CA MARKOV MODEL FOR MAPPING HISTORICAL AND PREDICTING FUTURE OF LULC IN JP NAGAR, BANGALORE

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ABSTRACT

Understanding and monitoring urban expansion and LULC change is vital because the majority of India's metropolitan cities are located in the heart of productive agricultural plains. It also assists municipal planners and leaders in making sound decisions for future growth. LULC dynamics mapping is necessary for urban planning and sustainable development. This article includes a survey of the literature on the use of the Cellular Automata Markov design to explain past trends and predict future LULC changes in JP Nagar, Bangalore. Twenty-five research publications from 2019 to 2023 that used the CA-Markov model for analyzing and forecasting LULC were surveyed, with an emphasis on urban environments similar to JP Nagar in Bangalore. Furthermore, the study investigates the data collecting year which impacts the historical perspective, the integration of models to increase reliability and accuracy, and the constraints. This survey's findings shed light on the viability and usefulness of the CA-Markov model for mapping past and forecasting future LULC in JP Nagar, Bangalore. This study lays the groundwork for future studies aimed at developing customized land use policies, urban planning strategies, and sustainable development initiatives for the region.

Keywords: *Cellular Automata Markov, LULC, Urban planning, future prediction, sustainable development, historical trends.*

1. INTRODUCTION

Urbanization has grown into a global issue, raising concerns among decision-makers and planners about the future effects on ecology. Modelling and predicting urban sprawl trends have become critical for environmental protection and sustainable development. Cities are altering in size and density as a result of the fast-growing populations. According to the most recent United Nations World Urbanization Prospects study, roughly 60% of the world's population will be urban by 2030 [1]. As a result, rapid urban population increase frequently triggers urbanization and changing LULC trends. Alterations in water bodies, vegetation cover, and wetlands, grassland, and open space could all result from alterations in the LULC pattern [2][3]. As a result, LULC alterations are becoming an important priority to be handled by city authorities for numerous environmental challenges caused by the urbanization. Because it influenced the environment both locally and globally, the latest data on LULC and Its change has emerged as a critical issue for activists, urban architects, and regulators alike. Numerous cities, especially in developing nations, have been negatively impacted by excessive and uncontrolled urban growth, which has increased strain on the environment in general, especially urban green cover. To understand both temporal and spatial links proficiently, urban growth modelling must consider the timing of the stretch crisis as well as substantial historical data. As a result, modelling methodologies can be enhanced by gaining a true understanding of the processes underlying urban expansion that influence potential land uses. “Remote sensing (RS) and geographic information system (GIS)” approaches to aid in comprehending geographical and temporal shifts, as well as all of the successful components [4].

The advent of the applications of remote sensing in the past few decades has resulted in the identification of different study areas, such as characterizing land use land cover shifts in an ecosystem in its natural state, analyzing geomorphological shifts of distinct landforms, and so on. Aside from the benefit that images taken remotely have brought to researchers and scientists in the fields of environment, geography, and geology, among other things, significant advancements in the field of mathematical modelling have occurred. The progress of mathematics and statistics further facilitates analysis in these types of studies. The CA model is modular and can be combined with different approaches to mimic and foresee urban growth trends [5][6]. Adaptability, simplicity, and the capacity to incorporate both the temporal and spatial aspects of the operations, as well as the potential to simulate complicated systems that are changing, are the primary explanations for the CA model's widespread application for promoting prospective spatial changes over the past decade. Simulations for altering land use are becoming more vital instruments for making decisions. They enable the detection and interpretation of shifting amounts, the prediction of future developments based on prior information, the assessment and validation of prospective maps relying on past trends, and the design of beneficial environmental policies. The state of a cellular automaton depends not only on its previous configuration but also on the state of the cells immediately next to the cell in the issue. The system's general efficiency is determined by all of the regionally set transition rules. Because of a shortage of systematic evaluation, the estimation and geographical allocation of UGS in India haven't been fully included into urban strategy, and consequently, the majority of India's major urban centers suffer similar challenges. In addition, little study has been undertaken in India on the estimation and shifts in UGS in the wake of urbanization, such as in Bangalore, Chandigarh, Bhopal, and Delhi.

1.1 Motivation And Challenges For The Survey

The desire to improve our comprehension of urban processes and assist with sustainable growth drove the literature review on the CA- Markov model for mapping past and predicting LULC changes in JP Nagar, Bangalore. We can acquire insights into the application of the CA Markov model in similar scenarios and discover best practices for LULC mapping and prediction by performing an in-depth review of existing literature. By synthesizing previous research, we may identify information gaps, investigate the model's strengths and shortcomings, and make suggestions for its efficient execution in JP Nagar.

