AI-driven Urban Growth Prediction: A Cellular Automata Approach with Geospatial and Machine Learning Integration

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ABSTRACT

Urban expansion is a critical challenge in rapidly growing cities, necessitating accurate prediction models for sustainable planning. This study employs a cellular automaton (CA) based machine learning model approach to predict urban growth in Jaipur city using Landsat 8 OLI data from 2011-2021. The analysis incorporates multiple spatial drivers including spatial factors for efficiently projecting the urban growth. The study revealed a 28.4% increase in built-up areas from 2011-2021 predominantly replacing green and barren lands. The transition schematics confirms that urbanization follows major road corridors while green spaces and water bodies accounting to its growth. Using CA technique, projected 2031 land use land cover (LULC) indicates continued outward expansion particularly in Jaipur's western and northern peripheries. The classification accuracy of LULC maps for 2011 and 2021 is 85.6% and 88.3% respectively with a kappa coefficient of 0.81. The CA-based prediction achieved a model accuracy of 0.89 validating its reliability. The findings highlight the urgent necessity for strategic zoning regulations, green infrastructure and transport-oriented development to ensure balance and systematic urban growth. This research serves as a valuable decision-support for urban planners, offering insights into future land-use changes and providing a foundation for sustainable urban policy formulation.

KEYWORDS

Urban growth prediction, Cellular automata, Supervised classification, Remote sensing, Machine learning.

1. Introduction

Urbanization is a paramount and significant global phenomenon that is actively shaping the landscape of the cities and geographical regions (Dadhich & Hanaoka, 2011). The unprecedented expansion of urban areas is triggered by numerous attributes like demographics, socioeconomics, and ultimately geographical characteristics that lead to land use land cover (LULC) transformations (Gupta, 2011; Punia & Singh, 2012; Sisodia et al., 2016). When it comes to the scenario of Indian context, the population growth as well as development factors are at an accelerated pace, urban expansion not only presents opportunities but also concerns that too alarming ones. On an initial level, it fosters economic development and ultimately enhances the liveability but on the further levels, it mounts pressure on natural resources, inconsistently tunes the ecosystem balance and stresses the existing infrastructure. Therefore, deciphering the urban growth prediction is a pivotal and a paramount layer for understanding urban planning as well as the corresponding management.

Remote sensing and geographic information systems (GIS) have presented trending and applicable techniques in monitoring urban expansion (sprawl) in an efficient manner. Availabilities of high-resolution imagery especially from Landsat enables the scientific community to analyze LULC variations. The most crucial advantage comes in the form of its temporal resolutions and availability of multiple bands that gives a pivotal baseline for analyzing the urban variations.

Tier 1 cities have always gained massive attention for studies and research but creates a big loophole due to the fact that emerging tier 1 cities and/or tier 2 cities poses treacherous concerns as well. Mobility advancements, infrastructure upliftment, and other related characteristics make the regions vulnerable to urban sprawl (Raman et al., 2018; Yadav, 2019). Among various predictive models, machine learning models serve as the optimum basis for analyzing urban growth/sprawl. The reason lies in their ability to acquire and capture spatial-temporal relationships which are generally complex and diverse in nature within the context of urban systems. Cellular-automata (CA) in particular, offers a robust analytical framework for executing the simulation of urban expansion through transition rules and stochastic processes.

This research work focuses and emphasizes on urban growth prediction for the city of Jaipur, Rajasthan through effective utilization of machine learning models. The overall approach is to understand the expansion of urban dynamics in the study area *viz.* Jaipur city and understand what the projection would be in the upcoming half-decade. Spatio-temporal pattern, trends and variation as a set is the paramount objective for which Landsat-8 OLI satellite dataset was examined and analyzed. The acquired satellite images come from the year 2011 and 2021 to have a clear prediction for the year 2031. Furthermore, LULC transition analysis was also conducted to have a granular insight about the city's urban variation, land transformation as well as potential environmental implications.

