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Quantifying and simulating urban growth through Multi-Temporal Land Use and Spatial Perspectives

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Abstract

Urbanisation is an irreversible phenomenon associated with the transition from rural areas and, coupled with unplanned and dispersed growth, has resulted in vast and uncontrolled changes to the natural landscape in impervious built-up regions. Such transformations result in severe and often irreversible ecological destruction, socio-economic inequity, and spatial disintegration, particularly around rapidly urbanising cities. Given these challenges, analyzing urban development that has undergone severe landscape transformations is necessary. This study aims to systematically quantify and analyse the spatiotemporal changes in the urban landscape of Bangalore city by utilizing very high-resolution satellite imagery from different periods to understand land-use changes. The study also aims to quantify urban areas and characterise landscape structure by integrating spatial metrics, which will evaluate the growth of landscape changes from various land uses to urban land use, identify spatial cohesiveness, and understand the complexity of these arrangements. Then, we utilized the knowledge of spatial configuration to visualize future land use transitions through the theory of cellular automata-based patch-generating land use simulation (CA-PLUS) model. The result indicates a noticeable upward trend in urban growth, from 42.81% (2012) to 63.40% (2023). Additionally, the analysis reveals that the layout of land is changing rapidly, with urban areas becoming more connected, while other types of land are becoming insufficient and broken up; however, the model predictable a future expansion of urban area land from 71.77% in 2036 to 73.26% in 2042, potentially leading to the development of a significant continuous growth. Such insights can assist decision-makers and urban planners in creating data-driven approaches to sustainable development, infrastructure optimisation, and planned growth.

Introduction

Urban growth refers to cities' physical and spatial expansion, transforming open space, forests, agricultural lands, and barren land into built-up residential, commercial, industrial, and infrastructural development areas. Monitoring this transformation to implement effective environmental management, infrastructure, and sustainable urban planning is essential. However, unplanned urban development can result in socio-economic inequalities, environmental degradation, and destabilization of basic facilities (Wijesingha et al., 2025). The world is rapidly changing as cities continue to grow at an alarming rate, particularly in developing countries in the Global South. Countries in Asia and Africa, such as India, China, and Nigeria, are experiencing rapid and unregulated urbanization through economic liberalization, rural to urban migration, and globalization (Verma et al., 2017; Martellozzo, 2018). This urban expansion usually takes the form of land fragmentation, socio-environmental disparity, and increased pressure on infrastructure and natural resources (Chaouad & Verzeroli, 2018; Sun et al., 2022). In this regard, India provides an example of relevance due to the pace of urbanization and the difficulties of managing urban growth effectively, which is especially prominent in large urban centers such as Bengaluru. The built-up area in Bengaluru increased tremendously between 2000 and 2013, and substantially deteriorated urban ecosystem services, which revealed that the city lacked the proper planning and sustainable growth trends (Aithal et al., 2014). The Land Use (LU) analysis has become a critical analytical approach to assess the extent of urbanization and environmental degradation in Bengaluru. Land Use is defined as human activity utilized on a portion of land, either residential, industrial, or agricultural. In contrast, land cover indicates the surface of physical and biological features, including vegetation, water surface, and built-up areas. When integrated with remote sensing and GIS, LU analysis allows accurate measurement of land transformation processes, including the encroachment of the built-up regions into natural landscapes and the resulting environmental impacts, because these dynamics are systematically captured in spatiotemporal information. This combined collection of geospatial analytics gives an efficient framework for evaluating the level and impact of land transformation. It facilitates evidence-based urban planning, outlines areas with ecological risk, and plans to regulate sustainable development and ecological restoration (Jaysawal & Saha, 2014). Various supervised classification techniques are used to analyze land use with the help of remote sensing. Among the most widely used methods are maximum likelihood classification (MLC) (Rawat et al., 2015), Random Forest (RF) (Kumar et al., 2023), and Support Vector Machine (SVM) (Kim et al., 2022). The MLC has been a fundamental approach in LU analysis, with a strong statistical basis and ease of implementation. It assumes that the spectral attributes of each land use type, which follow a multivariate Gaussian distribution, and assigns the pixel to the class with the maximum posterior probability, thereby considering the intra-class spectral variability. Empirical studies have proven MLC robust in various urban and ecological applications. This context (Ramachandra et al., 2005) exhibited the efficiency of detecting and mapping urban sprawl in the Indian metropolitan areas, including its ability to deal with spectrally inhomogeneous surfaces. (Bharath & Ramachandra, 2016) Implemented the MLC to evaluate temporal LU in Bengaluru with a high accuracy rate and demonstrate its usefulness in analyzing rapid urban change. To complement this, Sheikh et al. (2013) used MLC to track the changes in land cover of forest ecosystems, verifying its versatility to different types of land covers. Moreover, (Aithal et al., 2014) combined the outputs of MLC with spatial measures to simulate patterns in urban development and assess the effect of these patterns on environmental issues on a landscape scale, demonstrating its possibilities as a tool in strategic urban planning and environmental protection.

