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Simulating Urban Growth Scenarios for Sustainable Urban Management: A Case Study of Bankura Municipality, West Bengal, India

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Abstract : *In the present era, rapid and uncontrolled urbanisation is a primary concern for urban environmental sustainability. The Land Use and Land Cover (LULC) in the cities of emerging nations is undergoing rapid transformations at an exceptional rate. This research aims to investigate the changes that occurred in the LULC pattern in the Bankura municipality from 1994 to 2024, as well as to estimate the prospective LULC configuration for Bankura municipality for the year 2034. This research employed satellite imageries (Landsat 5/8/9) to examine the LULC changing pattern between 1994 and 2024. All the datasets have been classified using the Maximum Likelihood Classifier (MLC). At the same time, Cellular Automata (CA) model has been employed to forecast future LULC trends of the study region. The findings suggest that the constructed area has expanded considerably over the last several years. Over the past thirty years, there has been a noticeable decline in forest area, cultivated land, fallow land, and water bodies. The CA modelling results also demonstrate that the built-up area will increase in the future, while the analysis predicts a slow rate of change for other LULC classes. The research outcomes may be applied for sustainable land use planning in the municipality of Bankura, as well as in different cities.*

Key words: *Urban Growth, Land use land cover, Sustainable Urban Management, Future Prediction.*

Introduction

Urban growth is an evolving and complex socioeconomic process that transforms towns in terms of their dimensions, form, and population characteristics (Kaf et al. 2014; UN 2019). However, urbanisation has presented a significant challenge for most countries worldwide, as Disorganised urban development is often caused by a lack of adequate planning and governmental oversight

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(Samat et al., 2011). Individuals relocate to metropolitan areas due to increasing opportunities and amenities, including employment, educational institutions, healthcare services, and recreational activities (Hasan et al., 2020). The world is constantly becoming more urbanised; there are already 3.5 billion people living in cities, and it is expected that by 2030, this number will have increased by 60 per cent (Sustainable Development Goals, 2021). Over the following decades, emerging nations are expected to account for 95% of global urbanisation (World Urbanisation Prospects, 2018). Given that metropolitan regions account for approximately 60 per cent of global GDP, cities are a driving force behind progress in areas such as technology, human capital, poverty alleviation, and economic development (Sustainable Development Goal, 2021; UN, 2019).

In developing nations such as India, the population has grown significantly within medium-class metropolitan regions with populations of less than 1 million (United Nations, 2015). India is the second-largest populated country in the world, with 1.3 billion people as of 2015 (UN DESA, 2024), making it the seventh-largest country in terms of land area. India's urban population increased significantly from 11.4% in 1901 to 31.16% in 2011 (GoI, 2011). According to UN estimates, it is projected that by 2050, 60% of rural communities will be surrounded by cities. The natural environment and resources will face considerable strain due to the rapid urbanisation and increasing population density, along with the horizontal expansion of cities in developing countries like India (Zhang et al., 2017). Over the past four decades, India has undergone significant in-situ transformations in land use and land cover (LULC), including forest loss, changes in farmland, and rapid built-up expansion, driven by accelerating urbanization and industrial growth (Islam & Paul, 2018; Gharbia et al., 2016). This transformation is non-linear in nature (Bose & Chowdhury, 2020), as low-density areas gradually evolve into high-density zones due to rising land demand and urban desirability.

Rapid urban development, coupled with unsustainable exploitation of natural resources, has led to environmental degradation including deforestation, biodiversity loss, air pollution, the formation of slums, insufficient infrastructure, increased vulnerability to natural calamities, and growing demand for water resources. These changes contribute to broader challenges such as climate change, desertification, the emergence of urban heat islands, and the conversion of agricultural land for urban use (Kumar et al., 2019). Uncontrolled urban expansion, a result of poor planning and development oversight, remains a widespread issue in many developing countries (Bose & Chowdhury, 2020).

Understanding the alterations in land cover and their underlying anthropogenic and environmental drivers is essential (Singh et al., 2021). Such changes must be consistently monitored across spatial and temporal scales to answer what, where, when, and at what pace they occur (Mengistu & Salami, 2007). A limited number of cities worldwide have implemented systematic and intentional planning frameworks, negatively impacting long-term sustainability. Therefore, the application of advanced GIS techniques is crucial in effectively monitoring and analyzing land use and land cover changes driven by urbanisation. In Bankura Municipality, such transformations have already been observed. These methods have helped urban planners understand the pace and pattern of change, support informed spatial decision-making, and promote sustainable urban management.

However, most urban growth simulations in India focus on metropolitan or rapidly expanding Tier-I and Tier-II cities, often neglecting smaller cities with distinct socio-economic and environmental characteristics. This research gap extends to the integration of geospatial simulation tools like Cellular Automata (CA) or SLEUTH with local governance policies to build scenario-based planning frameworks for smaller urban centers like Bankura. There is also limited research connecting remote sensing data with urban planning principles and local-level decision-making for sustainable development in such regions.

This research is designed to investigate the changes in land use and land cover patterns caused by urbanisation in Bankura Municipality of West Bengal.

Aims and Objectives

1. To evaluate land use alterations over the past three decades (1994–2024) at each successive decadal interval
2. To examine the determinants of urban expansion of the study area
3. To formulate the prediction map of urban growth employing the CA-Markov chain model
4. To assist policymakers and planners in gaining a deeper comprehension of land transformation of the study area to assure sustainable management

Study Area

Bankura town serves as the Sub-Divisional Headquarters of Bankura district. In the year 1865, the town of Bankura was granted the status of a municipal municipality. The town has an area of 19.06 km² according to the 2001 census estimate. It comprises 24 wards and 12 Mouzas. Its precise location is between the coordinates of 87° 3' 36" north and 23° 14' 24" east longitude. Average Elevation - 46 m from MSL. During the summer, the temperature rises to 42 degrees Celsius. The average precipitation is 1,400 millimetres (55 inches), mostly occurring from June to September. Understanding the LULC of Bankura is essential for environmental management, planning, and sustainable development. Here is an overview of the typical LULC categories found in Bankura. Bankura municipality has numerous land use groups, including agriculture, vegetation, built-up areas, water bodies, fallow land, and sand deposits.

