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An Application of Cellular Automata (CA) and Markov Chain (MC) Model in Urban Growth Prediction: A case of Surat City, Gujarat, India

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Abstract

The main purpose of this study is to detect land use land cover change for 1990-2000, 2000-2010, and 2010-2020 using multispectral Landsat images as well as to simulate and predict urban growth of Surat city using Cellular Automata-based Markov Chain Model. Maximum likelihood supervise classification was used to generate LULC maps of the years 1990,2000,2010, and 2020 and the overall accuracy of these maps were 90%, 95%, 91.25%, and 96.25%, respectively. Two transition rules were commuted to predict the LULC of 2010 and 2020. For validation of these LULC maps, the Area Under Characteristics curve was used, and these maps' accuracy was 95.30% and 86.90%. This validation predicted LULC maps for the years 2035 and 2050. Transition rules of 2010-2035 showed that there will be a probability that 36.33% of vegetation area and 40.27% of the vacant land area will be transited into built-up by the year 2035, and it will be 49.20 % of the total area. Also, 57.77% of the vegetation area and 60.24% of the built-up area will be transformed into urban areas by the year 2050, almost 62.60 %. Analysis of LULC maps 2035 and 2050 exhibits that there will be abundant growth in all directions except the South Zone and Southwest Zone. Therefore, this study helps urban planners and decision-makers decide what to retain, where to plan for new development and type of development, what to connect, and what to protect in coming years.

1. Introduction

The current demographic transition from rural to urban areas is the most considerable shift of this century, bringing planning and development policy for micro and macro development (Chaudhuri & Clarke, 2019). This evaluation of the demographic transition process starts with the formation of towns and cities, and then it takes the size of metropolitan and urban agglomerations (Deep, 2014; Sahana et al., 2018). Urban sprawl has become a worldwide problem, especially for a developing nation. An indication of imbalance between urban spatial expansion and underlying population can characterize urban sprawl. Reasons behind the urban sprawl are high population growth, high accessibility to urban areas from suburban areas, and choice of people to live near peri-urban areas. Urban sprawl usually covers vegetation land, resulting in biodiversity loss and the heat island effect. So, assessing the impact of different land use planning schemes and development policies is essential to optimize the loss of natural land (Gao et al., 2020; Jokar Arsanjani et al., 2013).

Town planners generally used zoning to differentiate land use as a method of guiding and controlling the growth of urban areas. In the early development phase, this concept was applied in the planning of developed countries and is now in developing countries (He et al., 2018). Developing strategies for evaluating various urban development scenarios about potential implications for land use and the advancement of existing spatial plans and policies is vital for urban and regional planners (Al-Ahmadi et al., 2009). Stakeholders, such as those involved

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in research, modeling, forecasting, and policymaking related to planning for sustainable urban growth, are also concerned about the effects of piecemeal planning in large cities. However, the urbanization and urban development phase worldwide does not follow a uniform pattern. In developed countries, the concentration of population in medium-sized cities has risen dramatically. Most small and medium-sized cities in India are expected to be of regional significance by 2030. As a result, these cities will strengthen their socioeconomic conditions and infrastructure and serve the more extensive hinterland.

Land use land cover change is a complex and dynamic system resulting from spatial interaction between different land uses over some time. This has become a key process in optimizing land use in a step towards the development of sustainable smart cities (Deep, 2014; Shu et al., 2020). The urban system requires integrated tools that help guide and forecast urban growth because of its complex and dynamic nature. This time series dynamic process has complex interactions between land use, transportation, population, economy, river, topography, growth policies, culture, and politics. Planners have tried to project and guide urban growth using several simulation models (Gharaibeh et al., 2020; Mustafa et al., 2017; Thapa & Murayama, 2020; Tripathy & Kumar, 2019).

In urban planning, many researchers and decision-makers have applied different methods and models to simulate and predict urban sprawl. Remote sensing (RS) and Geographic Information systems (GIS) are some of the most used to detect spatial and temporal changes (Deep, 2014; Gharaibeh et al., 2020; Sahana et al., 2018; Tripathy & Kumar, 2019). It can be analyzed by modeling urban growth using different models like cellular automata (CA) (Mustafa et al. 2017; Xu & Gao, 2019), logistics regression (Okafor et al., 2020), Markov chain technique (Lu et al., 2018; Mosammam et al., 2017), SLEUTH (slope, land use, exclusion, urban extent, transportation, and hill shade), Fuzzy, genetic algorithm (Li et al., 2008), AHP (analytical hierarchy process) (Aburas et al., 2016), ANN (arithmetic neural network) (Gharaibeh et al., 2020), weights of evidence, conversion of land use and its effects (CLUE), entropy optimization (Gao et al., 2020) and land use transformation model to predict urban growth.

