ISSN: 2633-4828 Vol. 5 No. 4, December, 2023

International Journal of Applied Engineering and Technology

Integrating Markov Chain and Cellular Automata Models in GIS to Monitor and Predict Land Use and Cover Change in Rabigh City, Saudi Arabia

Layla Aljehani

Department of Geography and Geographic Information Systems, King Abdul-Aziz University, Jeddah 21589, Saudi Arabia,
Laljehani@kau.edu.sa

Date of Submission: 21st September 2023 Revised: 12th November 2023 Accepted: 24th November 2023

How to Cite: **Layla Aljehani (2023). Integrating Markov Chain and Cellular Automata Models in GIS to Monitor and Predict Land Use and Cover Change in Rabigh City, Saudi Arabia, International Journal of Applied Engineering and Technology, 5(4), pp.133-141.**

Abstract - **Observing changes in land use and land cover (LULC) is critical for developing strategies and policies that facilitate effective planning and equitable rapid growth in urban development areas. Hence, this research aimed to incorporate the cellular automata and Markov chain models by utilizing TerrSet software and geographical information system (GIS) methodologies to observe and identify the spatial and temporal LULC changes within the city of Rabigh, Saudi Arabia. The study utilized multi-temporal satellite images from 1993, 2003, 2013, and 2023, subjecting them to pre-processing techniques and analyzing them using the supervised maximum likelihood classification method. The objective was to investigate the historical land cover changes in the city from 1993 to 2023 by employing a GIS program. The study also used a combined cellular automata–Markov model to effectively model, validate, and utilize future LULC scenarios using TerrSet software. The findings indicated that the area used for agriculture has expanded by 33.8 km2, and built-up land has increased by 24.1 km2, for a loss of 42.2 km2 of barren land over the past twenty years. The projected LULC maps for 2033 and 2043 show that the transformation of barren land into built-up and agricultural areas will persist in the coming two decades. This phenomenon can be attributed to factors including urban expansion, government regeneration efforts, and the advancement of agricultural practices. The study offers valuable findings for developing strategic plans and implementing environmentally conscious land use management procedures.**

Keywords: **LULC, cellular automata, Markov model, TerrSet software, GIS.**

INTRODUCTION

The main consequences of urbanization and high population include important changes in land use and land cover (LULC), which affect the earth's surface locally, regionally, and globally over several decades [1]. Moreover, LULC change is a highly consequential phenomenon that is crucial in driving worldwide environmental transformations as a result of human activities.

Consequently, natural and human factors, developing countries are witnessing unprecedented urban growth and LULC change. This growth takes place in a random and unplanned manner, but it is done at the expense of agricultural lands; hence, urbanization causes significant damage and environmental and ecological problems over wide spatial areas [2, 3]. Land use (LU) consists of many different human uses, such as built-up land, agricultural land, and service land (e.g., hospitals, schools, shopping centers, and parks; [4]. The most important precondition for LULC change is the optimal use of land and awareness of the wear patterns of land use [5]. The ability to comprehend the issues that arise from changes in LULC, including their origins and consequences, has garnered the interest of scholars across various regions of the globe. Researchers focusing on models of land use changes in terms of time and space have exhibited significant enthusiasm toward applying these to alterations in LULC [6, 7]. Various studies have found that LULC change has enormous consequences for environmental system change, soil erosion, environment pollution, climate change, rising temperatures, ecological systems, and rainfall distribution, making it a significant threat to natural resource management [7-11]. This transformation of land has many direct and indirect effects on urban areas. Therefore, monitoring and predicting spatial and temporal LULC change provides fundamental information for decision-making related to planning, achieving sustainable evolution, and managing natural resources.

Over the last decades, the use of spatial analysis technology, for instance, geographical information systems (GIS) and remote sensing (RS), has accelerated the development of more complex methods for simulating future processes of the Earth's surface and offering support for land planning, policy-making, and management. Maps of LULC are essential as they provide observations of land change dynamics for analysis.

Therefore, previous studies have used GIS and Idris to study urban land use and forecast the future of land change [12, 13]. One such application is the cellular automata and Markov chain model, used in such modeling to predict and evaluate urban growth. The use of cellular automata (CA) has rapidly become the most common method for recreating historical landscapes and urban patterns and then forecasting potential outcomes based on various development methods [14-17]. He et al. (2006) [18] assert that a model based on CA can effectively be a symbol of non-linear, spatial, and stochastic phenomena. Moreover, the CA model can replicate and regulate intricate geographical processes while offering lucid comprehension of regional dynamics and worldwide trends of land utilization and coverage alteration. CA models provide a planning framework for reasonable urban spatial growth, which might reduce conflicts between land use and sustainability [19]. In a gridded CA model, cells are consistently sized and dispersed throughout the map [20], and procedures for converting rural cells to urban ones are specified [21]. Each cell's potential for transformation is based on the probability computed from urban development drivers [22, 23]. Parameterizing the transition rules may be done in various ways, from more traditional statistical methods to cutting-edge AI systems [24].

The utilization of Markov chain (MC) analysis has long been prevalent in the field of LULC change, as reported by Halmy et al., 2015 [25]. This approach involves a stochastic modeling technique. The underlying principle of its functionality is based on the physics postulate that the subsequent state is contingent solely upon the present state, as posited by Bell and Hinojosa (1977). The MC technique is used to observe the spatiotemporal dynamics of land-use changes based on transition matrices, as described by Guan et al., 2011 [26]. The CA–MC combined model has been proposed to account for both spatial and temporal shifts in LU. Specifically, Guan et al. (2011) have demonstrated that MC effectively controls temporal changes, and Nouri et al., 2014 [27] have shown that spatial changes can be determined using a spatial filter of the CA approach. Many specialized techniques have been included in CA modeling; however, evaluating different models using the same criteria remains essential. The utilization of the integrated CA–Markov model is a dependable approach to the computation of quantities and the formulation of spatial and temporal variability concerning the alteration of LULC. This can be attributed to the adept integration of RS information and GIS. Integrating the MC and CA models can transform the MC model outputs into spatially explicit outcomes, which are crucial for urban planning and design objectives. The result is a highly effective approach for examining LULC change across various spatial dimensions [28].