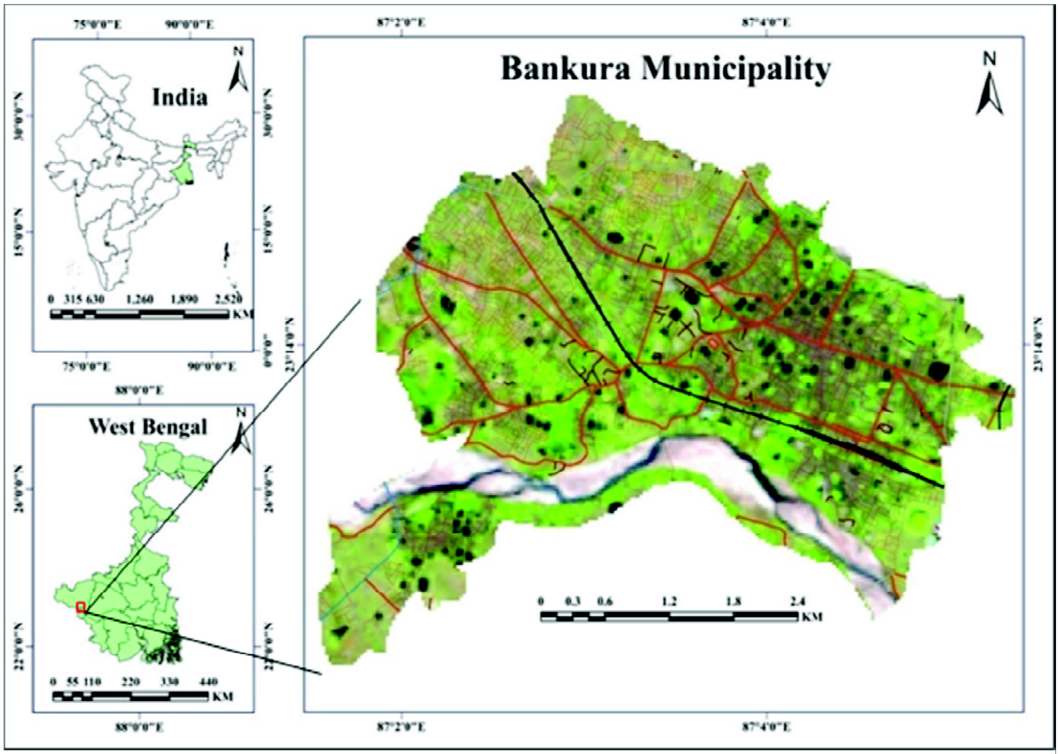

Fig. 1: Study area map

Materials and Methods

Data Collection

Data from both Landsat 5 and 8, which includes spectral and temporal information, were gathered from the USGS website. The data covers the Bankura municipality region for the time spans of 1994 to 2024. Distances from main roadways were calculated using OpenStreetMap (OSM) data and vector layers. The detail data used for the study has been presented in the Table 1. The pixel values or errors in the values were radiometrically fixed to improve and clarify the distant sensing data. This study involved a comparison of various datasets gathered from multiple sources across different timeframes, highlighting the significance of radiometric correction and calibration. In addition, urban areas were classified using Google Earth images, which serve as base maps, showing features such as water bodies, vegetation, agricultural land, fallow land, and sand deposits, among others. Additionally, they were tasked with identifying the spectral signatures of the image for various land use and land cover classes.

Table - 1: Detailing of the data and their source

Data Layer	Source	Available Period	Resolution (m)	Band combination
SRTM_DEM	USGS	1994	30	-
Landsat 5 TM	USGS	April, 1994	30	4,3,2
Landsat 5 TM	USGS	April,2004	30	4,3,2
Landsat 8 OLI	USGS	March, 2014	30	5,4,3
Landsat 9 OLI	USGS	April, 2024	30	5,4,3