Out of all models, the CA model is used widely because of its flexibility, ability to integrate the spatial and temporal dimensions of the process, and to model complex dynamic systems (Aburas et al., 2016). CA model is a discrete, repetitive, and dynamic system in which the state of each cell depends on previous conditions as well as the condition of the neighborhood (Lagarias, 2012). CA model can simulate and predict urban growth based on the assumption that past urban growth and local and regional interactions of different land uses. It is most suitable for the simulation of a spatial pattern. However, it does not help interpret urban growth because it cannot predict and simulate spatial changes (Hu & Lo, 2007).

Markov Chain (MC) model can quantify temporal changes in land use classes from one stage to another using a transition probability matrix but not spatial changes. In contrast, the CA automata model can predict and simulate spatial changes. MC model doesn't consider the effect of surrounding cells but only considers the states of cells at a different two-time period while quantifying land-use changes (Okafor et al., 2020). The ability to articulate time shifts from one time to another makes MC the best tool to model land-use changes and thus provides a framework for forecasting future changes. To overcome the limitation of both the MC and CA model, it is better to integrate the CA and MC model to identify spatial-temporal changes and quantify those changes for simulation and projection of urban growth. The integrated CA – MC model has been the most common method of simulating transition in urban development and land use over the last 10 years, perhaps because it does not demand a considerable amount of data, and the model itself is user-friendly, even for users who are not specialists (Milad et al., 2016).

Surat City has experienced unprecedented urban growth in the last three decades. Due to commercial and business activities, many workers migrated to Surat from surrounding states like Rajasthan, Uttar Pradesh, Madhya Pradesh, Maharashtra, and Bihar. It steered its natural resources like agricultural land and water bodies.

Therefore, this study was carried out to detect spatial changes in land use land cover from the year 1990 to 2020 to analyze the urban growth direction of the city as well as to predict urban growth for the years 2035 and 2050.

This paper comprises five sections. Section 2 discusses the functionality of the CA-based Markov Chain model, followed by section 3, which is about the study area profile and data used for the study. Section 4 comprises an analysis of maps and results of actual and predicted LULC maps. Section 5 concludes this study's applicability and future scope with advanced machine learning models.

2. Data and Methods

2.1. Study Area Profile

Surat is well-known for its major diamond polishing industries and the textile hub of Gujarat state of India. The city is located between latitudes 21°03' and 21°19' North and longitudes 72°41' and 73°00' East, having an area of 326.53 sq.km, as shown in Figure 1. It is 13 m above the mean sea level. Surat City has a population of 4.46 million and population density was 13,680 persons per sq.km as per census 2011. The city is located in the southern part of Gujarat state in western India. It lies near the mouth of the Tapti River in the Gulf of Khambhat (Cambay). The city has grown on both sides of river Tapti. Surat city is considered one of the fastest-growing cities in India. Surat city has a high migration rate from different parts of Gujarat and other states of India because of the diamond and textile industries. It is well connected by the Ahmedabad-Mumbai corridor. Surat has experienced rapid urbanization and expansion of urban boundaries due to its fast-growing population. Thus, future growth should be confined within the specified urban form delimited by urban growth boundaries to preserve agricultural areas and prevent urban sprawl.

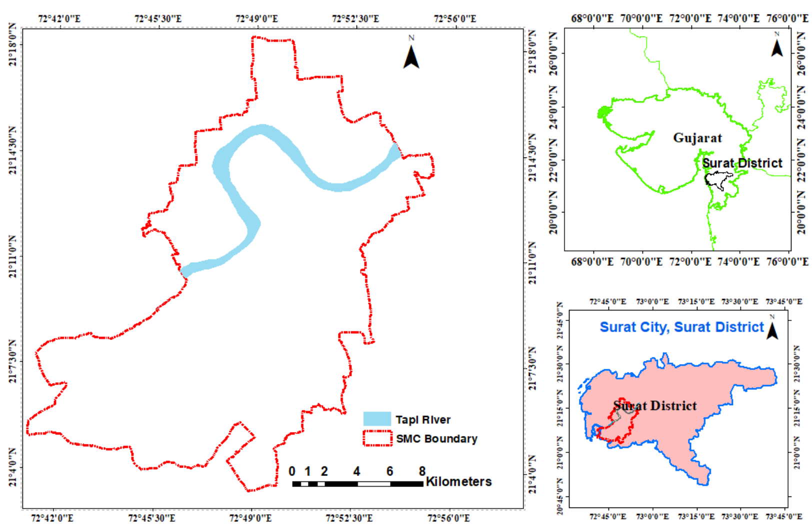

Figure 1. The Map of Surat City

2.2. Methodology of Cellular Automata (CA) and Markov Chain (MC) Model

Four satellite images were used to extract the land use maps for Surat City as part of the materials and methodology used in this study. The maximum likelihood classification technique, a supervised classification method, was used to classify images. Accurate polygons were chosen as training and study areas in order to classify the images. Four classes were used: built-up, agriculture, vacant land and water. Therefore, the resampling step was conducted after image classification.

Consequently, the analysis, simulation and future land use change prediction were conducted in the IDRISI-Selva software environment. Specifically, the number of land use classes and their changes in periods (1990, 2000, 2010 and 2020) was calculated using cross-tabulation analysis. Afterward, the CA–Markov model

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was applied to simulate and predict future land use changes in Surat city, as shown in the flowchart presented in Figure 2.

