The following stages are implemented throughout the process: the base map and LULC maps for the period (1990-2020) at ten-year intervals, in addition to transition probability images used to create LULC maps for 1990, 2000, 2010, and 2020. Using IDRISI Terrset software, the transition probability and prospective transition images are processed. Subsequently, a potential transition map for 2000–2010 is established to duplicate the land use land cover map for 2020, and the Markov transition probability estimation technique is used to model land use land cover maps for the period (2030-2050) at ten-year intervals based on 2010−2020. The CA-Markov model utilizes the time factor to identify patterns and factors that contribute to future modification:

$$S(t, t+1) = f(S(t), n) \quad (5)$$

where: n operates, representing the occurrence rate at any given moment, and $S(t+1)$ means the system status at the instant of $(t, t+1)$.

The CA-Markov model is frequently employed to anticipate future stability and change in LULC in a particular area, as well as to conduct ecological modeling and LULC monitoring. The following formula is employed to forecast future changes in LULC:

$$S(t, t+1) = S(t) * P_{ij} \quad (6)$$

where: $S(t+1)$ is the system status at the time $t+1$ and, $S(t)$ is the system status at time t, P_{ij} is the transition probability matrix in a state, which is defined as:

$$= \left\|P_{ij}\right\| = \left\| \begin{matrix} P1{,}1 & P1{,}2 & P1, n \\ P2{,}1 & P2{,}2 & P2, n \\ Pn, 1 & Pn, 2 & Pn, n \end{matrix} \right\| (0 \leq P_{ij} \leq 1) \quad (7)$$

where P represents the transition probability, P_{ij} represents the probability that a particular state will persist at any given time, and Pn represents the probability that it will transit from one state to another in the future.

A high transition probability is closer to (1) than a low transition probability (Nath *et al.*, 2023). A Markov chain analysis is conducted to generate a LULC transition matrix quantifying the probability of land cover changes between 1990-2000, 2000-2010, 2010-2020, and 1990-2020. This transition matrix served as a foundation for projecting future LULC dynamics. However, the Markov chain model exhibits limitations in capturing spatial dependencies, needing a mechanistic explanation for change processes and disregarding the spatial distribution of LULC, which are critical factors in simulating land cover patterns (Pandey *et al.*, 2021).

The cellular automata model is widely employed for the prediction of LULC due to its ability to simulate and regulate the dynamics of intricate spatial systems. A CA model comprises cells, cell space, neighborhood, time, and rules. It predicts new LULC patterns by considering the previous states of neighboring cells (Castro *et al.*, 2022). The influence of a neighbor on a cell's change is determined by their spatial proximity, with closer neighbors exerting a more significant impact. These weights are combined with transition probabilities to estimate the likelihood of changes in neighboring cells, preventing solely random predictions. Integrating Markov chain principles, the CA model incorporates the preceding LULC state and utilizes the conditions of neighboring cells to define transition rules (Koko *et al.*, 2020). The model's suitability for dynamic modelling within Geographic Information Systems and remote sensing environments is attributed to its analytical capabilities (Chuvieco, 2020). However, the CA model necessitates refinement to establish clear transition rules and modelling frameworks. As a result, integrating it with dynamic and other empirical models, like the Cellular Automata-Markov model, is essential for conducting a comprehensive analysis of LULC (Lacher *et al.*, 2023).

The procedures for running the CA-Markov model in the IDRISI-Selva program involve the following steps: The first stage entailed the execution of two models using land-cover maps for the periods 1990-2000, 2000-2010, 2010-2020, and 1990-2020. This process generated a transition probability matrix and a transition area matrix. The transition probability matrix is determined through cross-tabulation of multiple pairs of temporal images. Over a predetermined period, this matrix exhibits the likelihood of each land cover class transitioning to another. The transition area matrix contains the anticipated number of pixels that may transit from one land cover class to another over a specified number of time units. Simultaneously, the conditional probability map denotes the probability that each pixel of a land cover class will be situated at a site with a specific class after a particular time (Aneesha Satya *et al.*, 2020).