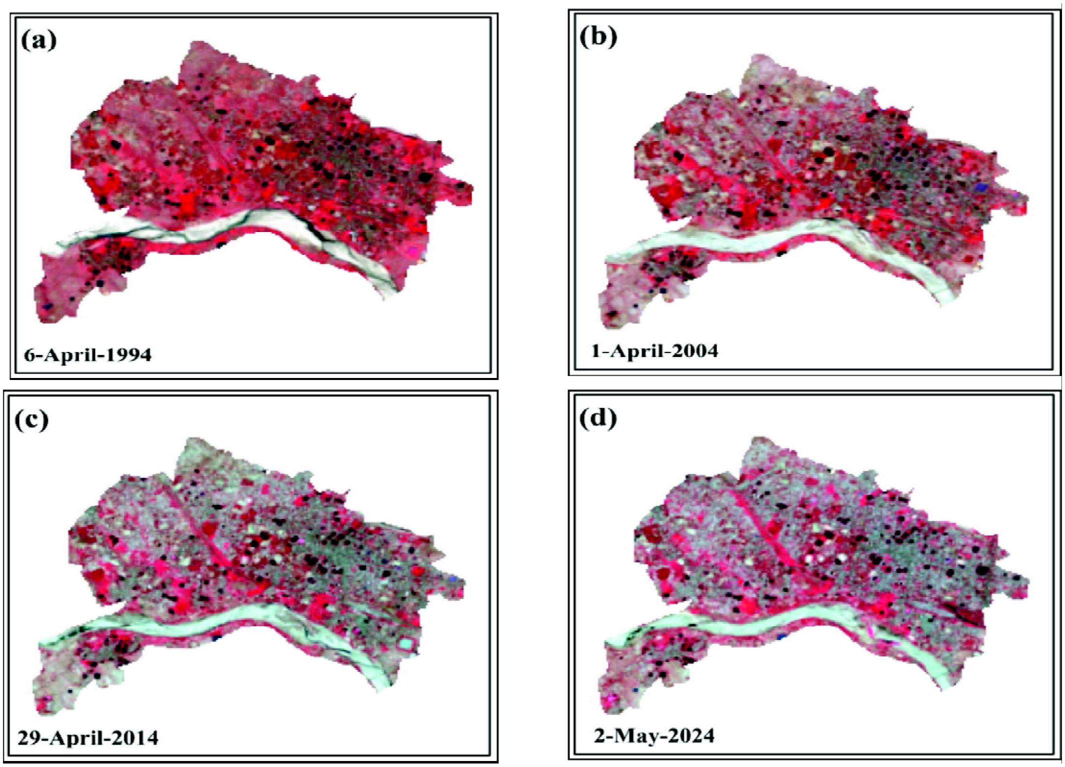

Fig. 2: Multi-temporal and multi-spectral data of a & b Landsat-5 TM, 1994, 2004 respectively, Landsat-8 OLI 2014, and Landsat-9 OLI 2024 covering Bankura municipality area.

Methodology

Image Classification

The satellite images are subsiding of the area of interest, geometric correction to align images with ground control points, and radiometric correction to remove atmospheric and sensor noise. The Dark Object Subtraction (DOS) method was used for atmospheric correction. The Maximum Likelihood Classifier (MLC), a supervised classification technique, was used to classify the pre-processed images in the ArcGIS and ERDAS Imagine environments. Major LULC categories, including built-up, agricultural, fallow, vegetation, and water bodies, have been included in the classification scheme.

Accuracy Assessment

Accuracy assessment was performed using the Kappa coefficient, based on ground-truth data and high-resolution reference imagery. The overall classification accuracy exceeded 85% across all years, which is considered acceptable for regional-scale LULC studies (Congalton et.al 2014).

Land Change Modelling

The Land Change Modeller (LCM), a component of the TerrSet 2020 software developed by Clark Labs, was utilised for post-classification change analysis. This tool facilitated the quantification of land cover transitions and detection of spatial and temporal change patterns between the selected years. The LCM also enabled identification of key land transformation pathways.

LULC Change Detection and Mapping

The present work monitors land use alterations by overlaying classified maps and generating change matrices. The results were visualised using change maps, which revealed the transformation of different land categories over time. These maps helped in identifying zones of urban expansion, agricultural decline, and vegetation loss.

Spatial Trend Analysis of LULC Changes

Directional trends and spatial expansion patterns were examined using GIS-based zonal analysis. This study demonstrated how urban growth tends to occur in specific directions, allowing for the identification of areas where land is changing the most in different buffer zones surrounding cities.

Modelling LULC Change Potential

To simulate future LULC scenarios, a Cellular Automata (CA)–Markov Chain Model was applied. Transition probability matrices were derived from the classified LULC maps of 1994 and 2004. These matrices, in combination with spatial neighbourhood rules, were used to predict the LULC distribution for the year 2014. The CA–Markov model was executed in the TerrSet environment.

Model Validation

The predictive accuracy of the CA–Markov model was evaluated by comparing the simulated 2014 LULC map with the real classified map of 2014. Cross-tabulation, overall accuracy, and Kappa