2.2.1. Cellular Automata (CA) Model

Generally, CA models aim to simulate the actual nature regulations. Land use change modeling using the CA technique is a preferred method because it gives explicit spatial modeling results based on a defined transition rule (Ward et al., 2000; White & Engelen, 2000). Moreover, CA automata model types are suitable to represent, analyze and forecast geographic processes due to the relationships among a raster grid (Mitsova et al., 2011). The CA automata are a practical tool in urban system simulations since population and land use change can be presented together.

Furthermore, cells of the cellular lattice can be aggregated efficiently with economic and transportation data. Thus, the urban areas can be effectively simulated by using proper neighborhoods of cells on the cellular grid. Moreover, theories of the urbanization process can be examined based on used spatial models (Mitsova et al., 2011). The CA model has been used increasingly in land use change and urban expansion modeling (He et al., 2006). It is worth mentioning that the time and space in CA model are considered as discrete units, and the space is considered as a regular grid (lattice) in two dimensions. The main aspect of CA model is the local interactions which reflect the dynamicity of system evolution (Wang et al., 2012). CA models are able to simulate stochastic, nonlinear and spatial processes. Many studies have illustrated that CA models have the potential to model the complex spatiotemporal process of land use change, urban systems and its patterns in an understandable manner (Barredo & Demicheli, 2003; He et al., 2006; Wang et al., 2012; Xian & Crane, 2005).

The significant components of CA models are as follows: (a) cells, (b) cell neighborhoods and (c) transition rules, i.e., the cell is the fundamental element of the automation system, i.e., the cell are organized in a lattice. The transition rule that defines the state of each cell for the coming time step depends on the current state of that cell and its surrounding neighborhood cells. After that, a land use change suitability map is required and the dynamics should be defined in the system. The primary expression of the CA model can be expressed as:

$$S(t, t+1) = f(S(t), N) \text{……………………. Eq. (1)}$$

where S is the states of discrete cellular, t is the time instant, t +1 is the coming future time instant, N is the cellular field and f is the transition rule of cellular states in local space.

2.2.2. Markov Chain (MC) Model

Markov chain model is based on the progression of the formation of Markov stochastic process systems for predicting one status being changed to another. The Markov chain model is commonly used to model and simulate changes, dimensions and trends of land use/cover (Sang et al., 2011; Weng, 2002). Markov chain model analyses and summarizes the change in land use by a number of probabilities transition areas from one status to a different status over a specified period. Additionally, the produced probabilities transition areas can be used to predict and discover the probable scenarios of future land use change and urban growth patterns. On the other hand, the Markov chain cannot model and simulate the changes in spatial distribution. Nevertheless, it is an effective and powerful model that can estimate and predict the quantity of land use change (Xin et al., 2012). The prediction of future land use changes can be calculated based on the conditional probability formula by using the following equation:

$$S(t+1) = \text{Pij x } S(t) \text{……………..Eq. (2)}$$

$$\text{Pij} = \begin{pmatrix} P_{11} & P_{12} & P_{1n} \\ P_{21} & P_{22} & P_{2n} \\ P_{n1} & P_{n2} & P_{nn} \end{pmatrix} \text{…………..Eq. (3)}$$

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

where S (t) is the state of the system at time t, S (t +1) is the state of the system at time (t +1); Pij is the matrix of transition probability in a state.

2.2.3. Validation of CA-MC Model by Receiver Operating Characteristic Curve (ROC)

Relative Operating Characteristics is an excellent method to assess the validity of a model that predicts the location of the occurrence of a class by comparing a suitability image depicting the likelihood of that class occurring. This technique compares predicted results with actual results and plot percentages of true positives against the percentage of false positives at a predefned threshold value (Hu & Lo, 2007; Sarkar & Chouhan, 2020). The ROC calculates the area under the curve (AUC), which threshold value lies in between 0 to 1, where 1 denotes a perfect match and 0 denote complete miss-match. By using this validation technique, LULC maps for year 2035 and 2050 were forecasted.

2.3. Preparation of Landuse Maps and Land Use Land Cover Change (LULC) Analysis

To perform Landuse land cover change analysis, Landsat 8 satellite images were downloaded from the portal of the United States Geological Survey (https://earthexplorer.usgs.gov/) of years 1990,2000,2010 and 2020 at no cost as shown in Table 1. After doing spatial, radiometric, and spectral corrections of satellite images, they were applied for LULC analysis. To supervise image classification, an image classification tool was used to generate a training sample of each land cover, which includes built-up, agriculture, vacant land, and water bodies. Then, final land use land cover raster maps were generated using the maximum likelihood classification tool for the years 1990,2000,2010, and 2020, as shown in Figure 3. For ground truth verification, twenty-five points were considered for each land cover using Google Earth Pro software to check the accuracy of classified LULC images. From that, the Confusion matrix was generated by cross-verifying twenty-five stratified random points of each land cover with ground truth points. Afterward, user accuracy, producer accuracy, and Kappa coefficient were calculated from the confusion matrix for LULC maps at 0.87, 0.93,0.88, and 0.95, respectively, for the years 1990,2000,2010, and 2020. The overall accuracy of maps was 90%, 95%, 91.25%, and 96.25%, respectively, which indicates that these LULC maps can be used for further processing of land use assessment.