Transition probability matrices for periods 1 and 2 are generated by employing a variety of historical land use scenarios for the periods 1990-2000 and 2000-2020. The second stage entailed using a standard 5x5 adjacency filter to ascertain the perimeter of each cell. The scenario-based approach is implemented to simulate the prospective land use pattern during the final stage. LULC maps classified for 1990 and 2000 are employed to calibrate and refine the Markov algorithm. Time 1 is utilized in 1990, while time 2 is utilized in 2000. Transition probabilities between time one and time two are employed to simulate the land use pattern in 2020. The cellular automata Markov model is validated to assess the accuracy of its predictions for the year 2020. This process involves a statistical method to differentiate between locational and quantitative errors by comparing two images (Zhang *et al.,* 2021). The Kappa statistic index is employed to ascertain the degree of concordance between the actual and forecast 2020 land cover maps. An acceptable Kappa index is obtained, indicating reliable land use modelling and prediction. Subsequently, the classified land cover map of 2020 is utilized as a baseline for predicting potential land use in 2030, 2040, and 2050.

The Markov chain model determines the change in land area from the base year to the projected year. This model generates prospective probabilities of land cover and land use and a more comprehensive understanding of how to adapt factors that influence land cover and land use change, which benefits decision-makers (Tadese *et al.,* 2021). This model clarifies the dynamics of land cover and land use, which is crucial for developing and planning various land use policies that will improve the management of appropriate land cover and land use (Getu and Bhat 2022). The model effectively anticipates future land use shifts by analyzing the underlying causes of land use alterations, the suitability of different land use combinations, and other influential elements like transportation infrastructure, waterways, and urban centers. This model is particularly effective in simulating land use patterns in dispersed regions. In addition, the research has demonstrated that the CA-Markov model is more effective than other models in accurately simulating land use patterns and landscapes including the Artificial Neural Networks-Cellular Automata (ANN-CA) model, the Future Land Use Simulation (FLUS) model, and the Conversion of Land Use and its Effects (CLUE) model (Nath *et al.,* 2020; and Wang *et al.,* 2021).

Model Calibration and Validation

In the absence of accurate evaluation data, it becomes necessary to make future adjustments to the procedures for assessing prediction accuracy, model calibration, and validation to improve the modeling process. In a study conducted by Nath *et al.* (2020), the chi-square test (χ^2) was used to verify the accuracy of estimated land use images compared to real-world data for 2020. However, this comparison alone may not be sufficient to accurately assess the spatial distribution of land use classes in the study area. Therefore, researchers resorted to using the Kappa index, a more accurate statistical tool, to handle this issue (Debnath *et al.,* 2023). This technique involved calculating three types of Kappa index: location Kappa ($K_{location}$), quantity Kappa ($K_{quantity}$), and no information Kappa (K_{no}), to distinguish between spatial and quantitative errors in the predicted and actual images. These indices are used to evaluate the accuracy of the CA-Markov model, where higher values show a higher level of concordance between the model and reality. Kappa index values range from 0 to 1, as values closer to 1 indicate perfect agreement. According to Beroho and colleagues (2024) (Beroho *et al.,* 2023), a Kappa value of less than 0.5 indicates poor agreement, while a value of 0.75 indicates moderate agreement, and a value greater than 0.75 indicates strong agreement.

Results and Discussion

Changes in LULC categories in Babil Governorate

The study area exhibited four LULC classes, with an assessment revealing historical transformations and change patterns for each. The main LULC types in the study area include urban lands, bare soil land, water bodies, and vegetation lands, and the total quantity has actually changed over the period 1990-2020. However, an evaluation of the transformations between these land cover categories showed a significant shift between them, as shown in Fig. 3 and Table 2. Babil Governorate faced several challenges, including urban expansion, loss of vegetation lands, and a decrease in water bodies.