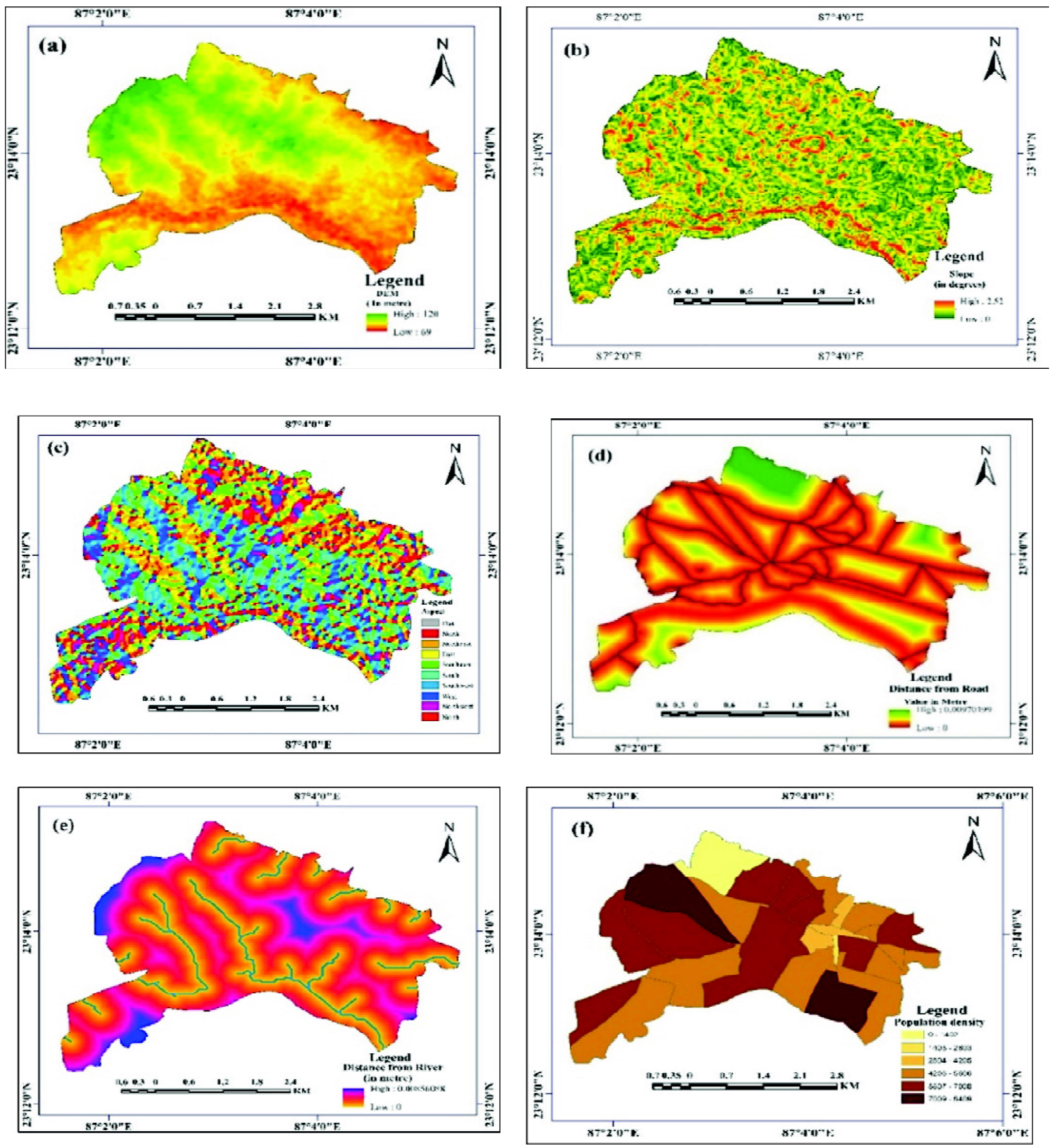

Fig. 3: LULC prediction parameters: (a) study area DEM, (b) slope, (c) aspect, (d) road distance (m), (e) water body distance, and (f) population density.

statistics were used for validation. The model's dependability for upcoming LULC projections was confirmed by the results, which showed a satisfactory match.

Parameters of Markov Chain model for urban growth analysis

This study selected the driver variables based on their impact on land use changes and the ease of obtaining spatial data. The Shuttle Radar Topography Mission (SRTM) dataset was used to get the Digital Elevation Model (DEM), slope, and aspect. This was done to account for how the land changes shape.

Road and water body distances were calculated using Euclidean distance functions in GIS to represent accessibility and hydrological proximity, both of which significantly affect land conversion potential. Population density data were integrated as a socio-economic factor to reflect anthropogenic pressure on land use change, particularly in urban zones. All predictor variables were standardised to a common spatial resolution and extent, and used as suitability layers within the CA–Markov framework for future LULC simulation.

Projection of Future LULC

After evaluating the model, the CA–Markov model was used to guess what LULC patterns would look like in the future. These projections are used to plan cities, manage land in a way that is good for the environment, and make policies that aim to reduce damage to the environment.

Result and Discussion

LULC change dynamic

Land use trends in the study area are revealed by the supervised categorization followed by image pre-processing, where red indicates built-up regions, blue water bodies, yellow agricultural land, light green vegetation cover, and brown fallow terrain (Fig.6). Image analysis reveals that vegetation comprised the largest area across all classes within the Bankura municipality, while the percentage of land coverage fluctuating over time. Between 1994 and 2004, the percentage of land covered by vegetation fell by nearly 2 square kilometers, from 33 percent (6.01 sq km) in 1994 to 35 percent (4.43 sq km) in 2004, 25 percent (87%) in 2014, and 25 percent (69%) in 2024 (Figure 5 & Table 2). Agricultural land made up 30.91 percent (5.62 sq km) of the total in 1994 decreased to only 15.68 percent (2.85 sq km) in 2024, showed a steady negative trend (Figure 5 & Table 2). Water bodies made up nearly 22% of the Bankura municipality's total area in 1994, but by 2024, that percentage had dropped to 4:6. (Table 2). The percentage of urban areas increased from 18.59 to 39.43 percent from 1994 to 2024 accounting for an aerial change of 3.38 sq to 7.17 sq km during the time period.