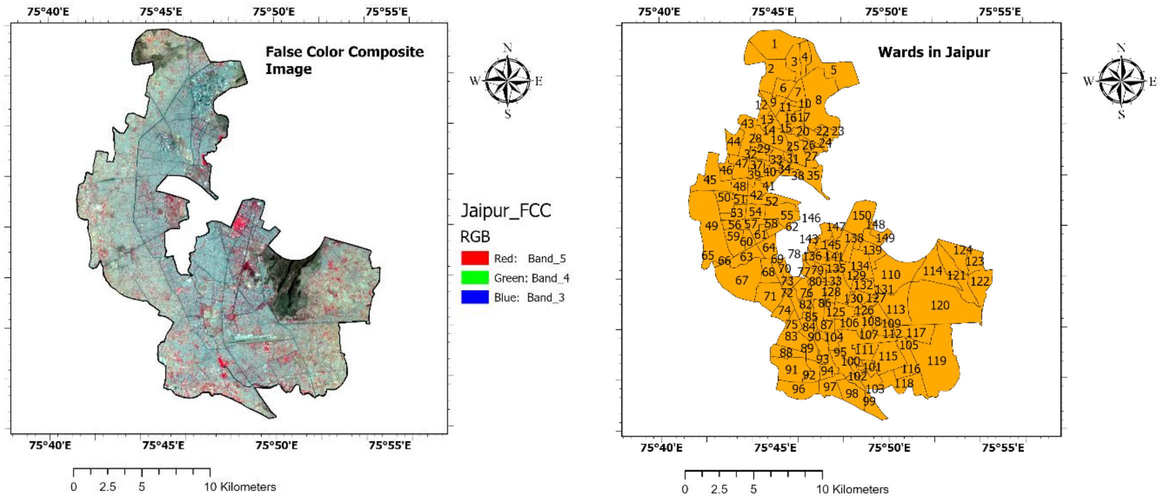
1.1 Significance of Urban Growth Prediction

Accurate and precise urban growth prediction is a core-fundamental baseline for efficient and effective city-planning. Additionally, serves as a strong baseline for environmental conservation as well as infrastructure development. A rapid-surge in urbanization has been evident over the years and if left unmonitored without efficient interventions, can pose alarming and dreadful challenges such as traffic congestion, loss of green-lands, increased urbanization and incremented air pollution. By predicting and anticipating the urban sprawl, probable administrators can frame effective decision-making regarding zoning regulations, proficiencies in transport-network planning and environmental management practices (Kodihal & Akhtar, 2023).

Cellular automata (CA) models have significantly emerged as an efficient go-to technique for analyzing urban growth. The critical ability comes in the form of spatial interactions presentability with neighbourhood effects. Unlike other state-of-the-art models (statistical), CA models integrate temporal and spatial dynamics in a seamless manner to have more realistic representation of urban growth processes. When proficiently fused with machine learning, CA technique can refine the transition probabilities and in turn, imparts accuracy in the prediction. This hybrid approach enhances the deciphering of complex urban systems and hence, offers a proficient data-driven baseline for policy formulation.

1.2 Jaipur's Urban Growth Trajectory

Jaipur, the capital city of Rajasthan has undergone significant spatial transformation in the recent years. As a major economic as well as cultural hub, the city has experienced an incremented infrastructural development along with population influx and commercial activities (Jawaid et al., 2017). Residential expansion, industrial hotspot emergence, coupled with new urban-transport corridors has revamped the entire urban landscape of Jaipur city. The schematic representation of Jaipur city is shown in figure 1.



(a) (b)

Figure 5.1. The schematic representation of Jaipur city **(a)** False color composite (fcc) image; **(b)** ward-dynamics in Jaipur

Analyzing the past-present combination of LULC patterns of Jaipur definitely provides valuable insights into the trends in urbanization. The period from 2011-2021 has witnessed substantial variations in built-up areas with agricultural lands and open spaces being transformed into residential-commercial zones (Deo et al., 2024). Through the utilization of CA models, this study aims to project Jaipur's urban sprawl/expansion by 2031 thus, offering an effective scientific basis for sustainable development strategies.

2. Methodological Framework

The urban growth modelling using cellular automata (CA) is a powerful-dominant approach that captures the complexity of urban landscapes of LULC change from spatio-temporal dynamics (Cheng & Masser, 2004; Han et al., 2009; Vliet et al., 2009). This research employs a CA-based framework for urban growth prediction for the city of Jaipur for the year 2031. The methodology integrates remote sensing, GIS, CA in a seamless manner to impart and mount effective precision in the outputs (Feng et al., 2011; Mitsova et al., 2011).