Combining these studies strengthens the importance of MLC as a practical, statistically-based approach to classification that can be used in high-resolution urban studies and ecological analysis at a larger scale.

The spatial metrics analysis aids in understanding the patterns and evaluating the spatial structure and morphological variation of alterations to the urban landscape over time. This simplifies the assessment of growth patterns, including fragmentation, compactness, and spatial distribution of urban growth. Herold et al., (2005) revealed the applicability of spatial metrics as quantitative indicators of dynamics of urban development, particularly when integrated with remote sensing-based land use classification. These metrics allow identifying significant spatiotemporal dynamics, including fragmentation and dispersion of built-up areas. Based on this, spatial metrics have been effectively applied in an urban context, which were initially developed within an ecology context to measure landscape composition and spatial configuration (Turner et al., 2005). Such quantitative measures reveal detailed insights and have been utilized in irregular development patterns and spatial intricacy in heterogeneous urban environments, which classification alone would fail to describe. They have also been observed to be useful in data-driven urban planning. The most common measures include edges, patches, and the aggregation index. When combined, shape and aggregation indicators can effectively characterize urban structure. Furthermore, zone-based techniques that apply spatial metrics within defined areas, such as urban centres, enable the identification of fine-scale growth patterns (Wu et al., 2003; Liu et al., 2010). Previous studies (Bhatta et al., 2010) have shown that integrating fragmentation and aggregation measures in micro-level analyses enhances the understanding of urban expansion, particularly in rapidly growing regions. However, while spatial metrics are highly effective for quantifying the configuration and structure of urban landscapes, they are limited in their ability to capture the dynamic processes driving landscape change. To mitigate this, spatially explicit modelling methods like Cellular Automata (CA) (Feng et al., 2011) have emerged. CA-based models approximate the LU transformation regarding gridded cells in space and rules of transitions according to the neighboring cells, allowing analysis of spatial patterns and transitions in time (Garouani et al., 2017). The CA-Markov model (Ozturk et al., 2015) has been utilized to predict LU change by spatially incorporating transition probabilities using historical LU data and a diffusion mechanism (Maurya, 2023). However, urban growth's non-linear, heterogeneous nature makes it difficult to be based on non-changing and non-different homogeneous transition rules. Hybrid models, such as CA-ANN (Xu et al., 2019) and CA-SLEUTH (Chandan et al., 2018), have been introduced to resolve such limitations. CA-ANN uses adaptive learning to estimate the transition probability better, and CA SLEUTH adds spatial realism to the topographic and infrastructural factors, including slope, road networks, and exclusion zones. Such improvements have meant that traditional CA models cannot provide realistic patch-scale process changes and dynamically combine multiple spatial driving forces. The Patch-generating Land Use Simulation (PLUS) model (Thottolil et al., 2024) is a significant contribution. By integrating Land Expansion Analysis Strategy (LEAS) and a cellular automaton based on multiple Random seeds (CARS), PLUS can be used to extract spatial decision rules based on historical transitions and to simulate land use as a contiguous patch of land and not as an isolated cell (Cui et al., 2022). This increases spatial realism and accurately recreates real landscape processes, particularly in heterogeneous and rapidly urbanizing places. The model indicates an improved performance, as confirmed by an accumulating amount of empirical research work. (Liang et al., 2021) Moreover, Zhang et al. (2022) revealed that PLUS performed better on spatial accuracy and landscape representation than CA-Markov and CLUE-S. The kappa coefficient of PLUS simulations was achieved at a level higher than 0.90 in Hunan Province, China (Zhaou et al., 2022), and Bharath et al. (2022) revealed its ability to capture fragmented urban expansion in metropolitan regions of India. In addition, the capacity of the model to allow the use of machine learning, simulation of patch-level dynamics, and reaction to more complex urban drivers make it highly appropriate to model LU dynamics in a spatially detailed and rapidly changing urban setting. Its ability to capture intricate growth processes such as informal development, policy-initiated growth, and environmental limitations provides a significant methodological advantage to the traditional CA-based models. Drawing on these strengths, this research aims to explore the spatial and temporal patterns of urbanization in the Bangalore metropolitan region, which is experiencing rapid and unplanned urban development. The study incorporates a three-phase methodology; (i) the Land use classification in the years 2012, 2014, 2018, and 2023 is conducted based on high-resolution satellite imagery by employing MLC to map and interpret the temporal dynamics of urban growth. (ii) the spatial metrics are calculated to quantify urban landscape patterns, including fragmentation, aggregation, and morphological complexity; and (iii) future urban land use was simulated using the CA-PLUS model through sequential incremental (5-year) interval predictions, culminating in final outputs for 2036 and 2042. The model incorporating machine learning techniques focused on rule extraction through the LEAS, CARS, and dynamics in Markov chains to produce a realistic patch-based land use transitions with complex urban dynamics.