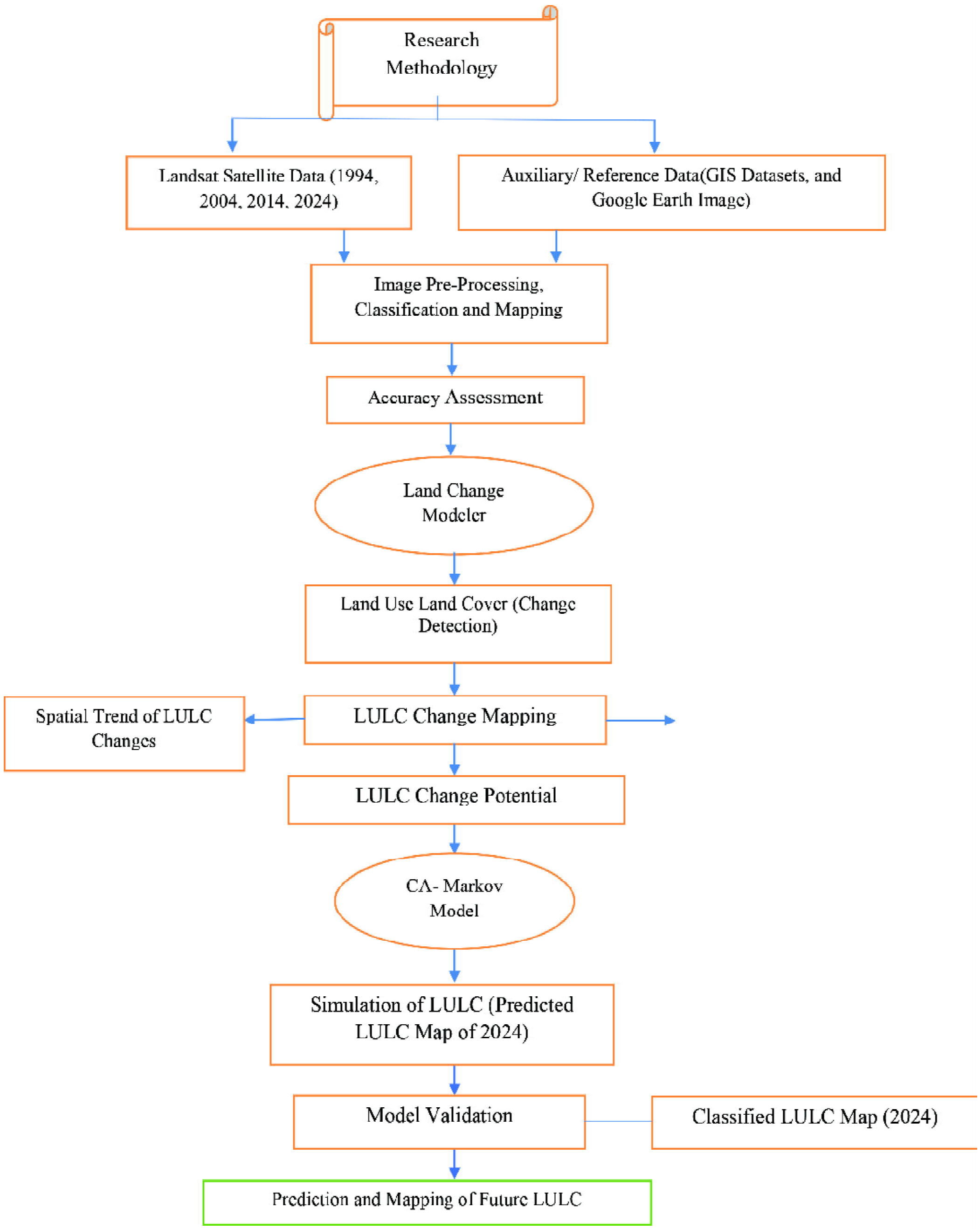

Fig 4. Methodological flowchart

Table 2: LULC classes from 1994 to 2024

Class	1994		2004		2014		2024	
	Area	%	Area	%	Area	%	Area	%
Vegetation	6.0174	33.07772	5.446	31.68	4.707	25.874	4.674	25.696
Agricultural land	5.6241	30.91575	4.697	25.82	3.6045	19.813	2.853	15.687
Built-up	3.3831	18.59694	4.293	23.603	5.9076	32.474	7.174	39.439
Water bodies	0.855	4.699946	0.874	4.943	1.0377	5.704	0.892	4.9047
Fallow land	1.1619	6.386979	1.047	5.758	1.8756	10.31	1.607	8.835
Sand deposits	1.1502	6.322664	1.341	7.376	1.0593	5.822	0.988	5.432

Source: Computed by Author based on Satellite Imageries, Area represented in sq km.

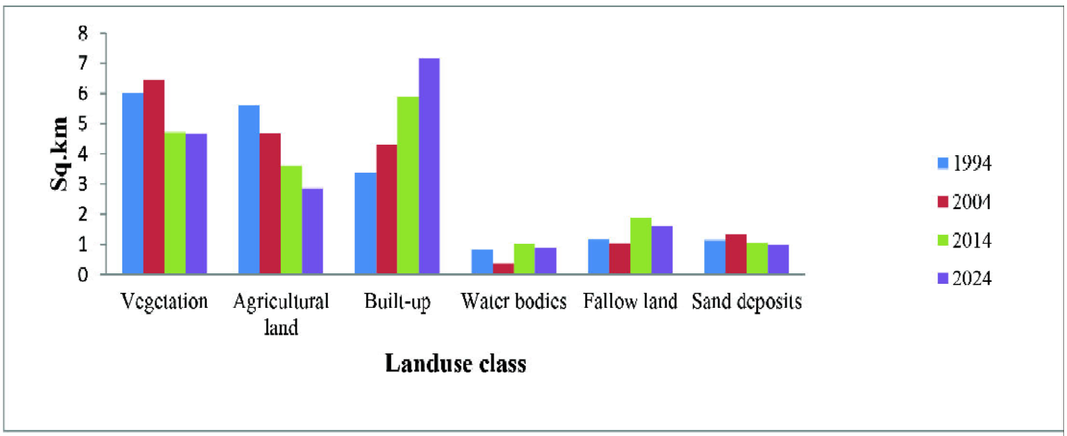

Fig. 5: Area wise different land use class with year.

The data clearly demonstrated a substantial increase in urbanisation from 1994 to 2024, which also corroborates the overall in-migration trend to the region. Fig. 5 shows the variations in several LULC between 1994 and 2024. Around 33 percent of the total area was covered by vegetation in 1994, which was 6.01 km² (Table 2). This percentage dropped to 35.43 percent in 2004 and then to 28.90 percent by 2024. Between 2014 and 2024, the classification saw a slight increase in the amount of vegetation cover because of the inclusion of park spaces with tree plantation, playgrounds, croplands, grasslands, and fallow areas. Additionally, the expansion of vegetative cover may have been impacted by several operations carried out by corporations and the government within the boundaries of the Bankura municipality.