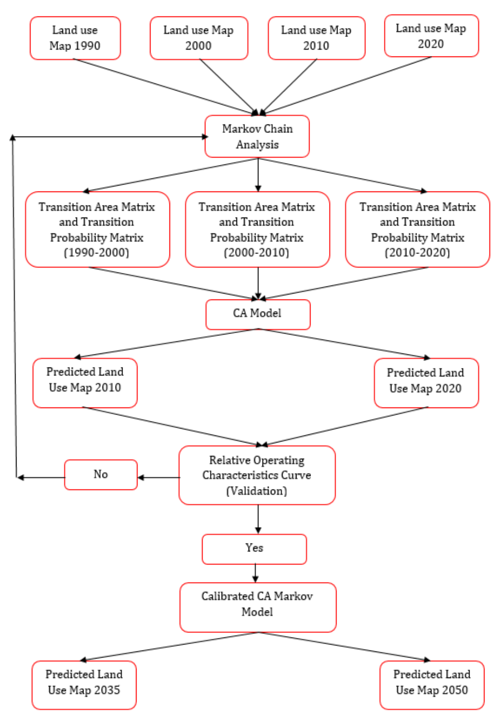

Figure 2. Flow chart of Applied CA Markov Model

Table 1. Metadata of Satellite Images

Year	Dataset	Sensor	Path/Row
1990	Landsat 5	TM	148/05
2000	Landsat 5	TM	
2010	Landsat 5	TM	
2020	Landsat 8	OLI/TIRS	

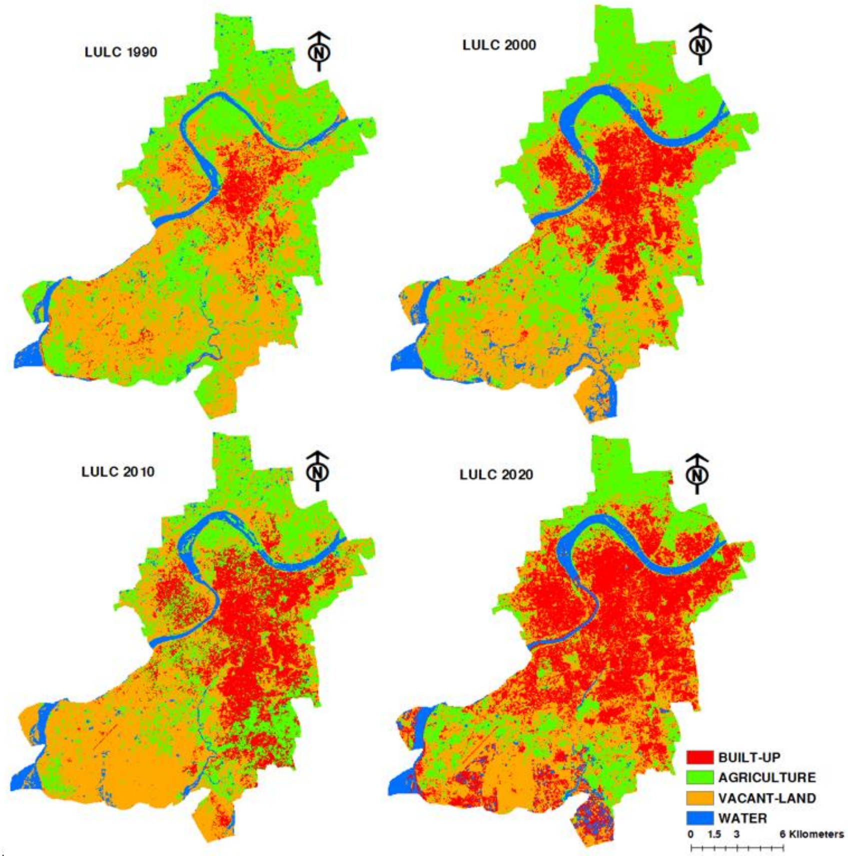

Figure 3. Land Use Land Cover Maps for the years 1990, 2000, 2010 and 2020

In 1990, 20.77 sq. km area was covered by built-up, 125.51 sq. km by vegetation, 155.62 sq. km by vacant land, and 17.23 sq. km by water bodies. In 2000, there was a gain in the built-up area by 140.25 % and it became 49.9 sq. km, while a loss in vegetation area by 11.26% and vacant land area by 15.58%. The built-up area was further increased to 35.27 %, which was 67.5 sq. km, vegetation area decreased by 20.18 %, which became 88.9 sq. km and vacant land area was increased by 8.99 % and it was 143.19 sq. km in the year 2010. A huge development took place in Surat city area from 2010 to 2020, including the outer ring road in the Surat Urban Development Authority area, the starting phase of Surat Metro and Diamond Burge in Khajod area, good public transport infrastructure in terms of Bus Rapid Transit System (BRTS) and Sitilink. These steps attracted many workers from the surrounding area for employment in the textile and diamond industries. Due to this, the built-up area increased by 78.66 % and became 120.6 sq. km, vegetation area again decreased by 39.65%, and vacant land area decreased by 21.13 % in 2020.