Performing a literature review on the CA Markov model for LULC mapping in JP Nagar, Bangalore, presents several obstacles. Accessing specific case studies or research undertaken in the local environment can be difficult due to a lack of available and accessible relevant material. It is critical to ensure the dependability and quality of the literature sources. To obtain relevant and up-to-date material, it is necessary to carefully select respected scholarly publications, meetings, and dependable databases. Synthesising multiple sources and harmonising disparate approaches, parameter values, and datasets can be difficult. To extract relevant insights and draw reliable conclusions, the literature must be critically examined and interpreted. Overcoming these obstacles is critical to ensuring that the literature review provides a complete and trustworthy foundation for comprehending the CA Markov model's usefulness in visualising historical and forecasting perspective LULC changes in JP Nagar, Bangalore.

1.2 Scope And Organization Of The Survey

The scope of the literature survey on the CA-Markov model for mapping historical and envisaging future LULC changes in JP Nagar, Bangalore would include reviewing the existing literature related to the role of CA-Markov model in predicting LULC changes in various places with similar landscapes to JP Nagar, Bangalore to design a study on JP Nagar, Bangalore and various integration models that improve the accuracy. The previous part provided an overview of the concerns associated with the lack of LULC prediction in urban expansion, as well as the function of the model in resolving the issues, as well as the rationale and challenges of the current investigation into the literature. On the basis of the review of the literature, the following sections examined the concept of LULC and its components, as well as the CA-Markov model for analyzing and predicting LULC with a focus on urban areas similar to JP Nagar in Bangalore.

2. EXAMINATION OF LULC AND ITS COMPONENTS

Observing, identifying, and forecasting LULC change is gaining traction in the scientific community as a promising technique for understanding human interactions with earth systems. Numerous studies have been undertaken at the regional, local, national, and worldwide levels to acknowledge the significance of LULC change [7][8]. These research endeavors span an extensive spectrum of LULC-related subjects, such as the impact of LULC change on “land degradation, deforestation, desertification, carbon dioxide emissions to the atmosphere, biodiversity, soil degradation, biogeochemical cycles, hydrologic processes, water and radiation budgets, trace gas emissions, climate, and food security”. Even though LULC change influences the environment, not all impacts are negative, since certain forms of LULC change are related to continued gains in food, resource-use efficiency, wealth, and well-being. Urbanization, industrialization, and infrastructure development such as dam construction, and road networks are all markers of a nation's progress, yet all of these activities need some form of land conversion. Consequently, in 1987, the Brundtland Commission proposed the concept of equitable growth, which includes sustainable land use. Identification and projection of LULC change processes are critical components of selecting, planning, and implementing land-use policies to satisfy the increasing needs of an expanding population [9].

Shifts in LULC have been rapid in emerging economies over the previous and present decades, and India is no exception, as LULC alterations have become more significant as population and livestock need for food and fodder have increased. The evolution of LULC is dynamic. It is difficult to gather real-time information on LULC modification using traditional approaches. Remote sensing and (GIS) are very beneficial for researching and comprehending

LULC evolution [10]. Satellite photos may offer an adequate way of gathering spatial and time-related data for the investigation and simulation of LULC progression. The usefulness of technologies such as GIS and remote sensing are being recognized in various fields around the globe, ranging from micro-scale to macro-scale. Satellite remote sensing, in conjunction with the use of GIS, has added a new dimension to LULC change research at many scales. In most cases, land cover and land use are intertwined. The categorization approach may assist in resolving any ambiguity between the two distinct names. Land and natural resource management demand periodic reviews of LULC processes. Prediction and simulation of future LULC change based solely on historical trends are exceedingly uncertain. The uncertainty stems mostly from a lack of proper understanding of the anthropogenic influence and political circumstances, both of which could be remedied in the future and change local growth patterns.

3. CA-MARKOV MODEL FOR ANALYZING AND FORECASTING LULC

A Markov method is often implemented to model an entity's future condition utilizing a current subsequent condition. The Markov model depicts the shift in LULC from one point in time to the following and acts as the basis for forecasting modifications in the future [11]. The dynamics of urban growth are linked to demographic factors, particularly in emerging countries. CA-Markov models, for example, can be utilized for predicting LULC condition in years to come. CA-Markov is a hybrid of cellular automata and Markov chains and is a LULC prediction approach that extends Markov change analysis by incorporating spatial contiguity and the anticipated spatial distribution of transitions. CA-Markov models can be used to simulate and track LULC change at both a spatial and temporal scale. The simulation outcomes can help administrators establish land-use strategies for ensuring the long-term sustainability of natural assets. The land-use modelling supplement current cognitive abilities by helping to better analyze and understand change in LULC dynamics.