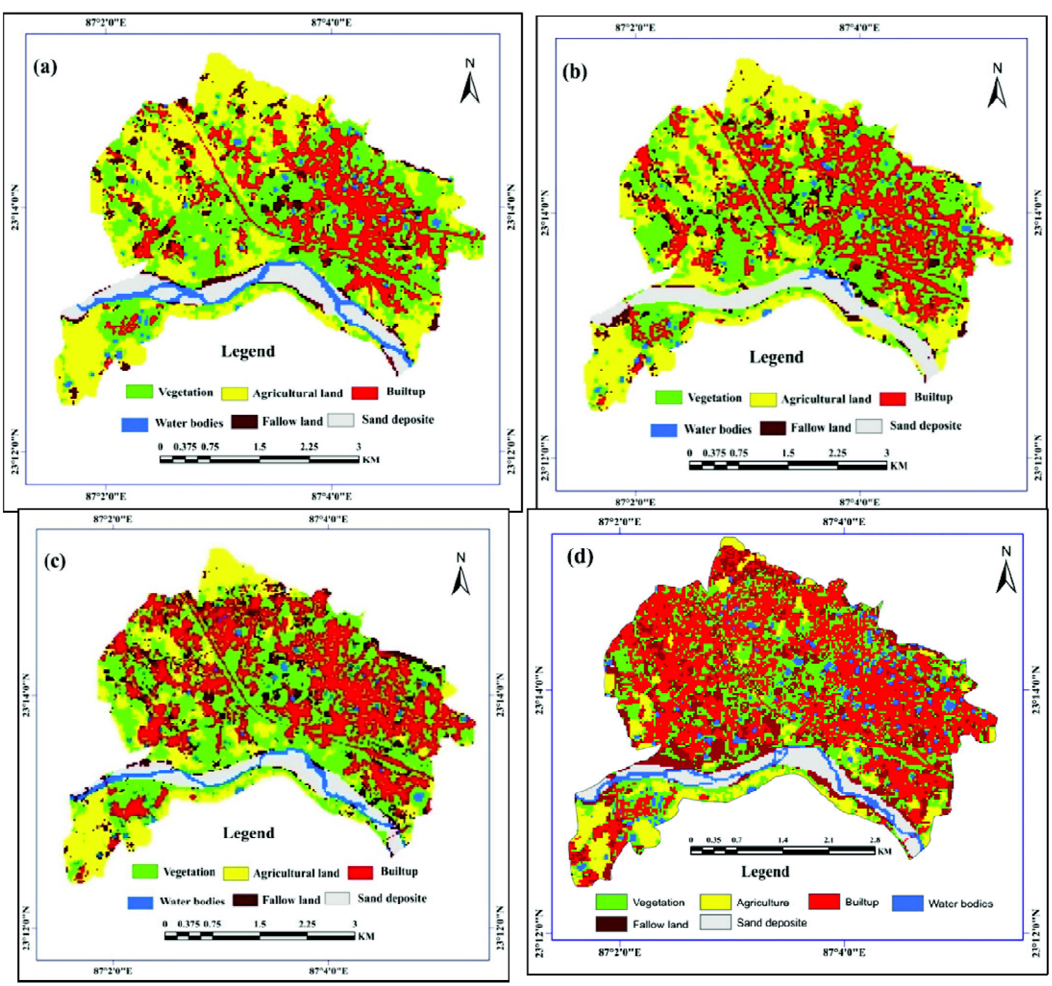

Fig. 6: LULC map of Bankura Municipality (a)1994,(b)2004,(c)2014,(d)2024.

Change detection analysis

The analysis of LULC changes from 1994 to 2034 reveals a dynamic transformation of the landscape driven by urban expansion, agricultural adjustments, and environmental shifts. Built-up areas consistently increased across time periods, indicating steady urban growth and infrastructural development. The most significant growth was observed between 2004–2014 (1.614 km²; 8.87%) and 2014–2024 (1.266 km²; 6.965%), reflecting accelerated urbanization in the recent decades (Table 3). Conversely, agricultural land initially expanded (1994–2014), but the rate of increase declined after 2014, suggesting a gradual conversion of farmland to urban and other non-agricultural uses. Vegetation cover showed modest gains up to 2014, but nearly stagnated during 2014–2024. The loss of vegetative cover directly jeopardizes ecological richness and indigenous livelihood systems of Bankura, which is renowned for its biodiversity and tribal communities that rely on forests. It indicates the potential environmental stress or deforestation, with only slight recovery projected by 2034. Fallow land and sand deposits also showed fluctuations, possibly due to seasonal changes, soil degradation, or shifting land management practices. Water bodies remained relatively stable with minor variations. Overall, the trends reflect a landscape undergoing continuous anthropogenic pressure, highlighting the need for sustainable urban planning, conservation of green spaces, and balanced land resource utilization to ensure long-term ecological stability.

Table 3: Area Change of LULC types of different year

LULC Class	Change Area (1994-2004)		Change Area (2004-2014)		Change Area (2014-2024)		Change Area (2014-2034)	
	$(Km)^2$	%	$(Km)^2$	%	$(Km)^2$	%	$(Km)^2$	%
Vegetation	0.5714	1.397	0.739	5.806	0.033	0.178	0.482	2.652
Agricultural land	0.927	5.095	1.092	6.007	0.751	4.126	0.108	0.594
Built-up	0.909	5.006	1.614	8.87	1.266	6.965	0.99	5.443
Water bodies	0.019	0.243	0.163	0.761	0.145	0.799	0.15	0.823
Fallow land	0.114	0.628	0.828	4.552	0.268	1.475	0.623	3.423
Sand deposits	0.19	1.053	0.281	1.554	0.071	0.39	0.157	0.865

Source: Computed by author

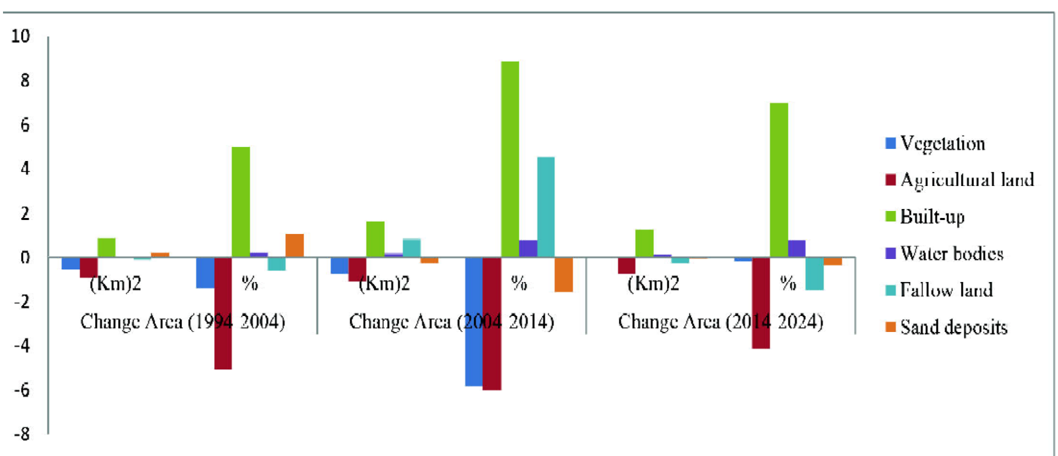

Fig. 7: *Gain and loss of LULC classes over time*

Fig. 7 illustrates the results of this study, which show that land cover and land usage varied over time. There are both rising and falling trends in all land use classes, with the exception of fallow land. The vegetation and agricultural areas exhibited a decreasing trend, whereas the built-up area consistently demonstrated a growing pattern within the Bankura municipality area. Fertile agricultural lands are being converted into residential and commercial properties, which reduces the net sown area and compromises local food security and agricultural employment. This change has the potential to upend traditional livelihoods and worsen rural-urban migration in Bankura, where a sizable section of the peri-urban population is employed in agriculture. Local flora and fauna are put in danger when vegetated land is removed, particularly natural forests, groves, and plantations, as this causes habitat destruction and fragmentation. An explanation for this observation could be that in the initial decade, certain areas of Fallow land were converted into farmland, resulting in their reclassification.