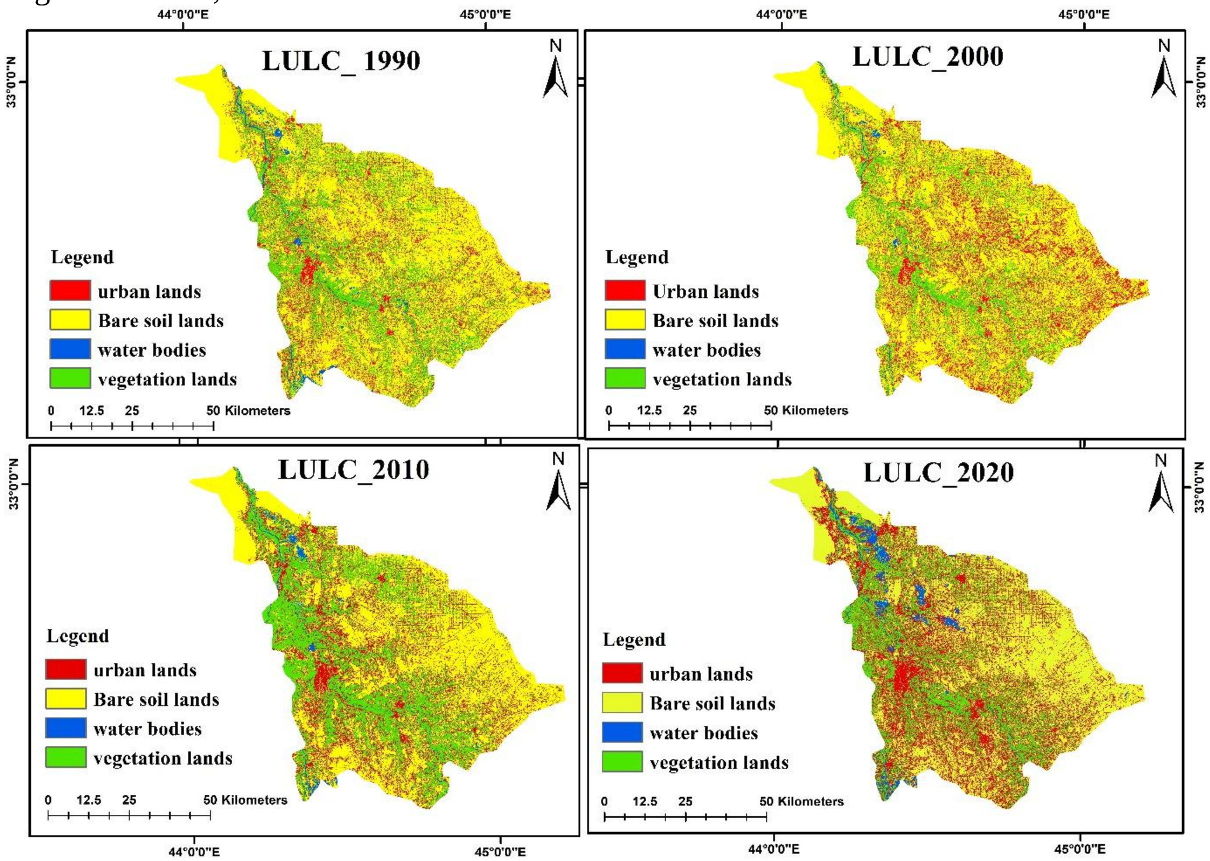

Fig. 3. LULC Changes in the Babil Governorate for 1990, 2000, 2010, and 2020.

Table 2: Distribution of LULC in Babil Governorate in 1990, 2000, 2010, and 2020.

Classes	1990		2000		2010		2020	
	Area (km^2)	Area %	Area (km^2)	Area %	Area (km^2)	Area %	Area (km^2)	Area %
Urban lands	921.8394	17.2770	1168.7976	21.9054	1160.6328	21.7524	1638.1863	30.7026
Bare soil lands	3034.5714	56.8735	3160.9935	59.2429	2525.7564	47.3373	2321.6850	43.5127
Water bodies	82.3518	1.5434	32.7924	0.6146	73.9260	1.3855	161.1567	3.0204
Vegetation lands	1296.8910	24.3061	973.0701	18.2371	1575.3384	29.5248	1214.6256	22.7643
Total	5335.6536	100	5335.6536	100	5335.6536	100	5335.6536	100