Recent research has simulated LULC changes worldwide utilizing the CA–Markov model using RS and GIS to monitor, map, and identify spatial–temporal LULC change. For instance, using CA and the MC model in Zaria City, Nigeria, revealed a rise in built-up areas [8].

Likewise, during Tehran's 1986–2006 urban expansion, which was simulated to calibrate and adapt the model, green and open areas decreased in built-up areas [3]. In El Jadida, Morocco, LULC change from 1999–2018 and urban development from 2010–2040 were examined using Markov chain analysis (MCA), which showed that built-up areas increased by 19.8 km2, with 12.8 km2 of this expansion replacing bare land and 7.1 km2 replacing vegetation. By 2040, the built-up area may reach 43.8 km2 [29]. Rimal et al. (2018) examined LULC change dynamics and modeled urban land growth in Kathmandu Valley cities and their environs. Urban cover increased by 346.85% from 1988 to 2016, replacing agricultural land. By 2024 and 2032, urban areas are projected to expand to 200 and 238 km2, respectively. In addition to using MCA to simulate spatial and temporal urban development patterns, another study used MCA to simulate the spatial and temporal patterns of urban development in Seremban, Malaysia, based on data collected between 1984 and 2010. The simulation results indicated a rise in urban expansion of 177 km2 by 2020, with a projected increase to 195.5 km2 by 2030 [30]. Landsat imagery was used to analyze urban development and LC changes in some of Saudi Arabian cities: the Eastern Area, Jeddah, Riyadh, Al-Taif, and Makkah. MC and CA modeling were used in the simulation model, and the simulated and reference maps were compared and verified. The simulation showed urban expansion in all five cities from 1985 to 2014 [31]. MCA has been widely applied using Idrisi and TerrSet software to analyze and predict urban land consumption. For example, a study was conducted in districts of Al Baha City between 2021 and 2047. The results showed that rangeland, woodland, shrubland, barren land, and sand made up 9.1% of the built-up area. Also, a simulation of the anticipated LULC change for the period 2021–2047 predicted the loss of 565 km2 of land, including sand, barren land, forest, and shrubland [32].

Rabigh, a city in Saudi Arabia, has undergone rapid urbanization in recent years, resulting in a significant increase in population. It has also experienced widespread urbanization over the past few decades. According to the data provided by the General Authority for Statistics, Rabigh had a population of approximately 40,361 in 2005. Subsequently, the population witnessed a significant rise, reaching 93,097 in 2010. By the end of 2023, the population of Rabigh is anticipated to increase to 112,000. This population growth is expected to result in the replacement of agricultural and other LULC areas with urban areas. Moreover, a combined CA–Markov model has yet to be implemented in Rabigh; thus, this area was selected as the study area. The study's objective was, first, to use supervised classification of satellite images from Landsat collected in 1993, 2003, 2013, and 2023 to observe changes in the land cover of Rabigh. Second, the CA–Markov model was utilized to predict and simulate land cover in 2033 and 2043. Finally, the GIS and MCA were integrated to enhance the CA–Markov model.

STUDY AREA

Rabigh is located in the Province of Makkah, ranking as the seventh-largest city in the province. Geographically, the coordinates of the location in question are 22° 47′ 9.77″ N and 39° 2′ 39.51″ E as shown in Fig 1. The metropolitan area of Rabigh is situated on the Red Sea shoreline, approximately 150 km from Jeddah City. The urban locality under examination is anticipated to be occupied by some 112,000 persons by 2023. It sits at an altitude of 13 meters (43 feet) above sea level and is near the boundary of the Madinah Province. The inception of the urban settlement can be traced to the pre-Islamic epoch that preceded the 7th century CE. Subsequently, the toponym Al-Juhfah was embraced and endured until the 17th century. Rabigh's advantageous geographical position along the Red Sea has enabled the inception of various noteworthy endeavors, including but not limited to the King Abdullah University of Science and Technology, the Petro Rabigh petrochemical company, and King Abdullah Economic City. The Rabigh Governorate comprises five distinct localities: Rabigh, Nuweiba, Abwa', Mastoura, and al-Qadimah.

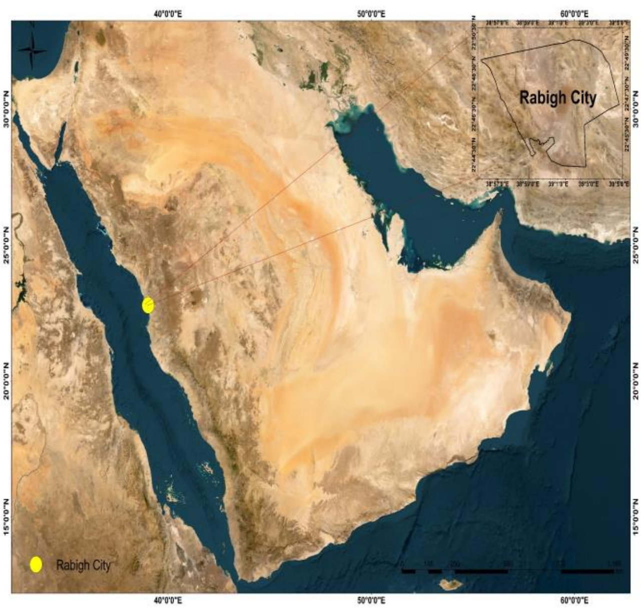


Fig. 1. Study area

METHODS

The present study used four satellite images taken at 10-year intervals from 1993 to 2023 to examine the dynamics of LULC change. The dataset consisted of Landsat TM imagery for 1993, Landsat ETM imagery for 2003, Landsat OLI imagery for 2013, and Landsat OLI imagery for 2023. In this study, the United States Geological Survey (USGS) was the source of the Landsat images that were collected. Table 1 lists the various satellite image datasets utilized in the research.