Data Acquisition and Preprocessing

The data is acquired from Landsat-8 OLI sensor (operational land imager) through which LULC data was extracted for the years 2011 and 2021. These datasets were pre-processed through the utilization of atmospheric and radiometric correction to avoid redundancy and also, geometric correction to avoid distortions. The LULC maps were generated using supervised classification employing support vector machine (SVM). Accuracy assessment was carried out using ground truth and confusion matrices to validate classification results. In addition to LULC data, multiple spatial variables that influences urban expansion were incorporated into the model described as follows:

- Central business districts (CBD) layers: Identifying major commercial hubs influencing urban growth
- Distance to roads: A key determinant of accessibility and development potential.
- Distance to rivers and drainages: Deciphering the impact of hydrological constraints on land conversion.
- Slope and elevation: Assessing the impact of terrain on urban development.
- Population density: Understand demographic pressures on urban expansion.

CA-based Urban Growth Prediction

The CA model is a grid-based simulation model where each cell's state is determined by its previous state, neighbourhood interactions as well as the transition rules (Aburas et al., 2016; Shafizadeh Moghadam & Helbich, 2013). The mathematical flow can be understood through the following set of equations:

$$S_{i,j}^{t+1} = f(S_{i,j}^{t}, N_{i,j}, P, R) \qquad \ldots (1)$$

Where:

$S_{i,j}^{t+1}$ represents the state of the cell at time *(t+1).*

$S_{i,j}^{t}$ represents state of the cell at previous time *t.*

$N_{i,j}$ represents the neighbourhood effect.

P represents transition probabilities and R refers to stochastic perturbations.

The next step comes in the form of estimating transition probabilities for LULC changes through a logistic regression model incorporating spatial variables as independent factors.

$$P(U) = \frac{1}{1 + e^{-(\beta_0 + \sum \beta_i X_{i})}} \qquad \ldots (2)$$

Where:

P(U) is cell transition probability for an urban state.

β_0 is the intercept and $\beta_i X_i$ are regression coefficients and independent spatial variables respectively.

The spatial interaction among neighbourhood cells was modelled using a weighted function shown as follows:

$$W_{i,j} = \sum_{m=-1}^{1} \sum_{n=-1}^{1} \alpha_{m,n} S_{i+m,j+n}^{t} \qquad \ldots (3)$$

Where $W_{i,j}$ is the neighbourhood effect and $\alpha_{m,n}$ represents the weight coefficients assigned based on historical-urban expansion patterns?

In simpler words, the model assigns higher weight to cells closer to existing urban areas therefore, reinforcing the principle of urban agglomeration. The CA model was implemented in a GIS environment using python-based geospatial libraries (Tong & Feng, 2020; Tripathy & Kumar, 2019; Wahyudi & Liu, 2016). The LULC layers from 2011 and 2021 were used for the model's training, while

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the predicted 2031 layer was based on estimated transition probabilities. The accuracy of the prediction was evaluated using Kappa coefficient and validation as shown.

$$Kappa = \frac{P_0 - P_e}{1 - P_e} \quad \dots (4)$$

P_0 is the observed agreement between predicted and actual LULC while, P_e is the expected agreement by chance.