3. Result and Discussion

3.1 Transition Rules

The transition probability matrix records the number of pixels expected to change from each land cover type to each other over the specified number of time units. The transition areas matrix was calculated using the

Markov model of IDRISI Selva for the years 1990-2000, 2000-2010 and 2010-2020. There is a probability that 3.29% of agriculture areas will be expected to change into built-up areas, 32.14% of areas into vacant land and 4.33% of areas into water bodies, while 60.23% of areas expect to persist in the year 2000. In vacant land, 17.97% of the areas will be transformed to build up, 4.92% of areas into water, while 55.44% expect to remain as it is in the year 2000. Regarding water bodies, 13.15% will convert into vacant land in 2000, as shown in Table 2.

Table 2. Transition Probability of Changing Land Use Land Cover Class from 1990-2000

Land use/ Land cover	Built-up	Agriculture	Vacant Land	Water
Built-up	99.20%	0.60%	0.63%	0.11%
Agriculture	3.29%	60.23%	32.14%	4.33%
Vacant Land	17.97%	21.67%	55.44%	4.92%
Water	1.18%	10.63%	13.15%	75.04%

There is a probability that 5.17% of agriculture areas will be expected to change into built-up areas, 45.04% of areas into vacant land and 1.59% areas into water bodies. In comparison, 48.20% of areas are expected to persist in 2010. In vacant land, 16.47% of areas will be transformed to build up, 1.82% of areas into the water, while 61.98% expect to remain as it is in 2010. Regarding water bodies, 27.03% will be converted into vacant land in 2010, as shown in Table 3.

Table 3. Transition Probability of Changing land use land cover class from 2000-2010

Land use/ Land cover	Built-up	Agriculture	Vacant Land	Water
Built-up	97.58%	1.38%	1.03%	0.01%
Agriculture	5.17%	48.20%	45.04%	1.59%
Vacant Land	16.47%	19.73%	61.98%	1.82%
Water	1.94%	12.90%	27.03%	58.13%

There is a probability that 25.49% of agriculture areas will be expected to change into built-up areas, 32.39% of areas into vacant land and 2.70% areas into water bodies. In comparison, 39.43% of areas are expected to persist in 2020. In vacant land, 29.37% of areas will be transformed to build-up, 3.05% of areas into water, while 49.93% expect to remain as it is in 2020. In the case of water bodies, 7.34% will convert into vacant land and 9.48% into agriculture in 2020, as shown in Table 4.

Table 4. Transition Probability of Changing Land Use Land Cover Class from 2010-2020

Land use/ Land cover	Built-up	Agriculture	Vacant Land	Water
Built-up	97.03%	0.34%	2.53%	0.10%
Agriculture	25.49%	39.43%	32.39%	2.70%
Vacant Land	29.37%	17.64%	49.93%	3.05%
Water	8.16%	9.48%	7.34%	75.02%

Results should be clear and concise. The results should summarize (scientific) findings rather than provide data in great detail. Please highlight differences between your results or findings and the previous publications by other researchers. For tables, they are sequentially numbered with the table title and number above the table. Tables should be centered in the column and fit to the window.

3.2 Prediction of Land Use Land Cover Maps

CA-MC is a combined Cellular Automata and Markov Chain land cover prediction procedure that adds an element of spatial contiguity and knowledge of the likely spatial distribution of transitions to Markov chain analysis. The transition areas matrix calculated using the Markov model was integrated into the CA -based Markov model to predict land use land cover maps for 2010 and 2020.

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3.2.1 Predicted land use land cover map of the year 2010

To predict the LULC map for year 2000, the LULC map of 1990 is considered the base map. The transition probability calculated in Table 2 was considered as changing probability from one land cover category to another for the year 1990-2000. It was assumed that the same probability will take place to change particular land use. The actual and Predicted LULC map of the year 2000 are shown in Figure 4.