Cellular Automata to predict LULC change

The results processed from the CA-Markov Chain are transmitted to cellular automata, resulting in the generation of three distinct output maps. The transition potential map illustrates the likelihood or capacity for transition among various categories of land utilization. The LULC classes will be used to construct transition potential maps, such as those for "vegetation to built-up" and "fallow land to water bodies" transitions.

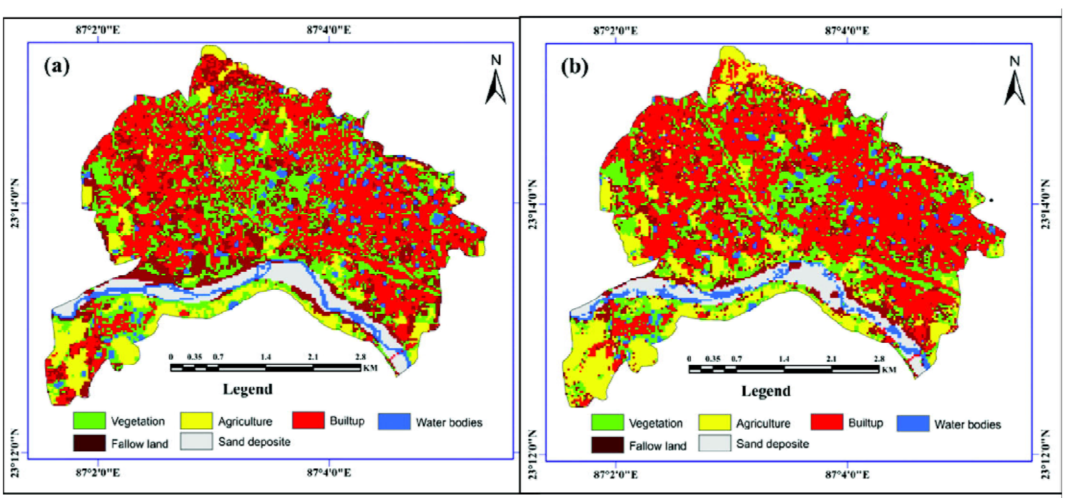

Fig. 8: Future prediction of LULC map (a) 2024, (b)2034

The purpose of the CA-Markov simulation was to use LULC inputs as geographical and temporal variables from 2014 to 2024 to predict future land use changes. The results show that the area of vegetation is expected to shrink by 2.65% between 2024 and 2034. The results suggest that the total amount of vegetation cover will remain relatively stable, at approximately 25.64% in 2024 and 23.04% in 2034. Fig. 8 illustrates our projected land use and land cover in the Bankura area. It is worth noting that the amount of bare land is expected to decrease by 8.83% in 2024 and 5.41% in 2034.

Table 4: Changes in LULC class from 2024 to 2034

LULC Class	2024		2034	
	Area	Percent	Area	Percent
Vegetation	4.674	25.696	4.192	23.044
Agricultural land	2.853	15.687	2.961	16.281
Built-up	7.174	39.439	8.164	44.882
Water bodies	0.892	4.9047	0.742	4.081
Fallow land	1.607	8.835	0.984	5.412
Sand deposits	0.988	5.432	1.145	6.297

Source: Computed by author

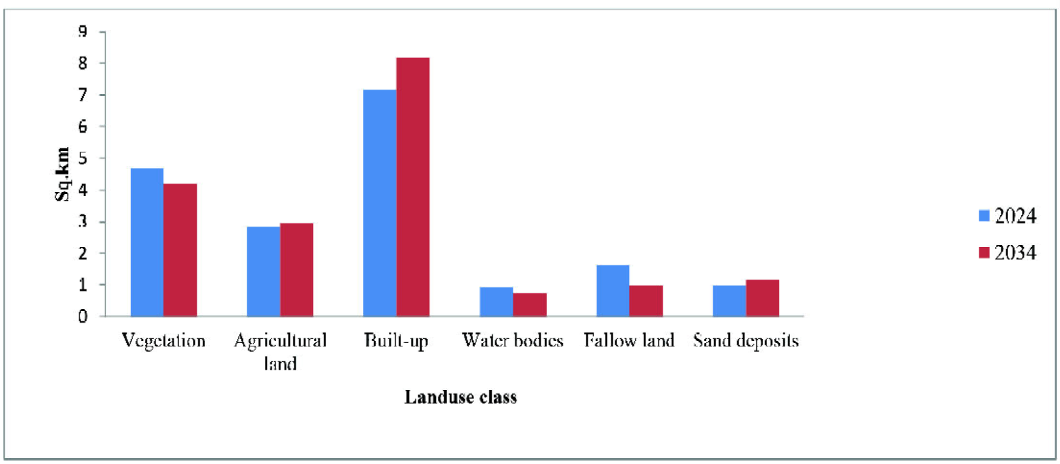

Fig. 9: *Changes* in LULC class from 2024 to 2034

The results of the model show a consistent decline in vegetation, with estimates of 25.69 percent for 2024 and 23.44 percent for 2034. This suggests that the accessible vegetation area may account for approximately 25.69% of the overall Bankura city area in 2024, potentially decreasing to 2.65% by 2034. As anticipated, urbanization is projected to rise by 44.88% by the year 2034. The model's findings suggest that the overall urban area is expected to account for approximately 39.43% of the Bankura municipality area in 2024, increasing to around 44.88% by

2034. This indicates that the water body area could represent approximately 4.90% of the total Bankura area in 2024, potentially decreasing to 0.82% by 2034. This suggests that regions formerly characterized by bare land, vegetation, and water bodies could experience a shift towards urban development (Table 4). It is important to highlight that within this CA-Markov chain framework, the existing roadway networks are utilized among the various input variables. Currently, the Bankura municipality lacks any strategy for the future development of roadways; as a result, the model may have underestimated the size of future cities.