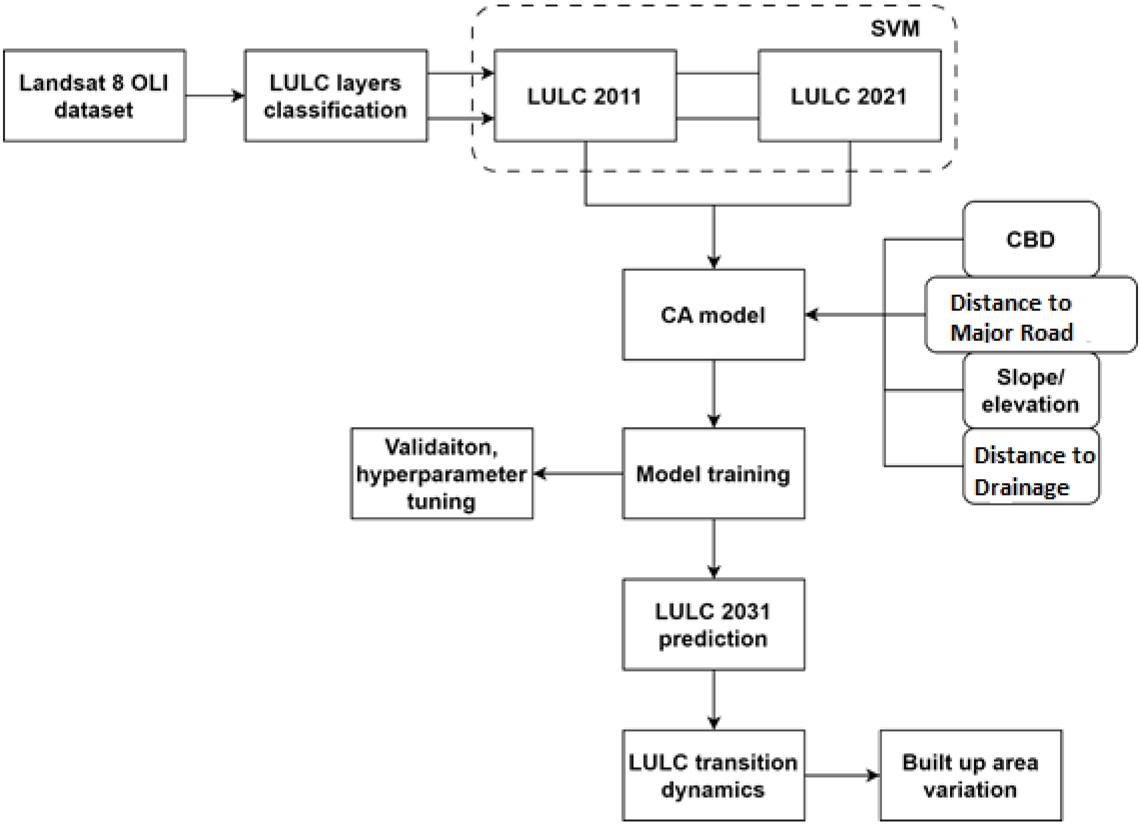


Figure 2: Methodological schema

A Kappa coefficient greater than 0.89 is considered to be a strong agreement, ensuring the reliability of the prediction results. The overall methodological framework is presented in figure 2.