Considering its merits, traditional CA is not adequate to provide precise modelling of urban processes because of constraints such as the entire structure's minimalism and its incapacity to model and foresee urban expansion utilizing quantifiable external inputs such as socioeconomic variables. As a result, to get better results, the typical CA model needs to be modified and combined with quantitative systems. This can be accomplished by incorporating numerical characteristics along with changing variables and by handling both spatial and temporal rules.

4. SURVEY OF LITERATURE ON CA- MARKOV MODEL FOR ANALYZING AND FORECASTING LULC AND ITS VARIOUS INTEGRATION STRATEGIES

Dinda *et al.* (2021) examined the decline in urban green space (UGS) and its relationship with land use and land cover (LULC) changes in the city of Kolkata. They used a multitemporal land utilization change paradigm using Landsat satellite data from 1980, 1991, 2001, 2011, and 2018. Three comparative land categorization methodologies were employed to assess urban development tendencies. The investigators used an integrated CA-MC architecture to forecast LULC shifts and potential UGS loss. They also employed numerous indicators to analyze the extent and intensity of urban expansion, the level of habitat alteration, and UGS absorption compared to all LULC types. The indices used included the “Land Use Dynamic Degree Index (LUDD), UGS Change Intensity Index (CII), and UGS Land Index”.

Furthermore, the study calculated the per-capita urban green space (PCG) to evaluate UGS accessibility. The researchers verified their model by comparing the results with both real and simulated LULC maps from 2018.

Haj *et al.* 2023 [13] used information and imagery from satellites from the “Lakhdar-Morocco sub-basin” over 20 years to anticipate projected patterns for the period 2019-2039 utilizing and contrasting both models CA-MARKOV and LCM. “Landsat 5-TM and Landsat 8-OLI photos”, from the years “2000, 2007, 2010, and 2019” were used. The categorization utilized was the guided approach with the greatest likelihood; the approach recognized four kinds of land use: water bodies, woodland, vegetation, and empty land with the urban area. The confusion matrix and the kappa index were used to validate forecast findings and estimate the model's precision.

Yatoo *et al.* 2020 [14] monitored urban expansion in the AMC area, comprising Ahmedabad City, from “1976 to 2017”. Using Landsat remote sensing satellite imagery from many time periods and dates, the Normalized Difference Built-Up Index, Normalized Difference Vegetation Index, and Built-Up Index were employed to analyze changes in urban space usage. The Prospective Outlook of AMC's urban land use forecast was predicted using CA and ANN methods in conjunction with GIS methodologies. The CA-ANN results were validated using the Kappa coefficient, and the scores of the Kappa local and Kappa histogram were derived.

Satya *et al.* 2020 [15] discussed the potential of CA-Markov chain-based 2D urban planning modelling modules in concurrence with GIS approaches. The Markov chain approach was utilized for validation and optimization by looking at the LULC of an adequate set of photos for the years 2004, 2006, and 2018. After validating the framework with LULC from 2018, an ANN was implemented to simulate the movement of LULC from a particular group to another, and cellular automata modelling was performed to estimate prospective LULC for the year 2052.

Ghosh *et al.* 2021 [16] performed a LULC analysis for the “Baghmundi Community Development (C.D.) Block of the Purulia district of West Bengal, India”, to track variations through time. LULC maps were created using RS and GIS techniques and Landsat photos from 1972, 1992, 1999, 2009, and 2019. Furthermore, the “Markov chain model” was utilized to predict the change in LULC in 2039. Thematic visualizations from years gone by show a variety of changes in LULC. The kappa coefficient was determined for the same periods to examine the degree of concord between the categorized LULC category and the surface LULC kind.

Mondal *et al.* 2020 [17] analyzed three regularly used urban growth models: “Multicriteria Cellular Automata-Markov Chain (MCCA-MC), Multilayer Perception Markov Chain (MLP-MC), and Slope, Land Use, Exclusion, Urban Extent, Transportation, and Hillshade (SLEUTH)”. The prediction analysis in Udaipur City considered land use as well as land cover data from 1977, 1992, 2000, 2008, and 2016 and developed driving parameters for urban growth. Although various resilient geographical approaches were recognized internationally, the research contains some of the most often and commonly used effective, analytical process-based models. The research popularized the advantages of spatial frameworks for urban land use policy.