Table 1.
Datasets of satellite images used in this research.

Years	Satellite	Path/Row	Sensor Type	UTM Zone	Resolution
1993	Landsat TM	170/044	TM	37	30
2003	Landsat ETM	170/044	TM	37	30
2013	Landsat OLI	170/044	OLI_TIRS	37	30
2023	Landsat OLI	170/044	OLI_TIRS	37	30

As illustrated in Figs. 2 and 3, this study was approached methodologically as follows: (1) The pre-processing was conducted using ArcGIS 10.8 software to process the Landsat data sets for LULC changes. (2) The supervised classification method was adopted, utilizing the maximum likelihood classification (MLC) algorithm, which is widely recognized as the most commonly accepted classification method employed for RS data [33]. Therefore, the MLC algorithm in ArcGIS software for supervised classification was employed to assess the LULC changes from 1993 to 2023. The classification of images was based on three LULC classes: agriculture areas, barren areas, and built-up areas, as outlined in Table 2. (3) Accuracy assessment represents the essential last step in the process of LULC classification [34], and it can be derived from the confusion matrix. Landsat high-resolution images and Google Earth were extensively utilized for accuracy assessment in the pixel selection process. After classification, the study's image contained 150 points for each year selected (1993, 2003, 2013, and 2023), of which 50 points represent agricultural areas, 50 points represent barren areas, and 50 points represent built-up areas. The overall accuracy, producer's accuracy, user's accuracy, and Kappa statistics were generated from the confusion matrix [35]. (4) The Markov model is an optimal theoretical framework that centers on developing Markovian stochastic processes for forecast and control purposes [36]. The Markov approach explains the quantification of transformation states between various land use types and the amount of transfer between different land use categories. Geographic research commonly employs a predictive method that is not associated with any subsequent effects and has become a significant tool for predicting future geographical characteristics [37]. Land use change predictions were computed using the conditional probability formula equation (1–2) [38, 39].

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

where S(t) and S(t+1) are the status of the system at time t or (t+1).

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

$$(0 \leq P_{ij} < 1 \text{ and } \sum_{j=1}^{N} P_{ij} = 1, (i, j = 1, 2, . ., n)).$$

where P_{ij} is the probability matrix of transition.

(5) The CA–Markov model effectively combines the benefits of the Markov and CA models to forecast and simulate future changes in land use in Rabigh, as shown in Figure 3. When integrated into the TerrSet 19.0.6 software, the CA–Markov model's prediction method consists of three steps. First, the Markov model is used to generate the transfer matrix and the state transition probability matrix, which involves using the CA model to forecast future land use. The study developed a potential transition matrix according to land use map conditions. The periods 1993–2003 and 2003–2013 were used to predict the changes in 2013 and 2023. The matrix was subsequently applied to forecast changes for 2013 and 2023, thereby facilitating the calibration and validation of the model. Moreover, the LU maps for 2013 and 2023 were used to forecast future changes in 2033 and 2043. Second, CA filters provide an obvious idea of the space ranking factor that could be changed based on the current state of the cells next to it. In this study, a neighborhood is defined by the normal 5×5 contiguity filter. Every cellular center is surrounded by a matrix space made up of 5×5 cells, which influences the changes in the cellular center. Third, the CA–Markov model was executed with a varying number of iterations, ranging from 1 to 200, to determine the best possible iteration number.

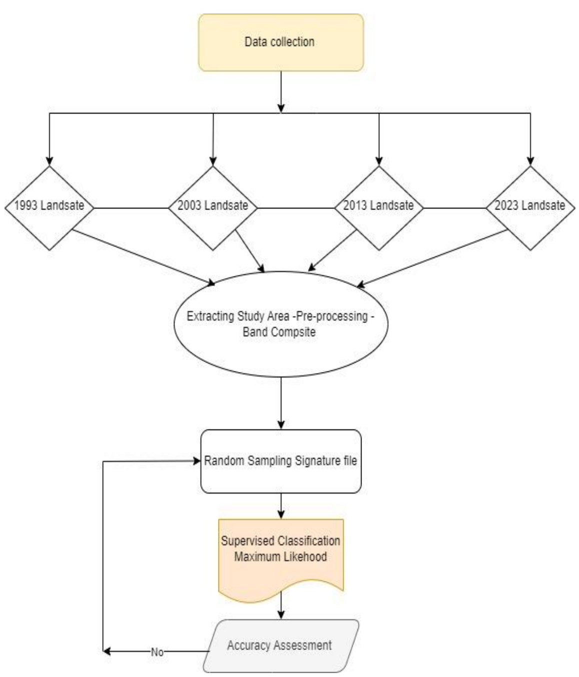


Fig. 2. Research methodological flowchart.