3. Results and Discussion

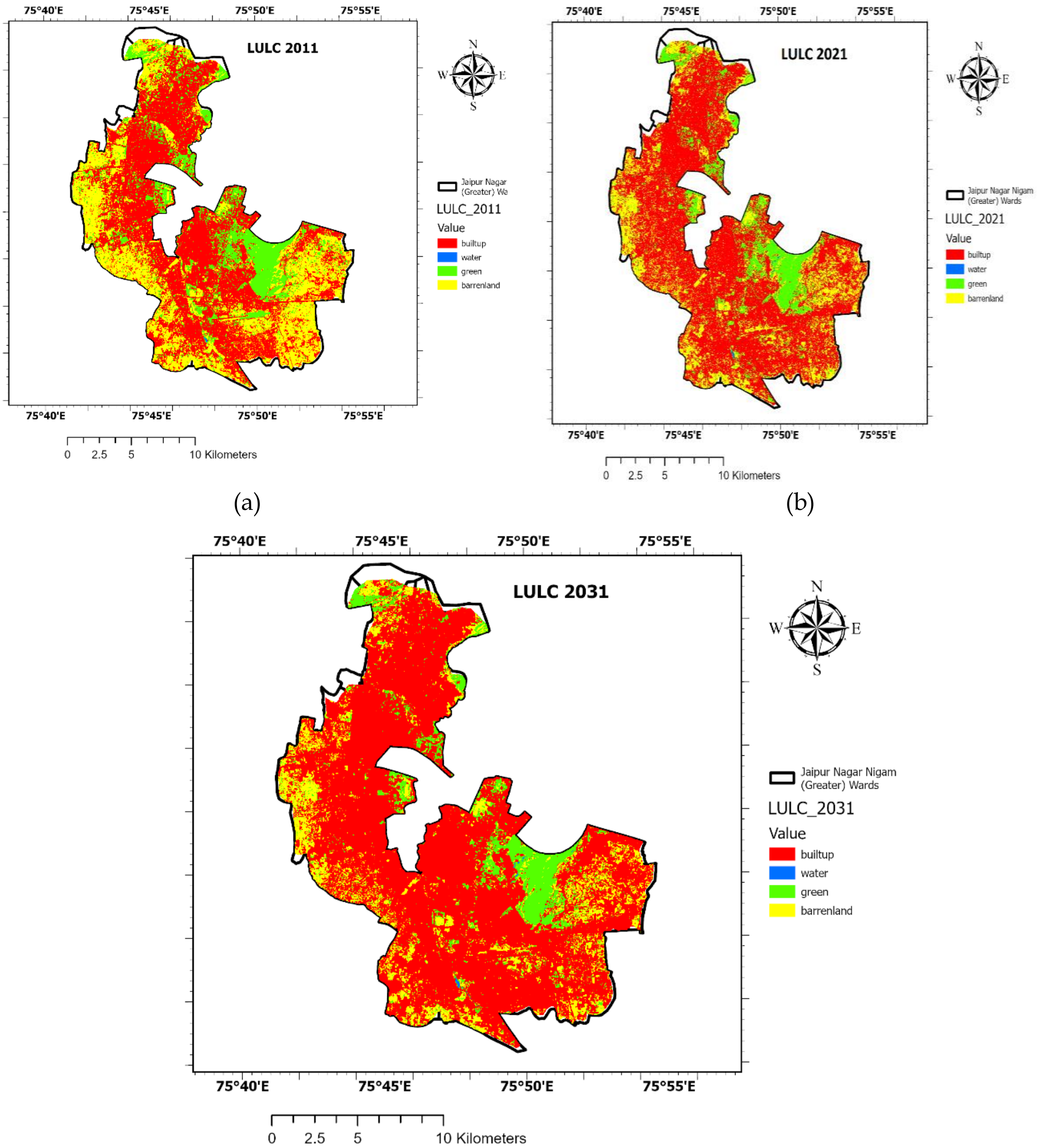
3.1 General

The results of the executed research portray valuable insights into the urban expansion dynamics of Jaipur, leveraging CA modelling with multi-layer factor spatial analysis. The predicted LULC of 2031 highlights key transformation patterns, spatial growth trajectories as well as potential urban sprawl indicators (Büchler et al., 2021). This brings to the attention that the urban expansion trends observed from 2011-2021, yielded proficient results of urban expansion in 2031.

3.2 Urban Growth Trends

The LULC analysis for Jaipur for the years 2011 and 2021, revealed substantial urban expansion already even before going towards the projection of 2031. The main attributes responsible for this includes:

- Increase in built-up areas due to barrenland being converted into built-up areas taking water and green vegetation into the account as well.
- Decline in vegetation and green areas that has been transformed into built-up areas.
- Growth along transportation networks was observed when creating multi-factor distance to roads layers.



(a) (b)

(c)

Figure 3: (a) LULC 2011; **(b)** LULC 2021; **(c)** LULC 2031

The LULC of 2011, 2021 are shown in figure 3 (a)-(b) while the projected LULC of 2031 is shown in figure 3 (c). It is evident that there is an increment in the built-up area or so called as the urban agglomeration from 2011 to 2031 (Shafizadeh-Moghadam et al., 2017). With 2031 being the heaviest capped urban expansion as evident in figure 3 (c). To have a more granular understanding of the changes in LULC dynamics, figure 4 shows the schematic portrayal.