Gaur *et al.* 2020 [18] carried out an ideal inter-comparison task (non-hybrid and hybrid predicts) utilizing numerous indicators of performance to determine the optimal forecasting technique for the ensuing forecast of future LULC. The concept was illustrated in the “Subarnarekha basin of Eastern India using LANDSAT data from 1989, 1994, 2006, and 2011”. Prior to LULC modelling, important land shifts in post-categorization images were detected using overlap and trend-surface assessment. Four incorporated designs, specifically the “Multilayer Perceptron-Markov Model (MLPMC), the Logistic Regression-Markov Model (LR-MC), and two hybrid models, particularly the Multilayer Perceptron-Cellular Automata-Markov Model (MLP-CA-MC) and the Logistic Regression-Cellular Automata-Markov Model (LR-CA-MC)”, were assessed for their appropriateness to forecast subsequent LULC for the reservoir.

Anand and Oinam 2020 [19] aimed to track and anticipate the region's prospective LULC using TerrSet's LCM. The LULC model was created using Landsat images from three separate years: “2007, 2014, and 2017”. Utilizing “Markov Chain and artificial neural network (ANN) evaluation”, an eventual LULC map of the inquiry region was constructed in LCM based on existing prior LULC maps. The driver variable, namely proximity to highways, distance from habitation, altitude, and gradient, was used to instruct the ANN.

Yadav and Ghosh 2021 [20] analyzed the LULC shift in Chennai using historical Landsat data from 1981 to 2011. The MLC was implemented to categorize the whole data set. Transition Potential Matrix, Pearson's Correlation Coefficient, MLC, and Land Use Dynamic Degree were employed to quantify the change in LULC. Furthermore, a spatiotemporal shift evaluation was carried out utilizing the post-classification compare strategy. The CA-Markov Model was assigned foresee LULC for the years 2021-2051.

Sajan *et al.* 2022 [21] evaluated the LULCC in the Indian government of Bihar's fastest-changing terrain region, District Muzaffarpur which was notable for its litchi farming, which has been seen to increase in acreage in recent years despite a decline in biological diversity. Employing CA-ANN and support vector classification techniques, they examined historical, future, and present trends in LULC in the “Muzaffarpur district”, and used “Landsat Satellite data from 1990, 2000, 2010, and 2020” to analyze the LULC of the research area. To estimate prospective LULC, the CA-ANN model was utilized to estimate the terrain for 2020 using LULC between 1990 and 2010. LULC for 2030 and 2050 were developed after adjusting and confirming the CA-ANN results. By contrasting the anticipated results with the initial LULC data for 2020, the created perspective LULC scenarios were confirmed using kappa index statistics.

Bagaria *et al.* 2021 [22] used temporal satellite data to analyze the evolving outline of LULC in the “East Godavari River Estuarine Ecosystem (EGREE) landscape”, from 1977 to 2015 and to forecast probable shifts in LULC by 2029. For prospective LULC estimation, the CAMM alongside and without the MCE and the MLP models were utilized. The study focused on LULC shift trends in EGREE, an important Indian estuary ecosystem and the findings was used as a baseline for policymakers as well as stakeholders in determining choices about development initiatives, the purchase of land, and the farming land transformation to other purposes.

Ghosh *et al.* 2021 [23] aimed to tackle the flaws in the reliable evaluations of ecological safety status, which has grown into a real problem due to distinct methods of evaluation producing varied outcomes employing combined DEMATEL-ANP system to choose factors that influence and determine the ecological safety in “Kolkata Metropolitan Area (KMA)”. Furthermore, CA- Markov chain model was used to model LULC evolution and anticipate the upcoming scenario in KMA. Landsat satellite imagery, as well as Google Earth imagery, were used to create LULC maps. The imagery from satellites was acquired based on certain criteria, including minimum visibility of cloud and views of foliage in phase. The socioeconomic and ecological indicators were extracted from the Survey of India data collection (2001-2011) and computerized using Google Earth.

Nath *et al*. 2020 [24] examined “Dujiangyan City and its environs (DCEN)” to observe the projected situation in the years “2025, 2030, and 2040 based on the 2018 modelling findings from the 2007 and 2018 LULC maps” and examined the variations in space and time associated with the future LULCC, following the 2008 large (8.0 Mw) seismic in southwest China's next probable FPLR area. The CA-Markov model and “multicriteria-based analytical hierarchy technique (MC-AHP)”, have been examined with the combination of GIS and remote sensing technology. The study depicts potential LULC scenarios for the years “2025, 2030, and 2040”, as well as the FPLR trend.