Table 2 presents data on land cover and land use in the region between 1990 and 2020, showing a significant increase in the area of urban land from 921.8394 km² to 1638.1863 km², attributed to population growth and urban expansion. Conversely, the area of bare soil land experienced a significant decrease from 3034.5714 km² to 2321.6850 km², as a result of conversion to other uses such as agriculture or construction. The area of water bodies also experienced fluctuations during the study period, depending on the volume of water imports from neighboring countries for the Euphrates River, as well as monthly releases from the governorate's water allocation and climate changes. The areas of vegetation land witnessed noticeable fluctuations between increases and decreases, mainly due to the expansion plans for crop cultivation implemented by the concerned authorities.

Overall, the data show significant shifts in land use between 1990 and 2020, represented by an expansion of urban and vegetation areas at the expense of a decrease in the area of bare soil land, reflecting population growth, urban expansion, and an increase in marketing plans for agricultural crop cultivation.

Cross-Tabulation Matrix Results

Based on the validation using Kappa indices, the CA-Markov model is deemed suitable for simulating the land cover and land use map for 2050 using transition probabilities from 1990 to 2020 and the 2020 class map as a baseline. Therefore, the model is deemed suitable for this application. The metrics are determined by employing the subsequent equations (Gasirabo *et al.*, 2023):

$$K_{no} = \frac{G_{(v)}\, H_{(n)}}{S_{(s)} - H_{(n)}} \quad (8)$$

$$K_{location} = \frac{G_{(v)}\, H_{(n)}}{S_{(v)} - H_{(v)}} \quad (9)$$

$$K_{standard} = \frac{G_{(v)}\, H_{(n)}}{S_{(s)} - H_{(v)}} \quad (10)$$

where: $G_{(v)}$, $H_{(v)}$, and $S_{(v)}$ provide moderate grid cell-level information, while $H_{(v)}$, $S_{(v)}$ and $S_{(s)}$ offer precise grid cell-level information across the topography.

An assessment is implemented to identify the components of agreement or disagreement (Table 3), and these reasons were categorized into two main classes: spatial distribution errors (0.1181) and quantity errors (0.0520). Thus, the results suggest that the primary cause of the discrepancy between the recorded and actual data was spatial distribution errors rather than quantity issues (refer to Fig. 4). Fig. 4 shows the simulation results. The results show a good similarity between the actual LULC of Babil Governorate in 2020 and the simulated land use and land cover. The model's performance in forecasting LULCCs was verified by simulating land use and land cover for 2020, utilizing transition probabilities for the period 1990-2000. Subsequently, the simulated results were compared to classified land use and land cover data for 2020, with differences in Kappa values employed as an accuracy measure.

The simulation analysis demonstrated a high level of agreement among the results, with Kappa indices of 0.79 for both K_{no}, and $K_{location}$, and 0.72 for $K_{standard}$, as shown in Table 4. This indicates the reliability and effectiveness of the model in predicting future land cover and land use in the biosphere. Furthermore, visual inspection reveals a relatively close match between the land cover and land use classes in the simulated data and the classified data for 2020. These findings suggest that the modeling outcomes are reliable and that the broad patterns of modeled land cover and land use closely align with real-world patterns.

Table 3: Validation assessment determines levels of agreement and disagreement between the two images.

Agreement / Disagree	Value	Value %
Agreement Chance	0.2000	20.00
Agreement Quantity	0.1853	18.53
Agreement Strata	0.0000	00.00
Agreement Grid cell	0.4445	44.45
Disagree Grid cell	0.1181	11.81
Disagree Strata	0.0000	00.00
Disagree Quantity	0.0520	5.20

Table 4: Validate the simulated 2020 Land Use Land Cover image.