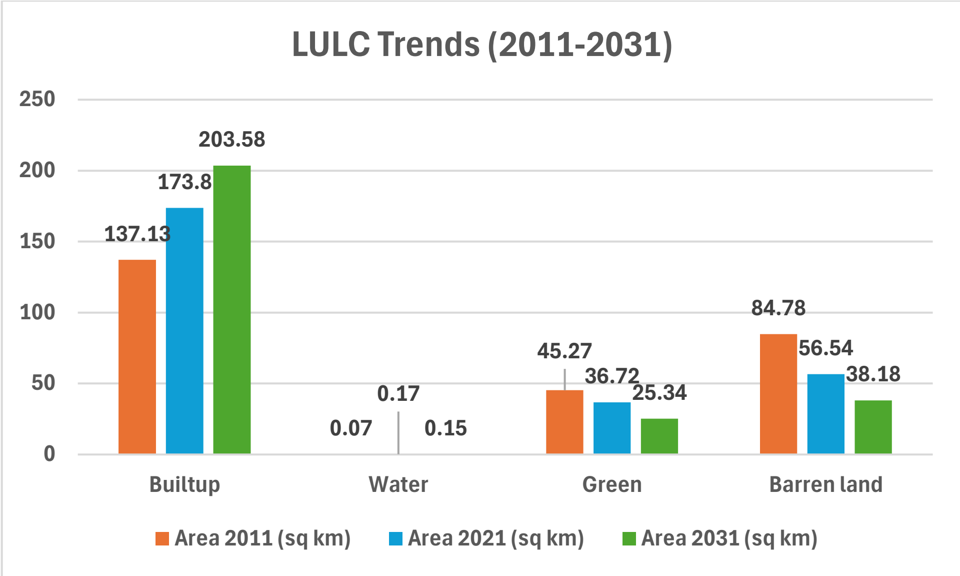


Figure 4: LULC trends

As clearly seen in figure 4, built-up has seen a heavy increment while green and barren land has seen heavy decrement with water being neutral as the city of Jaipur lies in the semi-arid region location extent in India. The reasons for decrease in green and barren land comes in the form of increase in built-up due to the fact that these classes got transformed into urban areas (Gómez et al., 2019; Khan & Sudheer, 2022; Kim et al., 2022). This surge or a rapid increment in built-up corresponds to the fact that the urban expansion is unplanned and hence, termed to as "urban sprawl". Table 1 shows the computational parametric information executed in this research.

Table 1: Computational parameters and accuracy metrics

Parameter	**Description**	**Remarks/Values**
Satellite data	Landsat 8 OLI	30 m spatial resolution
Classification method	LULC extraction	SVM
Classification accuracy	Overall accuracy of LULC maps	85.6% (2011) 88.3% (2021)
Kappa coefficient	LULC classification metric	0.78 (2011) 0.81 (2021)
Precision	Correctly predicted built-up areas	86.4% (2011) 88.9% (2021)
Recall	Proportion of actual urban areas correctly predicted	84.1% (2011) 87.6% (2021)
F1 score	Harmonic mean of precision and recall	85.2% (2011) 88.2% (2021)
CA model type	Urban growth simulation	CA model
Neighbourhood type	Influence of surrounding cells	Moore neighbourhood (3x3 Kernel)
CA model accuracy	Kappa coefficient for predicted vs actual LULC	0.89
Validation method	Model accuracy assessment	Observed vs Simulated LULC (2021)

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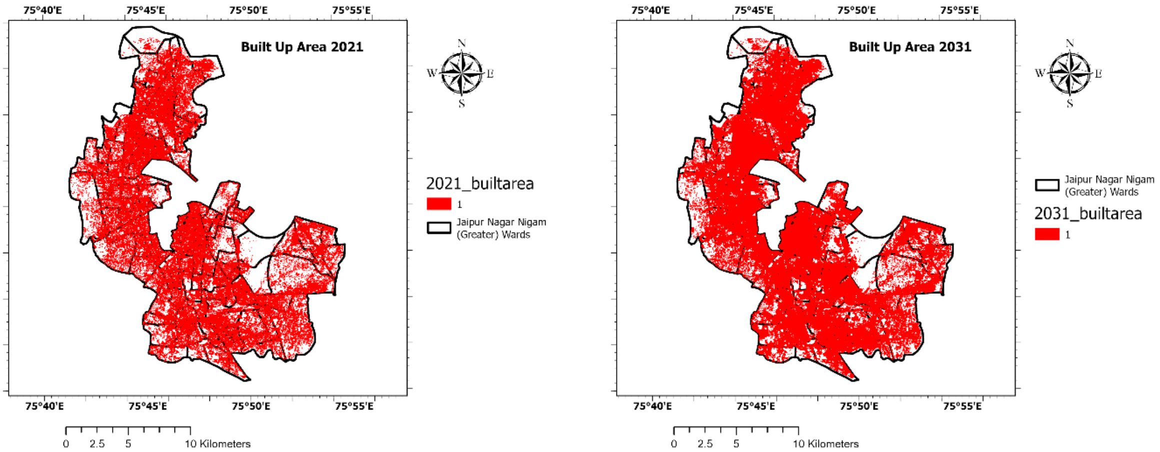
To decrypt the built-up dynamics, figure 5 shows the portrayal of built-up dynamics trend over the years.