Lahon *et al.* 2023 [25] determined and illustrated a spatiotemporal fluctuation in ecological quality of service in reactions to LULC change for “1990, 2000, 2010, and 2021”, and anticipated the same for “2030 and 2040”. In this study, “supervised classification and the CA-Markov model”, were employed for LULC categorization, as well as for forecasting the future. Between 1990 and 2040, there has been a significant increase in established regions, agricultural land, and aquatic life, coupled with a decrease in free water and plant life. Because of the explosive expansion of metropolitan areas, agricultural and aquatic land, the focus area's ecosystem service values increased significantly over the study period (1990-2021).

Bashir *et al.* 2022 [26] conducted research in the “Baramulla district of the North-Western Himalayas”, to examine existing and prospective modifications to LULC and to identify the factors that may influence future legislative decisions. They classified the study's region using the highest probability supervised classification and Landsat 2000, 2010, and 2020 satellite images. “The land-use transition matrix, Markov chain model, and CA-Markov model”, were used to evaluate the geographical distribution and chronological variation in LULC in 2030. The CA-Markov method was used to anticipate 2020 land cover, which was subsequently confirmed using actual 2020 land cover data (Kappa coefficient of 0.81). LULC was projected for the year 2030 after the simulation was calibrated and validated.

Maurya *et al.* 2023 [27] conducted a LULC analysis of change in Jaipur City, Rajasthan, India, for the years 2000, 2010, and 2020. Landsat data and a visualisation approach were used to create the LULC maps at an aspect ratio of 1:50,000. The images were classified into five distinct groups: foliage, agricultural, urban areas, empty land, and bodies of water. The recent LULC changing pattern was used to anticipate LULC. The present LULC evolution trend was projected and used to forecast the LULC map for “2020, 2030, 2040, and 2050”, using a CA Markov connected with a system of roads and the plan was confirmed by calculating the 2020 LULC shift and then contrasting it to the real 2020 LULC map.

Sarkar and Chouhan 2019 [28] modelled urban dynamics using a Markov Chain base simulation system to anticipate upcoming urbanization patterns and directions. In this study, “Markov Chain Analysis and Cellular Automata”, were utilized to simulate land-use patterns in the Siliguri Municipal Corporation area. According to simulation results, agricultural and forest land will deteriorate significantly between 1991 and 2033 due to fast urban enlargement. Widening growth has been noticed since 2001, and the southwestward development persists. To enhance the categorization outcomes, recoding was performed using field studies and Google Earth images and created the LULC map for 1991, 2001, 2011, and 2017. To follow spatial urban land-use growth patterns, IDRISI software was executed to develop a modelled LULC change model.

Natarajan and Radhakrishnan 2021 [29] investigated an exploratory study on the LULC alteration and its influence on the "urban Koraiyar basin, Tiruchirappalli City, South India", utilizing SCS-CN and GIS methodologies. Because the basin through which the river flows is positioned in a burgeoning city, substantial fluctuations in LULC have been observed towards the basin's margin. The influence of LULC variations on surface runoff was studied using GIS and multi-dated Landsat satellite data from 1986 to 2016 at 10-year intervals. The supervised categorization approach was used to generate LULC maps. In accordance with the study, there was a 1.04% increase in habitation territory from 1986 to 2016, notably in the northern region of the watershed. A Markov model assessment was done on previously gathered LULC maps to project anticipated prospective variations in LULC for the time frames 2026 to 2036, as well as a prediction for exterior runoff.

Pramanik *et al.* 2021 [30] explored the shifting nature of expansion in "Gurugram, India's millennium city" For evaluation, satellite photos from multiple time periods (i.e., "1991, 2000, 2009, 2014, 2018") were integrated with additional statistics. The LULC contours were generated using the maximum-likelihood supervised image categorization approach. "Multitemporal LULC transition matrices, urban footprint evaluation, and the procedure of new urban growth", were used to characterize urban dynamics. Furthermore, CA-Markov were used for prospective constructed forecast until 2030 to determine opportunities for growth as a prospective land utilization legislation proposal; and examined the integrity of "Gurugram's urban expansion path".

Rajakumari *et al.* 2020 [31] assessed the alterations in coastal features caused by human activity in the "Deshapran block of West Bengal's Purba East Medinipur district", and studied LULC variations over the past decades and their consequences on shoreline characteristics. The modifications were described in diverse circumstances with precise periods. Using the CA-MARKOV forecasting approach, the investigation was subsequently expanded and anticipated the shifts over the following decades. According to the anticipated analysis, unplanned aquaculture expansion will place significant strain on agriculture fields and shoreline traits and also jeopardize the "Deshapran block's" coastline movements.