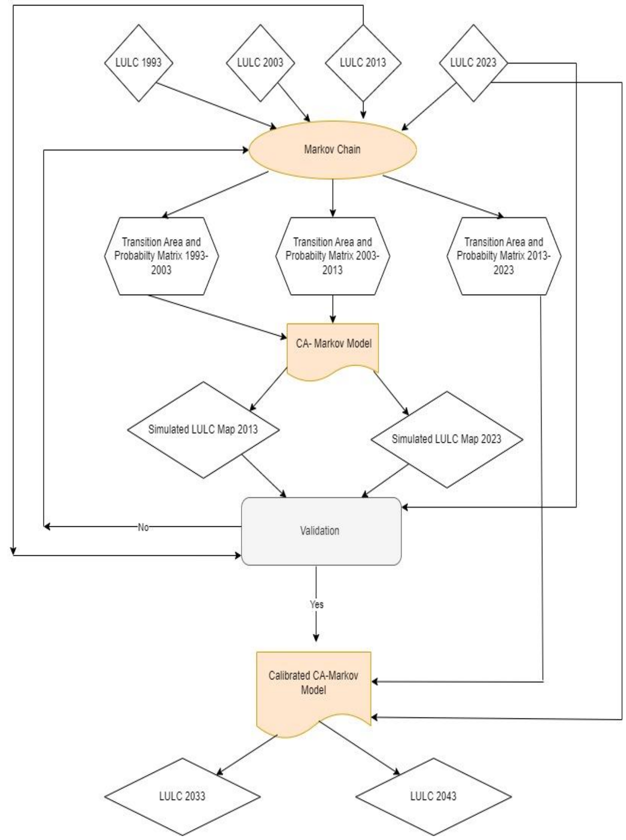


Fig. 3. Research methodological flowchart.

RESULTS AND DISCUSSION

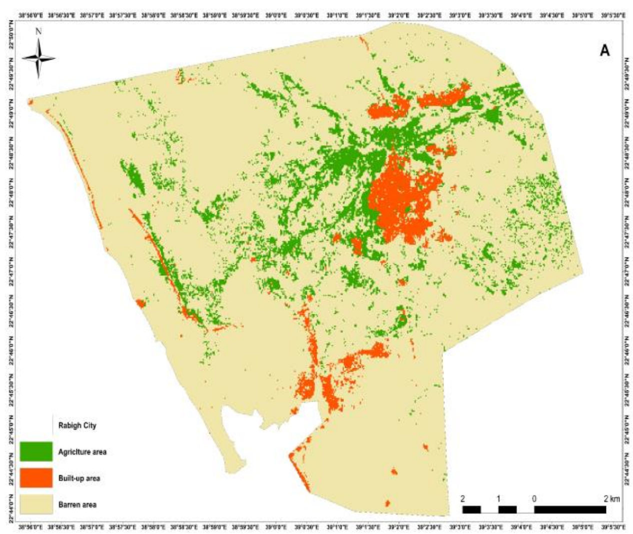
I. Supervised Classification Maximum Likelihood

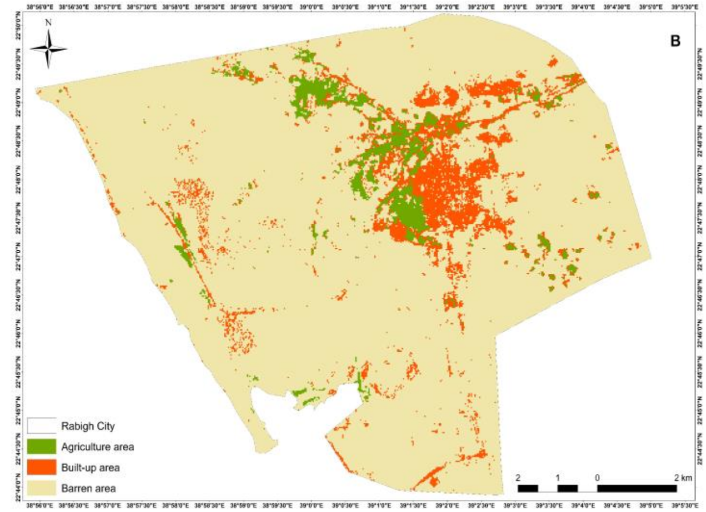
The study employed MLC techniques to generate LULC maps for 1993, 2003, 2013, and 2023. The outcomes of these techniques were analyzed and compared. The maximum likelihood classification technique involves determining the probability that a given pixel is associated with a specific class. One benefit of utilizing MLC is its reduced time consumption. The study area yielded superior outcomes with object-based classification instead of per-pixel classification. The study involved the selection of three distinct classes, namely agriculture area, built-up area, and barren area, for the purpose of imagery classification, as shown in Fig. 4. The findings showed that in 1993, the agriculture area accounted for 10.6 km2 (10%), the built-up area accounted for 5.2 km2 (5%), and the barren area accounted for 91 km2 (85%). In 2003, a reduction of 4.4 km2 (4.1%) occurred in the agricultural area due to a decrease in rainfall. This resulted in a corresponding reduction in the agricultural regions within the study area. Conversely, the built-up area increased to 8.4 km2 (7.9%), while the barren area expanded to 94 km2 (88%). The development of the built-up area was attributed to the various developmental policies of the Rabigh city government through development projects in Rabigh, particularly the construction of housing units.

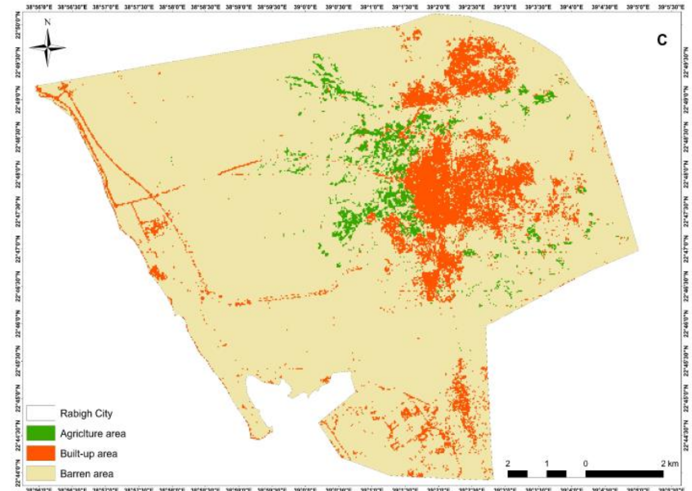
According to the classification outcomes for 2013, the agricultural region experienced a reduction of 2.9 km2, equivalent to 2.7% of the total area. Conversely, the built-up area increased by 11.6 km2, covering 10.9% of the entire area. The barren area constituted most of the region, covering 92 km2 (86.4% of the total area). According to the 2023 statistics, the agricultural and built-up areas experienced growth of 17.9 km2 (16.7%) and 18.4 km2 (17.3%), respectively. Conversely, the barren areas experienced a decline, decreasing to 70.6 km2 (66%). Table 2 presents the statistical information for each year.