(a) (b)

Figure 5: (a) Built-up 2021; **(b)** Built-up 2031

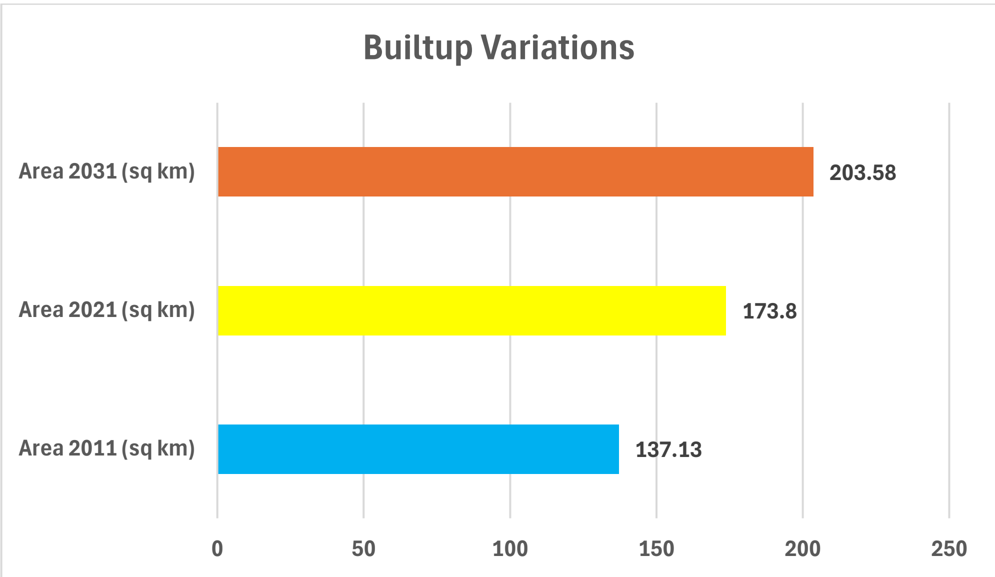


Figure 6: Built-up variations

Figure 6 portrays the variation of built-up in sq.km. area for the analyzed areas and there has been a steady increase in built-up with no signs of stoppages. To understand the incremented urban sprawl, it is necessary to decrypt the reasons behind it (Fontana et al., 2023; Gharaibeh et al., 2023; Tsagkis et al., 2023). To decrypt this, the LULC transition is shown in figure 7 while the variations in LULC transition is shown in figure 8.

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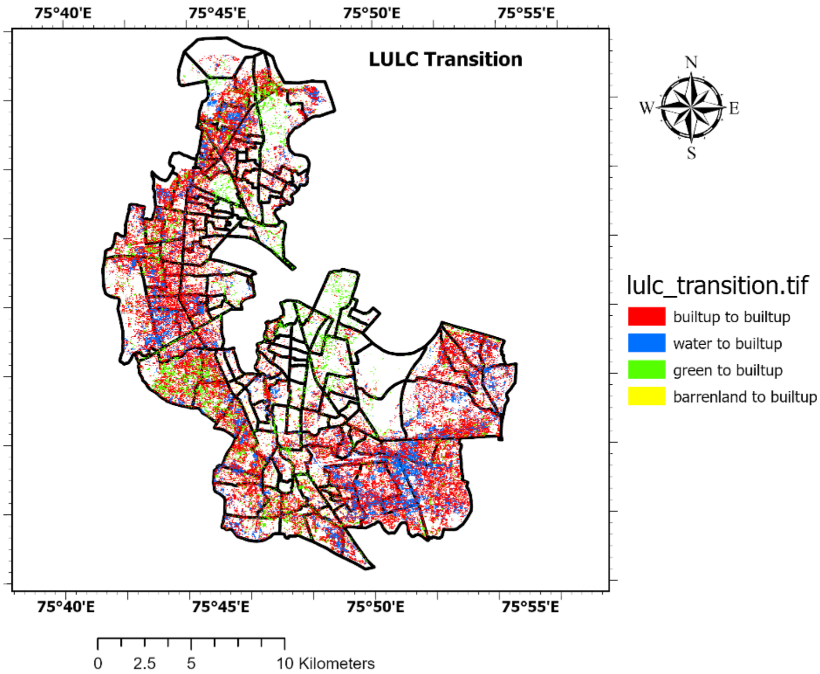