Tang and Di 2019 [32] used "multi-temporal Landsat imagery, the Markov- CA model, and socioeconomic factors", to examine ancient and potential agricultural destruction in the "Delhi metropolitan area", a globe's most quickly urbanizing locations. As a result, they categorized the LULC map using "multi-temporal Landsat images from 1994 to 2014", constructed and adjusted the Markov-CA model depending on the Markov probability of shift of LULC categories, CA diffusion coefficient, along with additional supporting elements, and analyzed the past farmland loss and anticipated subsequent farmland loss in the context of rapid urbanization between "1995 and 2030".

Vinayak *et al.* 2021 [33] predicted future LULC alterations over “Mumbai and its neighbouring areas in India”. A supervised classification technique was utilized with Landsat photos from “1992, 2002, and 2011” to determine the past behaviour of the LULC. Using geospatial dynamics and LULC from 1992 and 2002, a Markov chain model (MCM) constructed from multiple perceptron neural networks (MLPNN) was used for simulating the LULC in 2011, which was subsequently verified using kappa statistics. Following that, utilizing LULC between “2002 and 2011”, forecast LULC in 2050.

Mallick *et al.* 2021 [34] adopted the prediction-adaptation-resilience (PAR) strategy for analyzing projected urban terrain robustness and advancement objectives (SDGs). They opted for a little, unforeseen rising-up city in India, “Krishnanagar urban agglomeration (KUA)”, to test the PAR strategy and the LULC maps for the years 2000, 2010, and 2020 were created. They showed that the urbanized region in KUA expanded most dramatically in the last 20 years, “from 6.36 km^2 to 13.23 km^2”. The CA-Markov chain framework was used to forecast the upcoming prospective extent of urban expansion between 2030 and 2040.

Kundu *et al.* 2020 [35] employed GIS and remote sensing data to recognize urban changes and analyze trends in growth in Kolkata from 1978 to 2017. “The supervised Maximum Likelihood Classification technique”, was employed to categorize satellite information from multiple time periods into five categories: urban constructed regions, natural terrain, vegetation, farmland, and aquatic bodies. The range of the scale of urban expansion was quantified utilizing the “Shannon entropy method”, which shows that total entropy values were steadily increasing across the entire territory, implying that the urban expansion was continuously stretched in various locations. The CA-Markov chain framework was implemented to foresee occurrences in the future.

Theres *et al.* 2023 [36] examined the multimodal movements of LULC changes in “Salem and its adjacent areas from 2001 to 2020”, and modelled urban enlargement in 2030 using CA-Markov and GIS approaches. The data demonstrated a decline in altitude cover of vegetation and an upsurge in empty and established landscapes, with an abrupt shift from foliage cover to vacant ground. The city is being created as a smart community, which will end up resulting in significant expansion and development of the urban core during the next few years. “Landsat 8 OLI (Operational Land Imager) data for 2020 and Landsat 7 ETM+ (Enhanced Thematic Mapper Plus) information for segments of time between 2011 and 2001”, were utilized in this work to depict land use features. Earth Explorer was used for downloading the Level 1 picture, which was “georeferenced in WGS84 and mapped in UTMQGIS”, was used for environmental alterations, while “ERDAS Imagine 2014”, was used for various preparation approaches.

Table 1: Survey of literature studies on the CA- Markov model and its integration