Coefficient	Value	Value %
K_{no}	0.79	79 %
$K_{location}$	0.79	79 %
$K_{standard}$	0.72	72 %

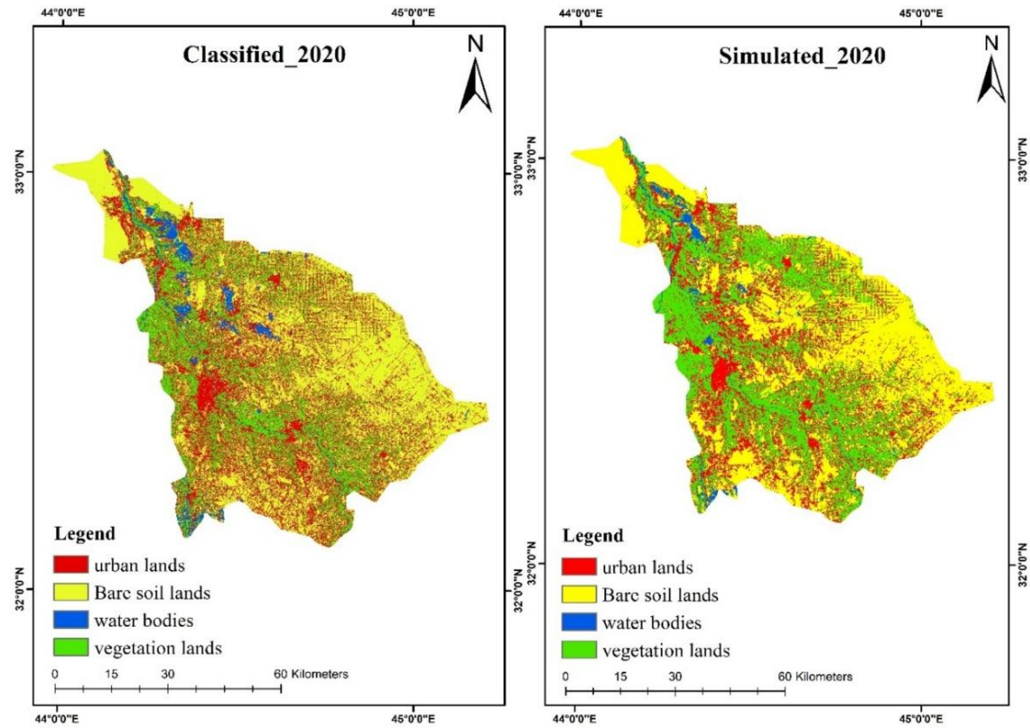

Fig. 4. Classified and simulated LULC maps for 2020: modelled and annotated.

LULCC Prediction Results in the Coming 2030, 2040 and 2050 years

A transition probability matrix is calculated to model the likelihood of land cover changes between 1990 and 2020 (Table 5). This matrix is then used to predict future land cover and land use patterns in the years 2030, 2040, and 2050.

Table 5. Transition probability matrix over the period 1990–2020.

	2020			
1990	**Urban lands**	**Bare soil lands**	**Water bodies**	**Vegetation lands**
Urban lands	0.4517	0.3515	0.0165	0.1804
Bare soil lands	0.2805	0.5894	0.0352	0.095
Water bodies	0.0929	0.1088	0.5885	0.2098
Vegetation lands	0.3631	0.1606	0.0203	0.4559