Table 2.
LU/LC classification results for 1993, 2003, 2013, and 2023.

LULC	1993		2003		2013		2023		
	Area km²	Area%	Area km²	Area%	Area km²	Area%	Area km²	Area%	Annual change (1993–2003)
Agriculture area	10.6	10	4.4	4.1	2.9	2.7	17.9	16.7	2.1
Built-up area	5.2	5	8.4	7.9	11.6	10.9	18.4	17.3	3.4
Barren area	91	85	94	88	92.4	86.4	70.6	66	86
Total area	106	100	106	100	106	100	106	100	91.5







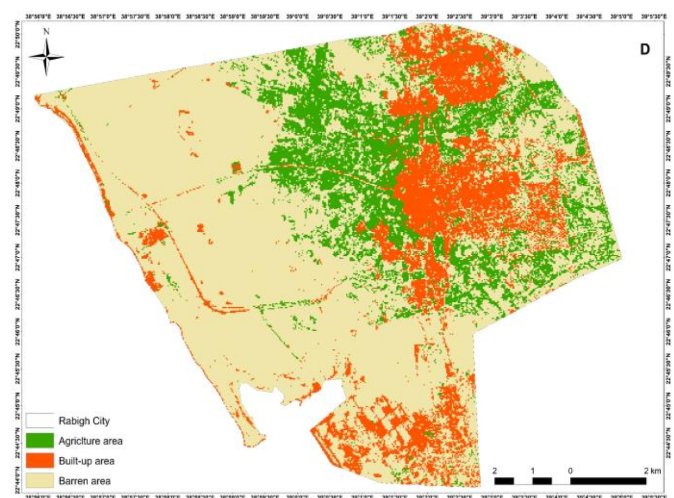


Fig. 4. Four LULC maps in different years: A 1993, B 2003, C 2013, and D 2023.

2. Accuracy Assessment

The accuracy assessment of image classifications pertaining to LULC classifications in the years 1993, 2003, 2013, and 2023 demonstrated a very good level of classification accuracy for all classes. Table 3 presents the overall and kappa statistics for the classification images in different years. The assessment with the highest level of accuracy was linked to the 2013 image, at a percentage of 90%. Conversely, the lowest level of accuracy was observed for the 1993 image at a rate of 80%. The kappa statistics fell within the range of substantial to almost perfect strength of agreement. Based on the results for the years selected, the substantial strength of agreement range is between 0.61 and 0.80, while the almost perfect strength of agreement range is between 0.81 and 1.00 [40]. In this study, the kappa statistics for 1993 and 2003 were within the substantial strength of agreement range, while those for 2013 and 2023 were within the perfect strength of agreement range.

Table 3.
The accuracy assessment of LULC classification in Rabigh city.

Class	1993		2003		2013		2023	
	Producer's	User's	Producer's	User's	Producer's	User's	Producer's	User's
Agriculture area	0.92	0.76	0.88	0.94	1	0.9	0.93	0.92
Built-up area	0.84	0.74	0.92	0.7	0.9	0.9	0.97	0.78
Barren area	0.70	0.92	0.79	0.94	0.81	0.9	0.80	0.98
Overall	80		86		90		89	
Kappa	0.71		0.79		0.85		0.84	

3- Markov Transitional Probability Matrix

The present study examined the dynamics of change within three LULC classes by applying a Markov chain analysis. The transition matrix of probabilities was used to quantify these changes over three distinct periods: 1993–2003, 2003–2013, and 2013–2023. Table 4 presents the transition matrix of probabilities, which exhibits a range of values from 0 to 1. The greater the value, the more likely the LULC class will shift from horizontal to vertical or vice versa. The probabilities of LULC classes persisting are represented by the diagonal values in the transition matrix for each period. In contrast, the non-diagonal elements indicate the probability of a transition between land cover classes during the given time frame. The matrix of transition probabilities displays the possible trajectories of LULC changes during 1993–2003, 2003–2013, and 2013–2023. The matrix indicates that the probability of barren areas transforming into built-up areas in the future has shown an upward trend, rising from 4.6% during 1993–2003 to 5.2% during 2003–2013 and declining to 3.6% in 2013–2023.

The probability of agricultural areas transitioning into built-up areas notably escalated from 1.7% during 1993–2003 to 5.1% in 2003–2013 and then rose to 8.7% from 2013 to 2023. Due to the city's expansion and fast population growth, primarily due to Rabigh's significant development initiatives, more and more formerly agricultural areas may soon be transformed into built-up areas. Also, the swift surge in the population of the urban center has resulted in a commensurate upsurge in the need for urban amenities and facilities.

Table 4.
Transition matrix of probabilities of periods: 1993–2003, 2003–2013, and 2013–2023.