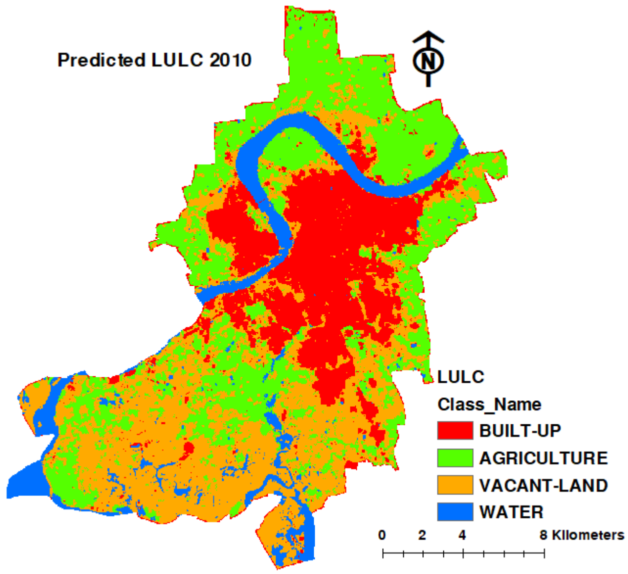

Figure 4. Predicted land use land cover Maps of year 2010

3.2.2 Predicted land use land cover map of the year 2020

To predict the LULC map for the year 2020, the LULC map of 2010 is considered a base map. The transition probability calculated in Table 3 was considered as changing probability from one land cover category to another for the year 2000-2010. It was assumed that the same probability will take place to change particular land use. The actual and predicted LULC map for the year 2020 is shown in Figure 5.

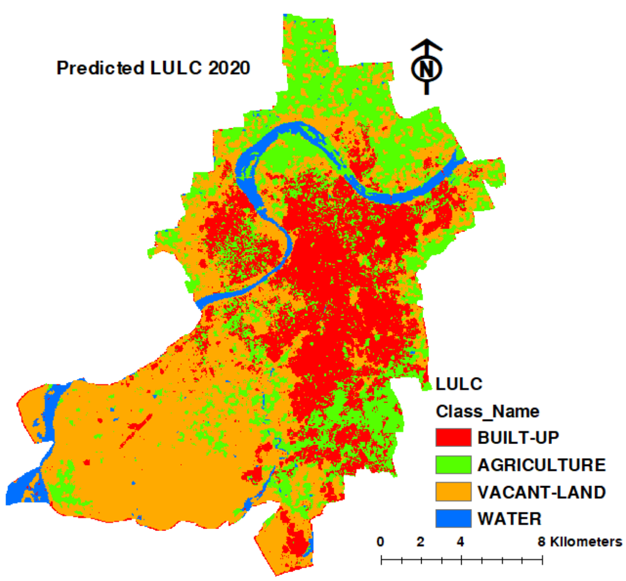

Figure 5. Predicted land use land cover Maps of the year 2020

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3.3 Model Predication Accuracy of Predicted LULC

Figure 6. shows the 95.30% probable accuracy that predicted LULC will be concentrated in the actual LULC map of the year 2010. Similarly, for the year 2020 (Figure 7.), an area under the curve is 86.90%. It shows that there will be 86.90% of areas that are available in the actual LULC map of the year 2020.

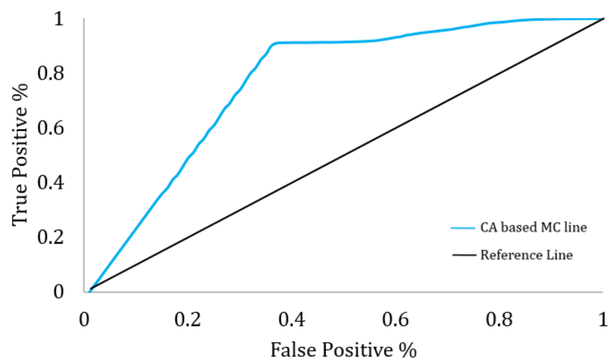

Figure 6. Model Prediction Accuracy of predicted LULC 2010

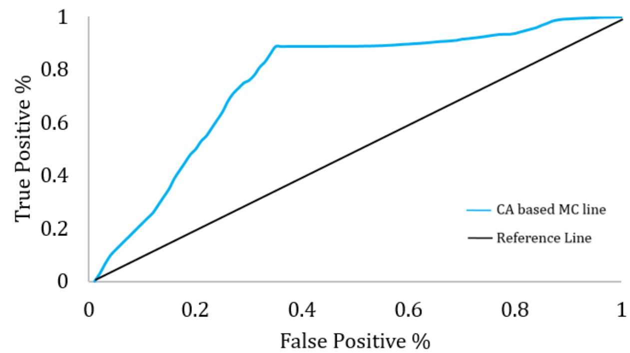

Figure 7. Model Prediction Accuracy of predicted LULC 2020

3.4 Predicted Map of LULC 2035 and LULC 2050

To predict LULC for 2035, transition areas (transition probabilities) were calculated using Markov chain analysis from 2010 to 2035, as shown in Table 5 and the predicted LULC map in Figure 8. It was assumed that the transition probability of LULC between 2010 and 2020 will remain the same for the next 15 years, also considering 2020 as a base year. There is a probability that 36.33% of agriculture areas will be expected to change into built-up areas, 33.50% of areas into vacant land and 3.66% areas into water bodies. In comparison, 26.51% of areas are expected to persist in 2020. In vacant land, 40.27% of areas will be transformed to build up, 3.97% of areas into the water, while 37.54% expect to remain as it is in 2020. Regarding water bodies, 10.64% will be converted into vacant land and 11.67% into agriculture in 2020.