The presented matrix shows the probability of land use changes between 1990 and 2020. The matrix indicates an increased probability of other land use types transforming into urban areas between 1990 and 2020. This trend is driven by factors such as population growth, urban expansion, and economic transformation. The matrix shows a probability of urban land transforming into bare soil land (0.3515) due to the security instability and military operations between 2003 and 2017 in the governorate. The matrix shows a probability of bare soil land transforming into urban land (0.2805). This may reflect changes in the direction of urban expansion due to the unstable security situation. The matrix indicates a low probability of water bodies transforming into other land-use types. This may be due to the importance of water bodies for ecosystems and the existence of laws to protect them. The matrix shows a probability of vegetation lands transforming into urban lands (0.3631) due to population growth and urban expansion. These changes are taken into account when forecasting future transformations in 2030, 2040, and 2050. Based on the ongoing changes, changes in LULC are designed, and a change map for the years 2030, 2040, and 2050 is obtained. From Fig. 6, it can be observed that the changes will occur mainly in water bodies and barren lands, and how their extent will expand. The study predicts a gradual increase in urban areas, a sharp decline in barren lands, and a significant growth in water bodies, with relative stability of green areas, reflecting the impacts of urban expansion, climate change, and changing land use patterns. In 2030, the area of urban land will reach approximately 0.2231847 square kilometers, increasing to 1875.1473 square kilometers in 2040, and then decreasing slightly to 2793.1860 square kilometers in 2050. These results indicate a trend towards urban expansion, which is common in many areas due to population growth and economic development. In contrast to urban areas, barren lands are expected to experience a significant decrease in their area. In 2030, the area of barren land will be approximately 2156.8860 square kilometers, decreasing to 2089.2600 square kilometers in 2040, and then decreasing further to 1810.1160 square kilometers in 2050. This decrease may be attributed to several factors, such as urban expansion or changing land use for other purposes. Regarding water bodies, they are expected to experience a significant increase in their area. In 2030, the area of water bodies will be approximately 228.1797 square kilometers, increasing to 259.7607 square kilometers in 2040, and then experiencing a significant jump to 554.4297 square kilometers in 2050. This significant increase may be the result of the construction of dams and reservoirs, changes in rainfall patterns, or other factors affecting the water cycle. On the other hand, green areas are expected to experience relatively minor changes during the projected period. In 2030, the area of land covered by vegetation will be approximately 1103.5656 square kilometers, increasing slightly to 1111.4856 square kilometers in 2040, and then decreasing slightly to 1110.8286 square kilometers in 2050. These results indicate a relative stability in the area of green land with some minor fluctuations (Fig. 5 and Table 6).

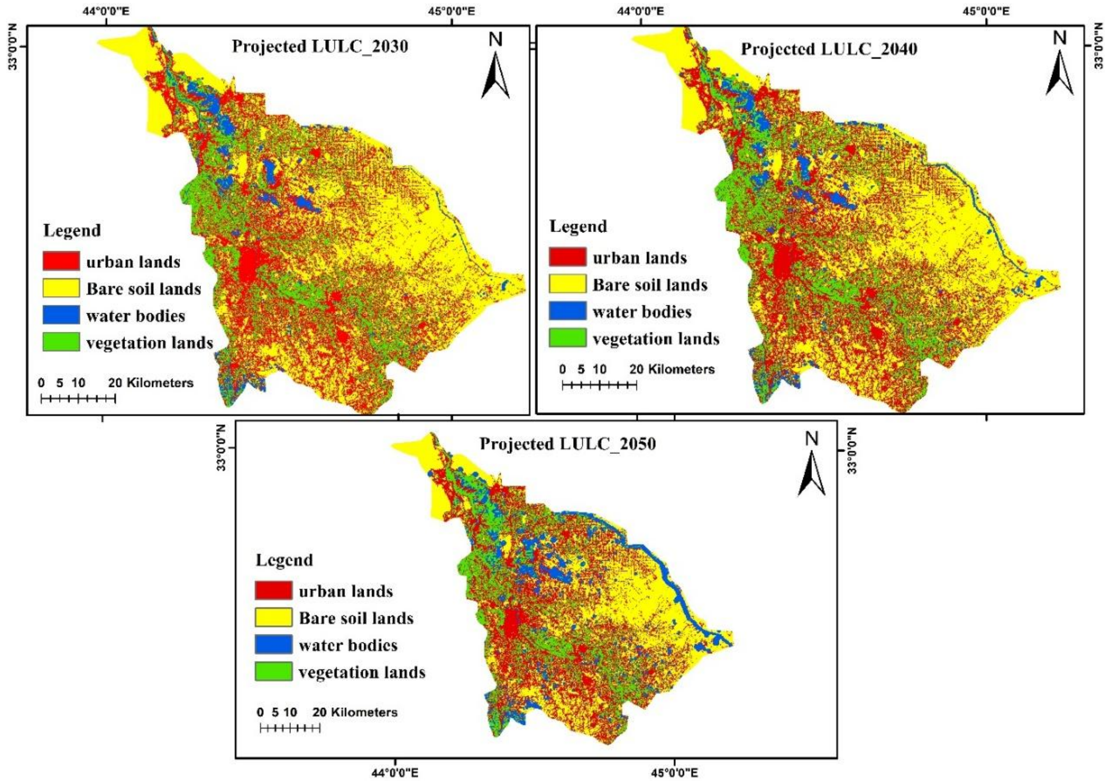

Fig. 5. Projected LULC for 2030, 2040, and 2050.