Year	LULC	Agriculture	Built-up	Barren
1993–2003	Agriculture	0.1607	0.1710	0.6683
	Built-up	0.0039	0.5310	0.4651
	Barren	0.0690	0.1357	0.7952
2003–2013	Agriculture	0.2784	0.0515	0.6701
	Built-up	0.0777	0.3968	0.5255
	Barren	0.0299	0.1979	0.7722
2013–2023	Agriculture	0.5357	0.0879	0.3764
	Built-up	0.1395	0.4941	0.3664
	Barren	0.3068	0.1916	0.5016

4- The Validation of the Model and the Prediction of Future LULC Change

To forecast LULC changes for the next two decades, the existing LULC data from 2013 and 2023 were utilized. Using cross-tabulation techniques on these two LULC maps, probability statistics for LULC changes in 2033 and 2043 were generated. The CA–Markov model integrates the principles of Markov chain methodology and CA filters. Once the Markov transition probability was obtained, the CA Markov model utilized the matrix of transition probability and probability images to forecast LULC changes over a 20-year timeframe, specifically in 2033 and 2043. The complete number of iterations is determined by a number of time steps. In the case of a 20-year model, completing the run in 200 iterations is suggested. To accurately predict future LU trends, the CA–Markov model was initially used to forecast the LU indicated in 2013. Subsequently, the model was employed to predict LU change in the year 2023 to ascertain the dependability of the model. When optimizing the model's performance, the LU change maps were predicted using different iteration numbers, specifically the iteration of the number that yielded the most favorable outcomes. To validate the model, the study compared the projected LU maps for 2013 and 2023 with the real maps. This comparison was conducted based on the kappa index statistic, which allowed for an assessment of the model's validity with regard to quantity and location [41, 42]. Fig. 5 demonstrates the relationship between the kappa index and the number of iterations. Based on the data presented in Fig. 5, the model demonstrated its highest level of performance in 50 iterations while predicting LU for the year 2023.

This optimal performance is indicated by a kappa standard of 0.7649, a kappa location of 0.9129, and a kappa number of 0.8003. Additionally, the model successfully predicted land use in the year 2013. It achieved this simulation in 200 iterations, with a kappa standard of 0.7995, a kappa location of 1.0000, and a kappa number of 0.8809. The validation results demonstrate good agreement between the observed and projected maps. The validation step yields the calculation of the optimum transition rules to the model, utilizing a predetermined number of iterations. These rules were subsequently employed to forecast LULC in 2033 and 2043. The future LULC maps for 2033 and 2043 were simulations based on the successful role modeling of the LULC in 2013 and 2023. The future patterns of LULC were predicted based on the 2023 LULC map as a reference map, transition potential maps, and the area of transition matrices from the 2013–2023 period, as seen in Figs. 6 and 7.

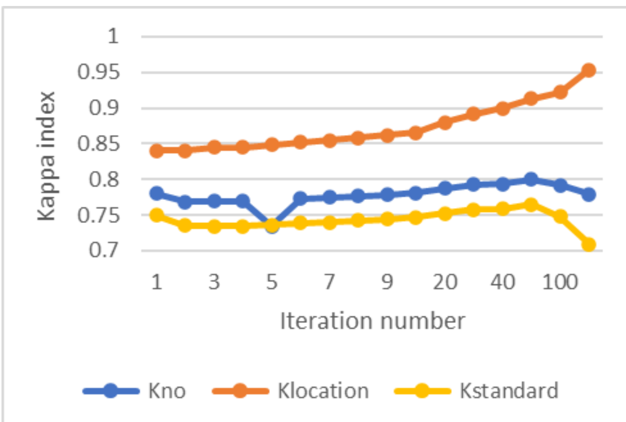


Fig. 5. Kappa statistics and number of iterations.

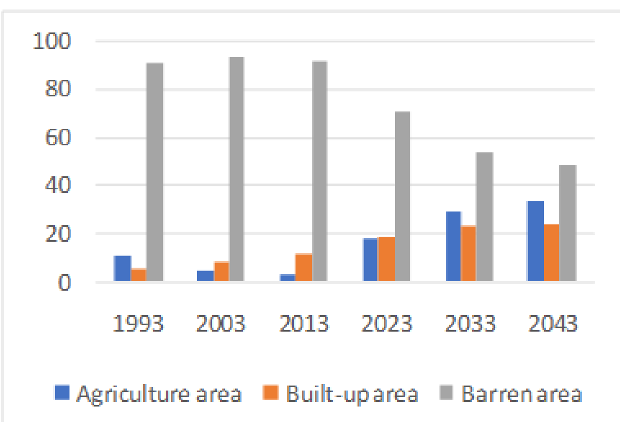


Fig. 6. Previous and forecasted LULC change in km^2.

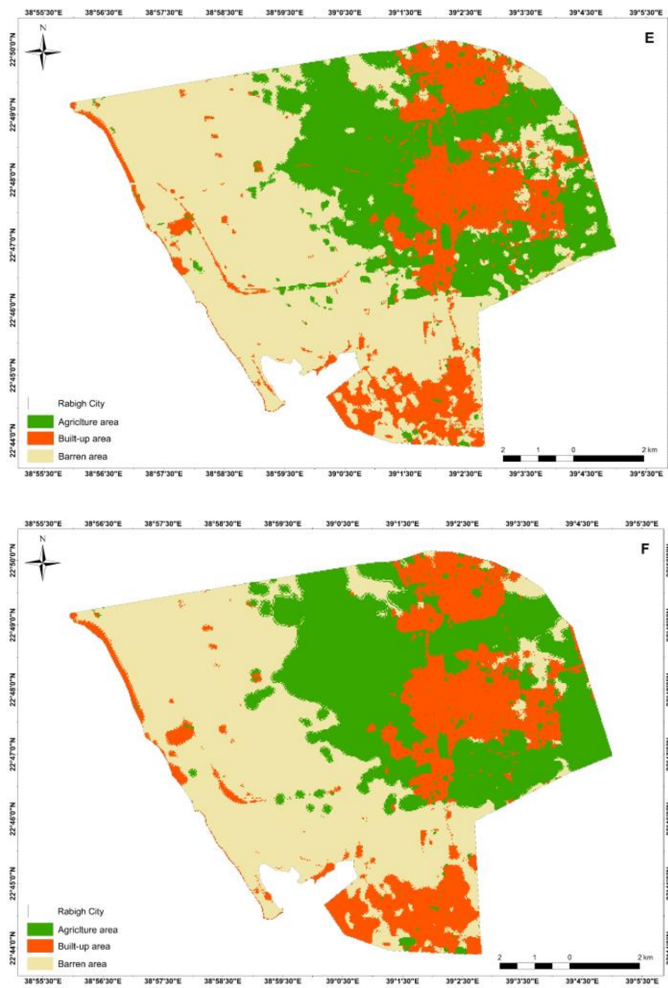


Fig. 7. Predicted LULC maps E 2033 and F 2043.