Citation No.	**Author and Year**	**City, Data collected platform**	**Models used**	**Future predicted year**
[12]	Dinda *et al*., 2021	Kolkata, Landsat satellite data	CA-MC	2025-2035
[13]	Haj *et al.* 2023	Lakhdar-Morocco sub-basin, Landsat 5-TM and Landsat 8-OLI	CA-MARKOV and LCM.	2039
[14]	Yatoo *et al.* 2020	Ahmedabad, Landsat	CA-ANN	2027
[15]	Satya *et al.* 2020	Warangal, Telangana, GIS	CA-MC	2052
[16]	Ghosh *et al.* 2021	“Baghmundi C.D. Block of Purulia district, West Bengal”, RS and GIS	Markov chain model	2039
[17]	Mondal *et al.* 2020	Udaipur City, Landsat images	MCCA-MC, MLP-MC, SLEUTH	2031
[18]	Gaur *et al.* 2020	“Subarnarekha basin of Eastern India”, LANDSAT imagery	MLPMC, LR-MC, MLP-CA-MC) and LR-CA-MC	2030
[19]	Anand and Oinam 2020	Manipur River basin, Landsat satellite images	MC- ANN	2030
[20]	Yadav and Ghosh 2021	Chennai, Temporal Landsat data	CA-MC, MLC	2021-2051
[21]	Sajan *et al.* 2022	Muzaffarpur, Bihar, Landsat Satellite data, Google Earth images	CA-ANN	2030, 2050
[22]	Bagaria *et al.* 2021	East Godavari River Estuarine Ecosystem, Landsat 8 OLI, Landsat 4–5 TM	Cellular Automata-Markov model	2029
[23]	Ghosh *et al.* 2021	Kolkata Metropolitan Area, The Landsat satellite images	DEMATEL-ANP + CA-Markov models	2019-2030, 2030-2040
[24]	Nath *et al*. 2020	Dujiangyan City, GIS and remote sensing techniques	CA-Markov	2025, 2030, 2040
[25]	Lahon *et al.* 2023	Brahmaputra basin in Assam, United State Geological Survey (USGS) Earth Explorer	CA-Markov	Upto 2040

[26]	Bashir *et al.* 2022	North-Western Himalayan (NWH) regions, Enhanced ETM+, Landsat 7, and Landsat 8 OLI	CA-Markov	2030
[27]	Maurya *et al.* 2023	Jaipur City, Rajasthan, Landsat 5 TM, Landsat 8 OLI	CA-Markov	2030- 2050
[28]	Sarkar and Chouhan 2019	Metropolitan city Siliguri, Google Earth image	CA-Markov	Upto 2033
[29]	Natarajan and Radhakrishnan 2021	Tiruchirappalli, GIS	Markov model analysis	2026, 2036
[30]	Pramanik *et al.* 2021	Gurugram, the 'millennium city', Multitemporal satellite imageries	CA-Markov	2030
[31]	Rajakumari *et al.* 2020	"Deshapran block of Purba East Medinipur district of West Bengal", Remote Sensing and GIS	CA-Markov	2027 and 2037
[32]	Tang and Di 2019	Delhi metropolitan area, multi-temporal Landsat images	CA-Markov	Upto 2030
[33]	Vinayak *et al.* 2021	suburban regions of Mumbai, Landsat Archive L1 satellite data, USGS	MLPNN-based Markov chain model (MCM)	2050
[34]	Mallick *et al.* 2021	Krishnanagar urban agglomeration, Landsat 5 and 8	CA-Markov	2030 and 2040
[35]	Kundu *et al.* 2020	Kolkata, remote sensing data and GIS	CA-Markov	2031
[36]	Theres *et al.* 2023	Salem, Tamilnadu, Landsat 8 OLI and Landsat 7 ETM+	CA-Markov and geospatial techniques.	2030

5. LIMITATIONS FROM THE SURVEYED RESEARCH STUDIES ON CA-MARKOV MODEL

The execution of the CA-Markov approach without driver parameters has the benefit of providing an initial situation for urban development and evolution that can be compared to models which involve driver parameters. This analysis gives insight into the varying significance of multiple variables and how they interact as urban development drivers. However, there are numerous constraints to consider. The constant fragmentation of census units across census cycles makes precise prediction impossible. This fragmentation makes accurately capturing and projecting urban growth trends difficult. The model is based on freely and publicly available remote sensing data with a spatial resolution of 30 metres [12]. As a result, the results must be evaluated in light of this spatial resolution. For more precise analysis, higher-resolution data would be ideal.

The model does not evaluate growth direction independently. This means that more research is needed to determine the influence of issues such as “green space loss, conservation and priority area assessment, and the ecological sustainability of urban green spaces”. The incorporation of these aspects might improve knowledge of urban growth dynamics. Another disadvantage of the CA-Markov model is its emphasis on pattern resemblance, which might lead to it being perceived as a "black box" with low explanatory capacity. To address this, it may be advantageous to establish an agent-based approach in an analogous area and then contrast its efficacy against that of the CA-ANN approach in order to gain an improved comprehension of the processes that underlie it.

While Markov Chains are effective for analysing and simulating LUCC, they are insufficient for predicting spatially explicit LUCC. This is due to their assumption regarding the statistical isolation of spatial units, which does not account for changing events such as urban expansion, which is driven by human behaviour and decision-making. The model's forecasts are further influenced by the significant variety of environmental, economic, and agronomic variables among India's regions. Furthermore, the large time intervals between data collection may result in the growth of new vegetation development in the vicinity, affecting the degree of plant cover. Soft categorization algorithms with shorter time intervals may be useful in addressing this problem and reducing errors. It is critical to understand that no single approach can be the optimal simulator for all ecosystems. As a result, a combination of modelling methodologies, particularly in rapidly urbanising areas, is crucial to convey the intricate nature and variety of urban activities and shifts in land use.