Table 6. Statistical distribution of the modeled LULC in 2020, 2030, 2034, and 2050.

Classes	2020		2030		2040		2050	
	Area (km^2)	Area %	Area (km^2)	Area %	Area (km^2)	Area %	Area (km^2)	Area %
Urban lands	1638.1863	30.7026	1847.0223	34.6166	1875.1473	35.1437	1860.2793	34.8651
Bare soil lands	2321.6850	43.5127	2156.8860	40.4240	2089.2600	39.1566	1810.1160	33.9249
Water bodies	161.1567	3.0204	228.1797	4.2765	259.7607	4.8684	554.4297	10.3910
Vegetation lands	1214.6256	22.7643	1103.5656	20.6829	1111.4856	20.8313	1110.8286	20.8190
Total	**5335.6536**	**100**	**5335.6536**	**100**	**5335.6536**	**100**	**5335.6536**	**100**

The results indicate the likelihood of significant transformations in Land Use and Land Cover (LULC) patterns within the study area as demonstrated by the Cellular Automata-Markov (CA-Markov) model. This model has proven highly efficient in simulating spatiotemporal changes in LULC patterns, confirming the area's exposure to varying levels of dynamics and change. Therefore, strategic land use planning and water resource management are of paramount importance under these circumstances. Studying how land is used and how it has changed in the past, along with the reasons for these changes, is crucial for predicting how land will be used in the future. Science supports this hypothesis, and this is precisely the approach taken in this study (Keshtkar and Voigt, 2016). Therefore, documenting these transformations is essential to support future decision-making. However, given this study's focus on direct driving factors, uncertainty about future LULC patterns necessitates the integration of additional factors into the modeling process, such as population changes, changes in the climate, natural disasters, and the state of the economy. This would contribute to a deeper understanding of the complex LULC change processes and thus the development of more comprehensive and effective management strategies.

Conclusion

This study aims to assess and predict future changes in Land Use and Land Cover (LULC) in Babil Governorate. In order to achieve this goal, a hybrid-integrated model combining cellular automata and Markov chains is employed. GIS techniques and multi-temporal satellite data are used to monitor changes in LULC from 1990 to 2020.

By reviewing the transformation of LULC changes in Babil Governorate from 1990 to 2020, it reveals a significant increase in urban area, primarily due to population growth and urban expansion. Conversely, barren lands experienced a noticeable decline as they were converted to other uses such as agriculture and construction. Water bodies, on the other hand, exhibited fluctuations in their area during the study period, influenced by climate changes and water imports from neighboring countries. Additionally, the area of green lands increased due to the rise in marketing plans for crops. Overall, these results demonstrate substantial transformations in land use within the governorate, with urban and green areas expanding at the expense of barren lands, reflecting the demographic, economic, and environmental changes experienced by the governorate.

The study divides the LULC maps into four primary classes: urban areas, barren lands, water bodies, and green areas. This detailed classification enabled a comprehensive understanding of the spatial distribution of different land use types in the governorate, facilitating the prediction of future scenarios. The accuracy of the simulated LULC map for 2020 is assessed using the Kappa index, and the evaluation results show agreement with the map extracted from satellite images, confirming the efficiency of the model used in the simulation. The analysis reveals that the factors influencing LULC changes vary with the type of cover and evolve.

The advanced CA-Markov model is used to simulate LULC patterns in the governorate until 2050. The simulation results demonstrate the model's ability to generate accurate future LULC scenarios, indicating its high efficiency in this field. Despite the promising results obtained by the study, it is essential to emphasize the importance of integrating the latest local population statistics into future simulation models. This is because population growth is a significant factor influencing land use changes, and neglecting it could reduce the accuracy of predictions. Therefore, future studies should focus on analyzing the complex relationship between population growth and LULC changes for a more comprehensive understanding of long-term environmental change processes and their impact on the sustainability of natural resources.

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