According to the simulation findings obtained from the CA–Markov model, the built-up area is predicted to experience growth from 18.4 km^2 in 2023 to around 22.8 km^2 in 2033. The extent of the agriculture area is projected to undergo a notable increase, expanding from 17.9 km^2 to approximately 29.6 km^2 within the timeframe spanning from 2023 to 2033. The extent of the barren area is projected to experience a decrease from 70.6 km^2 in 2023 to about 54.4 km^2 by 2033. In a similar vein, the simulation model conducted for 2043 projected a notable expansion in the built-up area, with an estimated rise from 18.4 km^2 in 2023 to around 24.1 km^2 by 2043. The projected growth of the agriculture area is anticipated to rise from 17.9 km^2 in 2023 to approximately 33.8 km^2 by the year 2043. The extent of the barren area is projected to experience a significant reduction, decreasing from 70.6 km^2 to around 48.8 km^2.

Notably, the CA–Markov model applied in this study successfully simulated and predicted upcoming LULC patterns using two maps. This highlights the usefulness of the model of CA–Markov in circumstances with limited data availability. In the context of urban growth, the alteration of LULC is influenced by various factors, including biophysical characteristics such as the slope, aspect, and LC, as well as socioeconomic variables such as population density and distance to the central business district [4]. It is essential to consider these factors in addition to LULC history when examining the impact of urban expansion on LULC change. Therefore, by integrating these factors into the CA–Markov model, the understanding of LULC change in urban areas is anticipated to be enhanced, thereby improving the model's capacity to predict LULC change.

CONCLUSIONS

The current study demonstrates the development of a model to forecast the temporal and spatial patterns of LULC in Rabigh. Between 1993 and 2023, the categorization of land use and land cover experienced persistent and ongoing alteration. The Markov chain model has been widely recognized as the most suitable and precise approach for analyzing and forecasting for twenty-year periods. The study used this approach to create predictive LU and LC maps for 2033 and 2043. More specifically, it attempted to identify, replicate, and forecast patterns of growth until the years 2033 and 2043. The findings project that by 2043, a 33.8 km^2 expansion in agricultural land and a 24.1 km^2 expansion in built-up areas will occur. These changes are anticipated to be accompanied by a reduction of 48.8 km^2 in barren areas compared to the LULC data from 1993. This study holds significant importance for urban planning and decision-making, particularly concerning future planning endeavors for modern cities. Additionally, the study illustrated the utility of satellite data in analyzing temporal changes in land use and land cover within a specific period. To enhance understanding of land use changes and the factors that influence them, it is essential to integrate biophysical and socioeconomic data into the CA–Markov chain model.

Availability of data and material

The data is available in USGS; however, the data analysis of this study will be available from the author upon request.

Competing interests

I declare that I have no competing interest to disclose.

Funding

There has been no financial support received for this study.

REFERENCES

[1] Ildoromi, A., et al., Land use change prediction using markov chain and ca markov model (case study: Gareen Watershed). Journal of Watershed Management Research, 2015. 8(16): p. 232-240.

[2] Rimal, B., et al., Monitoring and modeling of spatiotemporal urban expansion and land-use/land-cover change using integrated Markov chain cellular automata model. ISPRS International Journal of Geo-Information, 2017. 6(9): p. 288.

[3] Arsanjani, J.J., W. Kainz, and A.J. Mousivand, Tracking dynamic land-use change using spatially explicit Markov Chain based on cellular automata: the case of Tehran. International Journal of Image and Data Fusion, 2011. 2(4): p. 329-345.

[4] Al-sharif, A.A. and B. Pradhan, Monitoring and predicting land use change in Tripoli Metropolitan City using an integrated Markov chain and cellular automata models in GIS. Arabian journal of geosciences, 2014. 7: p. 4291-4301.

[5] Ghalehteimouri, K.J., et al., Predicting spatial and decadal of land use and land cover change using integrated cellular automata Markov chain model based scenarios (2019–2049) Zarriné-Rūd River Basin in Iran. Environmental Challenges, 2022. 6: p. 100399.

[6] Wu, X., et al., Land use/cover dynamics in response to changes in environmental and socio-political forces in the upper reaches of the Yangtze River, China. Sensors, 2008. 8(12): p. 8104-8122.

[7] Keshtkar, H. and W. Voigt, A spatiotemporal analysis of landscape change using an integrated Markov chain and cellular automata models. Modeling Earth Systems and Environment, 2016. 2: p. 1-13.

[8] Koko, A.F., et al., Monitoring and predicting spatio-temporal land use/land cover changes in Zaria City, Nigeria, through an integrated cellular automata and markov chain model (CA-Markov). Sustainability, 2020. 12(24): p. 10452.

[9] Bhattacharya, R.K., N.D. Chatterjee, and K. Das, An integrated GIS approach to analyze the impact of land use change and land cover alteration on ground water potential level: A study in Kangsabati Basin, India. Groundwater for sustainable development, 2020. 11: p. 100399.

[10] Kafy, A.-A., et al., Modelling future land use land cover changes and their impacts on land surface temperatures in Rajshahi, Bangladesh. Remote Sensing Applications: Society and Environment, 2020. 18: p. 100314.

[11] Pielke Sr, R.A., et al., An overview of regional land-use and land-cover impacts on rainfall. Tellus B: Chemical and Physical Meteorology, 2007. 59(3): p. 587-601.