There are also various data-related restrictions. Some analysis omitted datasets linked to ecosystem services, spatiotemporal consumption data for combining ecological pressure indices, and input from the government and stakeholders. Incorporating these additional data sources and perspectives would improve the model's comprehensiveness and accuracy. Other limitations include “satellite picture resolution, algorithm limits in land-use and land-cover classification, and the CA-Markov model's failure to properly account for human disturbances and spatial changes in the terrain”. These issues add to the difficulties experienced by poor and underdeveloped countries, where data and information on unplanned urbanisation are frequently insufficient.

While the CA-Markov model requires more time and resources to validate and predict, it still has the risk of producing incorrect predictions due to the assumption of uniform transition probabilities. To better reflect the dynamic and non-linear nature of urban development, the model's transition probabilities could be refined. Finally, the current model predominantly combines driving elements in a linear combination via the “neighbourhood effect and Markov transition probability” [32]. However, this linear assumption may not hold in practice and requires additional research for improvement.

6. JP NAGAR- URBAN GROWTH SCENARIO AND THE NEED TO PREDICT LULC CHANGE

With the growing prominence of corporate players, the Karnataka Government has constructed an 'IT Corridor' in Bangalore. The aforementioned industry corridor connects “Whitefield with Koramangala, Hosur Road, HSR Layout, Electronics City, JP Nagar, and Banashankari”. With the expansion of the IT industry in Bangalore, there is now a substantial rise in the city's mobile and permanent populace, pushing it to 6.5 million, putting it as the third-most populated municipality in India and expanding at a dizzying rate of 38% each year [37]. The distinct IT corridor mentioned above serves as the foundation for Bangalore's residential hub as well. Because the majority of IT companies are located along this corridor, their employees, understandably, seek to live nearby. Thus, most IT workers prefer “Airport Road, M.G. Road, Hosur Road, Cunningham Road, Infantry Road, Whitefield, Electronic City, Koramangala, J.P. Nagar, Jayanagar, and HAL”. Bangalore is currently the world's third richest city, with a wealth base that is growing at a 35% annual rate4. The urban decadal growth rate (2001-2011) is higher than the rural rate, with 46.7% and 16.5% for urban and rural areas, respectively. Due to substantial migration for employment, education, and marriage, Bengaluru's urban population increased rapidly between 2001 and 2011, outpacing both India's and Karnataka's decadal growth rates. Bengaluru Urban accounts for 82% of the BMR population, which is partly due to a significant migrant population from adjacent states [38].

As a consequence of financial expansion and immense population growth, substantial development difficulties, especially with urban land management, have grown prevalent. It renders it challenging for urban planning authorities to develop Master Plans and forecast how the city and its environs will change in the years to come. Because of the abundance of structures that have grown around work hubs and along their peripheries, different scenarios with expected population forecasts cannot accurately factor in expanding corridors.

7. CONCLUSIONS

In conclusion, comprehending and tracking urban expansion and Land Use and Land Cover (LULC) change are critical to the long-term development of metropolitan towns located on productive agricultural plains, such as JP Nagar in Bangalore, India. This article provides a comprehensive review of 25 research publications from 2019 to 2023 that used the CA-Markov model to analyse and predict LULC changes in similar metropolitan contexts. The results of this survey demonstrate the validity and practicality of the CA-Markov model in mapping historical LULC patterns and forecasting future shifts in JP Nagar, Bangalore. Researchers have improved the dependability and accuracy of their predictions by combining the CA-Markov model with additional analytical approaches and data sources. The study also emphasises the significance of taking the data collecting year into account, as it affects the historical viewpoint and provides vital insights into the dynamics of LULC changes through time.

The ramifications of this research go beyond academic curiosity, as the survey results can help shape customised land use policies, urban planning strategies, and sustainable development initiatives for JP Nagar and other similar areas. Municipal planners and leaders can benefit from the CA-Markov model's insights, allowing them to make informed decisions about future growth and development while balancing agricultural and urban expansion needs. It is crucial to highlight that, while the CA-Markov model is useful, it has limits. The study emphasises restrictions such as data availability and quality, model assumptions, and the requirement for constant validation and calibration. Addressing these issues will be critical for furthering the CA-Markov model's refinement and enhancing its forecasting powers.

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