Model validation

A comparison between the projected and actual 2024 maps was conducted to confirm the model's accuracy (Gidey et al. 2017). The output forecast for 2020 shows a kappa coefficient of 0.96 and a wholeness of 98.63%. The data points to the LCM model's ability to accurately forecast future developments. Although the model used in this study is a reliable way to perform the simulation, there are a number of uncertainties about the future predictions for different land type classifications, including the following: The modifications made in the future It is impossible to accurately assess through modelling the effects of natural processes influencing land use patterns as well as government land development policies and master plans. According to the model, the current patterns of land use and land cover will have an impact on future changes (Keshtkar and Voigt 2016). Over time, the essential components continue to change. Because it changes the locations of settlements and patterns of density, the transformation of the transportation network has a direct effect on the direction and structure of urban expansion. It is crucial to select the most beneficial set of driving forces to improve the accuracy of model predictions (Arsanjani et al., 2013; Wang et al., 2021).

Implications for Sustainable Urban Management

The Bankura Municipality requires a thorough and long-term approach based on urban planning principles, as evidenced by observed and simulated changes in Land Use and Land Cover (LULC). The constant growth of built-up areas, especially at the expense of farmland, fallow land, and vegetation, is a sign of a change that could endanger the environment, urban resilience, and the balance between people and nature if it is not managed well. It is essential to employ sustainable urban management strategies that strike a balance between development needs and environmental protection. Strategic land-use zoning should be implemented to conserve remaining vegetative and agricultural landscapes, especially in the peri-urban zones, which are most vulnerable to encroachment. The establishment of urban green belts and ecological buffers around sensitive ecosystems such as rivers, wetlands, and forests can help maintain ecological connectivity and regulate microclimatic conditions. Moreover, integrating principles of compact and Transit-Oriented Development (TOD) can reduce horizontal urban expansion and encourage efficient land utilisation. Urban growth should be directed along existing infrastructure corridors, thereby minimising environmental degradation and infrastructure costs. Water-Sensitive Urban Design (WSUD) practices should be incorporated into municipal planning to ensure the protection and restoration of water bodies, which are declining as per simulation results. Additionally, urban policies must promote inclusive and participatory planning that involves local stakeholders in decision-making processes. Community-based land management and awareness initiatives can enhance stewardship and ensure long-term sustainability.

The Bankura Municipality case may gain from the useful landmarks provided by the numerous urban growth simulation studies conducted throughout India that have shown the effectiveness of geospatial modelling in managing sustainable urban expansion. Roy et al. (2022) analysed urban sprawl using the CA-Markov model and discovered substantial encroachment into agricultural lands, especially along transportation corridors in the Asansol Municipal Corporation area of West Bengal. Although Asansol faces greater industrial and demographic pressure, this pattern is similar to Bankura's peripheral growth trends. Similar to this, Ghosh and Das (2021) replicated future land use changes in Durgapur and found a lack of integrated planning and fast urban expansion toward the periphery. Despite being less developed than Durgapur, Bankura is just as vulnerable to unchecked growth in the absence of strategic planning measures.

Finally, predictive modelling tools like CA–Markov serve as valuable decision-support systems that allow planners to visualise future growth scenarios and proactively address land-use conflicts. The results of this study can therefore inform sustainable urban policy frameworks, ensuring that urban growth in Bankura proceeds in an environmentally responsible, economically viable, and socially inclusive manner.

Policy Implementation

The effective policy implementation is essential to effectively transform the insights from urban growth simulation into concrete results for sustainable urban management in Bankura Municipality. Land use control, zoning laws, and the creation of integrated urban plans that strike a balance between environmental sustainability and growth should be given top priority by local authorities in light of the anticipated scenarios for urban expansion. In order to prevent urban sprawl and preserve agricultural and environmentally sensitive areas, policies should support infill development and the adaptive reuse of underutilized land. The outcomes of the simulation can also direct housing, sanitation, and transportation infrastructure investments, guaranteeing fair service delivery in both core and peripheral wards. Planners should be able to update land use plans on a regular basis using real-time data by institutionalizing the integration of geospatial tools into municipal governance workflows. Public involvement, urban planners' capacity building, and interagency coordination are crucial for ensuring the efficacy of policies. The viability and impact of such policies will be further increased by coordinating local strategies with state-level urban development missions like the Smart Cities Mission and AMRUT. Finally, Bankura can manage urban growth proactively with the aid of a simulation-informed policy approach, guaranteeing that development stays resilient, inclusive, and sustainable.

Conclusions

In addition to conventional Land mapping, monitoring, and modelling of land use and land cover techniques, using the combined CA Markov model can forecast shifts in LULC and its geographic dispersion and orientation in urban regions, such as Bankura city. The report anticipates urban growth in Bankura will largely occur along the transit network. CA simulations indicate that built-up areas (both dense and sparse) will increase by 8.16 km² in residential, commercial, and industrial regions by 2034. Validation results show 78.63% accuracy for cellular automata markov simulation. If the current land use pattern, population growth, and commercial development continue, built-up areas are likely to occupy a large portion of Bankura municipality by 2034. This model's primary drawback is its concentration on pattern similarity and its "black box" nature; hence, it may be better to use an agent-based model in a comparable domain and examine its performance in comparison to CA-Markov. This research on LULC transformation and its future forecast can assist local urban planners and administrators in constructing sustainable cities and improving living circumstances. Although there have been reports of traditional LULC mapping in Bankura using multi-temporal RS data, there has been a dearth of published basic modelling research that attempts to predict the onset of urban expansion. Despite the limitations of each technique, these studies collectively enhance our understanding of trends in urban development.

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