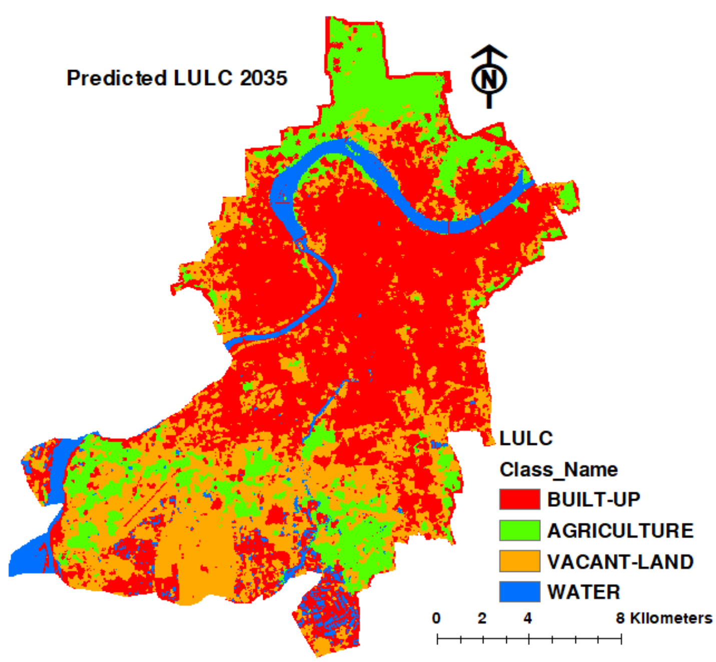

Figure 8. Predicted LULC map of 2035

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Table 5. Transition Probability of Changing Land Use Land Cover Class from 2010-2035

Land use/ Land cover	Built-up	Agriculture	Vacant Land	Water
Built-up	95.86%	0.64%	3.34%	0.17%
Agriculture	36.33%	26.51%	33.50%	3.66%
Vacant Land	40.27%	18.23%	37.54%	3.97%
Water	12.94%	11.67%	10.60%	64.79%

To predict LULC for 2050, transition areas (transition probabilities) were calculated using Markov chain analysis from 2010 to 2050, as shown in Table 6 and predicted LULC map 2050, as shown in Figure 9. It was assumed that the transition probability of LULC between 2010 and 2020 will remain the same for the next 30 years, also considering 2020 as a base year. There is a probability that 57.77% of agriculture areas will be expected to change into built-up areas, 23.30% of areas into vacant land and 4.62% of areas into water bodies. In comparison, 14.31% of areas are expected to persist in 2020. In vacant land, 60.24% of areas will be transformed to build up, 4.69% of areas into water, while 22.55% expect to remain as it is in 2020. Regarding water bodies, 14.80% will be converted into vacant land and 12.44% into agriculture in 2020.

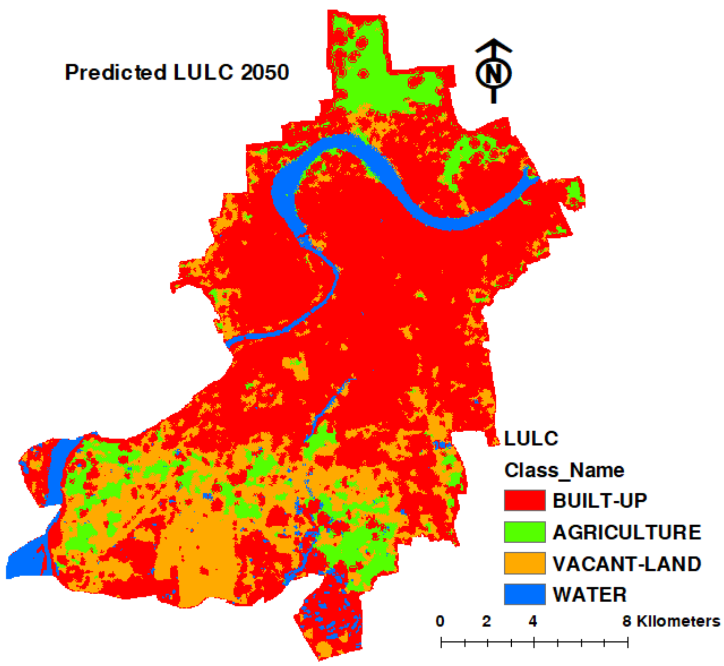

Figure 9. Predicted LULC map of 2050

Table 6. Transition Probability of Changing Land Use Land Cover Class from 2010-2050

Land use/ Land cover	Built-up	Agriculture	Vacant Land	Water
Built-up	93.54%	1.39%	4.64%	0.43%
Agriculture	57.77%	14.31%	23.30%	4.62%
Vacant Land	60.24%	12.52%	22.55%	4.69%
Water	29.45%	12.44%	14.80%	43.31%