Figure 7: LULC transition

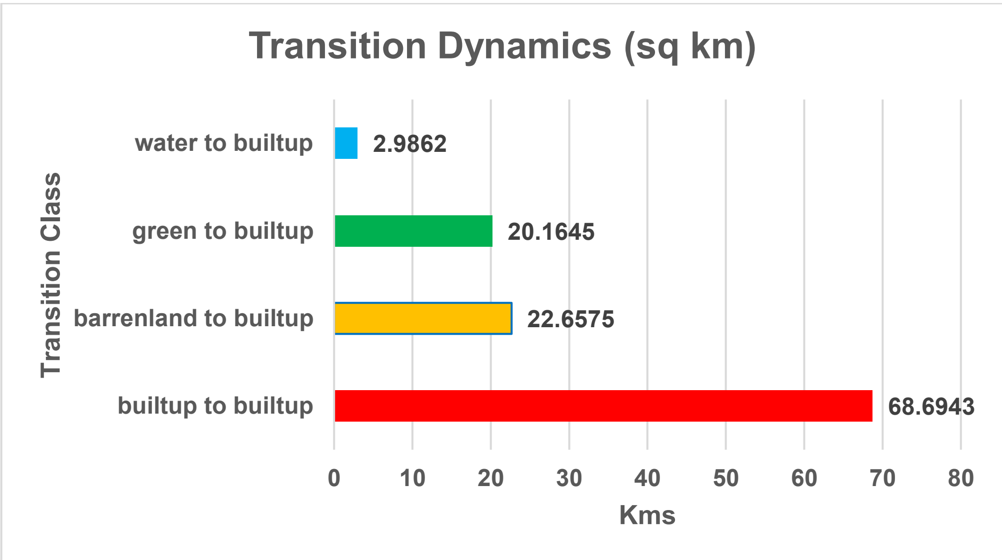

Figure 8: LULC transition variation

Built-up to built-up is the most rapidly surging transition with barren land to built-up as the second most influencing factor. Furthermore, green areas being converted into built-up land. Although the water to built-up transition shows the smallest contribution, it remains a notable change. The combined transition from green and barren land to built-up areas highlights the ongoing trend of rapid urban expansion.

The predicted 2031 LULC projects a continued expansion of Jaipur's urban footprint with the following key trends:

- Peripheral growth intensification corresponding to progress outward, particularly in western and northern Jaipur where land conversion is highest.
- Urbanization along new infrastructure developments is another key attribute implying expansion along road networks emphasizing role of infrastructure in shaping future growth.
- Reduction in agricultural and barren lands portrays a rapid decline in non-urban land classes is projected raising concerns about potential environmental and agricultural sustainability.

Policy/Strategic Implications

The following strategic implications are necessary to be intervened in order to have a sustainable future ahead.

- Smart growth and zoning regulations through controlled urban expansion zones, restricting unplanned sprawl and encouraging high-density mixed-use development.
- Green infrastructure development through the promotion of urban areas, green belts as well as rooftop gardens to mitigate heat island effects.
- Sustainable transport-oriented development through public transport network expansion as well as pedestrian-friendly infrastructure.
- Water and resource management through the protection of existing water bodies and by correspondingly improving the drainage systems.
- Public participation and governance through engagement of local communities in urban planning, ensuring inclusive development and environmental-friendly decision-making.

4. Conclusion and Future Scope

The research work presented a comprehensive approach to urban growth prediction for the city of Jaipur using a cellular-automata (CA) machine learning model. Through remote sensing data integration acquired from Landsat-8 OLI (2011-2021) with multiple spatial parameters such as distance to roads, rivers, drainages, slope, elevation and population density. The adapted model effectively simulated urban expansion through the prediction of future LULC changes for the year 2031. The results indicated significant urban expansion particularly in the peripheral areas highlighting the influence of transport corridors as well as economic activity on urban sprawl. The transition layer confirmed that green and barren lands are rapidly getting transformed into built-up areas. The research also underscored the necessity for strategic zoning regulations, green infrastructure development as well as transport-oriented urban planning in order to manage the city's expansion effectively. The extracted findings served as a valuable tool for policymakers and urban planners in formulating sustainable city development strategies.

Furthermore, CA model approach proved to be an effective method for urban growth prediction portraying strong spatial accuracy when the future prediction was achieved. The high kappa coefficient validated the model's performance. While this research provided a robust framework for urban growth prediction, further exploration is required for strengthening the domain of urban sprawl prediction using remote sensing and machine learning. Integration of socio-economic factors, climate change considerations, multi-city comparative analysis as well as hybrid machine learning models are the way ahead for a robust framework for urban growth prediction. By addressing these areas, growth predictive models can evolve into more dynamic and adaptable tools with the aim of aiding in the creation of resilient, well-planned and sustainable cities.

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