[12] Wang, J. and I.N. Maduako, Spatio-temporal urban growth dynamics of Lagos Metropolitan Region of Nigeria based on Hybrid methods for LULC modeling and prediction. European Journal of Remote Sensing, 2018. 51(1): p. 251-265.

[13] Yuan, F., Urban growth monitoring and projection using remote sensing and geographic information systems: a case study in the twin cities metropolitan area, Minnesota. Geocarto International, 2010. 25(3): p. 213-230.

[14] Arsanjani, J.J., et al., Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. International Journal of Applied Earth Observation and Geoinformation, 2013. 21: p. 265-275.

[15] Santé, I., et al., Cellular automata models for the simulation of real-world urban processes: A review and analysis. Landscape and urban planning, 2010. 96(2): p. 108-122.

[16] Liu, Y. and Y. Feng, Simulating the impact of economic and environmental strategies on future urban growth scenarios in Ningbo, China. Sustainability, 2016. 8(10): p. 1045.

[17] Feng, Y., et al., Projection of land surface temperature considering the effects of future land change in the Taihu Lake Basin of China. Global and Planetary Change, 2018. 167: p. 24-34.

[18] He, C., et al., Modeling urban expansion scenarios by coupling cellular automata model and system dynamic model in Beijing, China. Applied Geography, 2006. 26(3-4): p. 323-345.

[19] Li, X. and A.G.-O. Yeh, Modelling sustainable urban development by the integration of constrained cellular automata and GIS. International journal of geographical information science, 2000. 14(2): p. 131-152.

[20] Toffoli, T. and N. Margolus, Cellular automata machines: a new environment for modeling. 1987: MIT press.

[21] Wu, F., SimLand: a prototype to simulate land conversion through the integrated GIS and CA with AHP-derived transition rules. International Journal of Geographical Information Science, 1998. 12(1): p. 63-82.

[22] Feng, Y., et al., Simulation of dynamic urban growth with partial least squares regression-based cellular automata in a GIS environment. ISPRS International Journal of Geo-Information, 2016. 5(12): p. 243.

[23] Yu, Y., et al., Modeling urban collaborative growth dynamics using a multiscale simulation model for the Wuhan urban agglomeration area, China. ISPRS International Journal of Geo-Information, 2018. 7(5): p. 176.

[24] Liu, X., et al., A multi-type ant colony optimization (MACO) method for optimal land use allocation in large areas. International Journal of Geographical Information Science, 2012. 26(7): p. 1325-1343.

[25] Halmy, M.W.A., et al., Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. Applied Geography, 2015. 63: p. 101-112.

[26] Guan, D., et al., Modeling urban land use change by the integration of cellular automaton and Markov model. Ecological modelling, 2011. 222(20-22): p. 3761-3772.

[27] Nouri, J., et al., Predicting urban land use changes using a CA–Markov model. Arabian Journal for Science and Engineering, 2014. 39: p. 5565-5573.

[28] Clarke, K.C. and L.J. Gaydos, Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. International journal of geographical information science, 1998. 12(7): p. 699-714.

[29] Saadani, S., et al., Simulating spatial–temporal urban growth of a Moroccan metropolitan using CA–Markov model. Spatial Information Research, 2020. 28: p. 609-621.

[30] Aburas, M.M., et al., Spatio-temporal simulation of future urban growth trends using an integrated CA-Markov model. Arabian Journal of Geosciences, 2021. 14: p. 1-12.

[31] Alqurashi, A.F., L. Kumar, and P. Sinha, Urban land cover change modelling using time-series satellite images: A case study of urban growth in five cities of Saudi Arabia. Remote Sensing, 2016. 8(10): p. 838.

[32] Alsharif, M., et al., Land Use Land Cover Change Analysis for Urban Growth Prediction Using Landsat Satellite Data and Markov Chain Model for Al Baha Region Saudi Arabia. Forests, 2022. 13(10): p. 1530.

[33] Foody, G.M., Status of land cover classification accuracy assessment. Remote sensing of environment, 2002. 80(1): p. 185-201.

[34] Aljehani, L., The Impact of the Haramain High-Speed Train on Land Prices and Urban Growth in the Neighborhoods of Tibah Municipality, Jeddah, Saudi Arabia. Current Urban Studies, 2023. 11(3): p. 415-446.

[35] Jensen, J.R., Introductory digital image processing: a remote sensing perspective. 1996: Prentice-Hall Inc.

[36] Jiang, G., F. Zhang, and X. Kong, Determining conversion direction of rural residential land consolidation in Beijing mountainous areas. Transactions of the Chinese Society of Agricultural Engineering, 2009. 25(2): p. 214-221.

[37] Sang, L., et al., Simulation of land use spatial pattern of towns and villages based on CA–Markov model. Mathematical and Computer Modelling, 2011. 54(3-4): p. 938-943.

[38] Hou, X., B. Chang, and X. Yu, Land use change in Hexi corridor based on CA-Markov methods. Nongye Gongcheng Xuebao(Transactions of the Chinese Society of Agricultural Engineering), 2004. 20(5): p. 286-291.

[39] Yang, G., Y. Liu, and Z. Wu, Analysis and simulation of land-use temporal and spatial pattern based on CA-Markov model. 武汉大学学报● 信息科学版, 2007. 32(5): p. 414-418.

[40] Rwanga, S.S. and J.M. Ndambuki, Accuracy assessment of land use/land cover classification using remote sensing and GIS. International Journal of Geosciences, 2017. 8(04): p. 611.

[41] Kamusoko, C., et al., Rural sustainability under threat in Zimbabwe–simulation of future land use/cover changes in the Bindura district based on the Markov-cellular automata model. Applied Geography, 2009. 29(3): p. 435-447.

[42] Wang, S.Q., X. Zheng, and X. Zang, Accuracy assessments of land use change simulation based on Markov-cellular automata model. Procedia Environmental Sciences, 2012. 13: p. 1238-1245.