3.5 Discussion

Over thirty years, the city has experienced vast urbanization as the built-up area increased by 480.64% at the expense of vegetation loss by almost 97.16% from 1990 to 2020. Which proximity factors like national and state highways (Li et al., 2018), central business district (Thapa & Murayama, 2020), the airport (Zhou et al., 2020), the railway station (Yang et al., 2020), the bus stations (Bharath et al., 2018), BRTS and Sitilink, development of outer ring road and metro; government interventions like town planning schemes, development plan (Sheladiya, 2023), educational and health facilities, parks (Lu et al., 2018), low land price in outer skirt, diamond and textile industries (Sheladiya, 2023) as socioeconomic factors played significant role in urbanization of Surat city. The resulting value by the AOC curve indicated that the prediction accuracy of forecasted LULC maps of 2010 and 2020 was 95.30% and 86.90%, which was relatively higher and good compared to the CA-MC model used by Kallvetty and Bandopadhyay (2018) and Rahnama (2021). It was found that the incorporation of GIS and land use/ cover maps derived from remote sensing data with the CA– Markov model was capable of modeling and simulating spatial and temporal land use change efficiently for the years 2035 and 2050 (Kamusoko et al., 2009; Mitsova et al., 2011; Myint & Wang, 2006) Therefore, the predicted LULC maps for the year 2035 and 2050 showed that city should have 48.16% and 61.28% concrete jungles because of rapid urbanization and mega infrastructure projects like metro, dedicated industrial freight corridor, diamond burge (Sheladiya, 2023).

Taubenböck et al. (2012) monitor the rate of urbanization for twenty-seven mega cities across the world but not analyzed and modeled that how dynamic structure of LULC changes over the period. However, our study on Surat city focusing towards changes in dynamic structure of LULC with transition probability over the period of thirty years. Yin et al. (2011) carried out LULC analysis from 1979 to 2009 but not used mathematical modelling like CA-MC. It becomes vital when we are dealing with large scale temporal datasets to determine the accuracy of resulted maps.

The reliability of land use change modeling methods can be improved by combining two or more simulation techniques to integrate the advantages of each model (Xin et al., 2012). It is worth mentioning that CA–Markov model has been used recently in dynamic spatial phenomenon simulation and future land use change prediction (Wang et al., 2012). Moreover, the integrated CA–Markov chain model takes advantage of the Markov chain of land use change quantities prediction and dynamic explicit spatial simulation of the CA model. Thus, the CA–Markov model can be appropriate for spatial modeling of land use change (Xin et al., 2012). Consequently, the incorporation of GIS and land use/ cover maps derived from remote sensing data with CA–Markov model is capable of modeling and simulating spatial and temporal land use change efficiently (Kamusoko et al., 2009; Mitsova et al., 2011; Myint & Wang, 2006). Moreover, the CA–Markov model provides reliable land use change simulation results and overcomes the lack of socioeconomic, statistical, and historical data (Sang et al., 2011). In the CA–Markov modeling process, the temporal changes of land use classes are directed in the Markov chain process based on produced transition matrices, whereas the spatial changes are controlled by transition potential maps, configuration of neighborhoods, and local transition rule during CA model process (Guan et al., 2020; White & Engelen, 2000).

Town planners generally used zoning to differentiate land use as a method of guiding and controlling the growth of urban areas. In the early development phase, this concept was applied in the planning of developed countries and is now in developing countries (He et al., 2018). Therefore, this study will provide deep insights to urban and regional planners in developing strategies for evaluating various urban development scenarios about potential implications for land use and the advancement of existing spatial plans and policies in the Indian context (Al-Ahmadi et al., 2009).

4. Conclusion

Augmentation of classified land use land cover maps of 1990, 2000, 2010 and 2020 into CA–Markov chain model for Surat City area were modelled and simulated successfully. The overall modeling success was 95.30 % for the projected land use map 2035 and 86.90 % for the predicted land use map 2050. One good advantage of the applied CA–Markov chain model is that the model needs limited data to simulate and predict any future land use change explicitly, i.e., at least two land use maps in different time instants. On the other hand, the CA–Markov chain model cannot analyze and explain urban land use change driving factors, such as biophysical and socioeconomic factors, which are very important to manage, guide current situations and prepare wise plans for future demands. The land use change analysis of the period 1990-2020 demonstrated a continuous decrease in vegetation and vacant lands.

Additionally, the annual decline rate of vegetation areas has increased in the last decade. The predicted land use situations in 2035 and 2050 reveal alarming accelerated loss of vegetation lands in the study area. Furthermore, based on predicted results, the future urban area would expand in a much-dispersed mode.

These findings indicate that the situation will worsen in the future. For that, controlling increased urban growth and protecting agricultural areas is necessary to promote rational land use and a sustainable urban environment. However, to better understand land use changes and their driving forces, it's necessary to incorporate biophysical and socioeconomic data in the CA–Markov chain model. This aim can be achieved by integrating another model involving these factors, like the logistic regression model, AHP model and other data mining approaches.

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6. References

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