Study Area

Bangalore, the capital of Karnataka, is one of the fastest-growing metropolitan regions in India. It is geographically situated between 12°49’5” N to 13°8’32” N latitude and 77°27’29” E to 77°47’2” E longitude at 900 m above mean sea level, covering an administrative area of its current spatial extent, approximately 741 km² (Aithal et al., 2013). Based on Census of India data, the city’s population increased from 5.7 million in 2001 to over 8.5 million in 2011, with an urban population density rising from 2,985 to 4,378 persons/km² during the same period (Census of India, 2001; 2011).

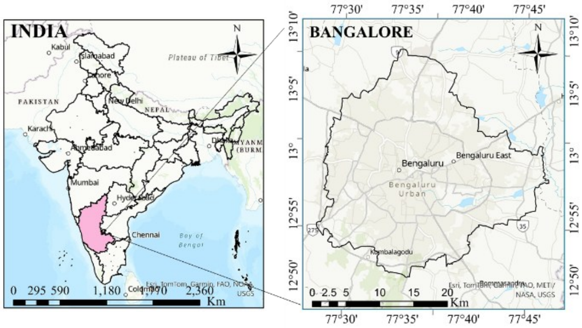


Figure 1. Study Area considered for the analysis

Materials and Methods

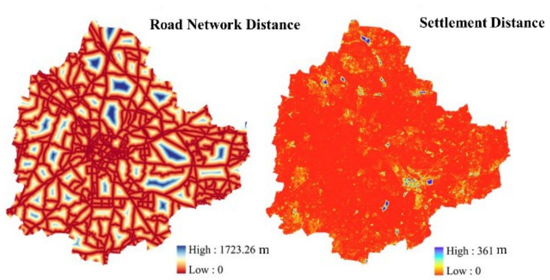
3.1 Dataset

To carry out a spatiotemporal analysis of land use patterns in urban regions, this study utilized the multi-temporal LISS-IV imagery of Resourcesat for the years (2012, 2014, 2018, and

2023), acquired through the NRSC Bhoonidhi portal. The LISS-IV sensor has three spectral bands: red, green, and near-infrared (NIR) within a spatial resolution of 5.8 m. These years were selected based on the availability of cloud-free images and to provide a balanced and continuous temporal structure that covers periods of urban growth and can be used to draw concrete evaluations about the previous urban growth to predict future trends of urban expansion. Table 1 describes the datasets employed in this study. A set of secondary datasets was combined with classified land use maps to provide more comprehensive modeling of urban growth dynamics. OpenStreetMap (OSM) was used to extract proximal measures such as road networks and settlement proximity, which were converted into Euclidean distance layers. Water bodies were constraint variables, whereas ward-level population, economic information, and district-level GDP were socio-economic drivers. The SRTM-DEM (USGS) was utilized as a source of topographic variables, as shown in Figure 2. As input to the urban growth simulation model, these data were systematically classified into four sets, proximal, constraint, socioeconomic, and topographic, to represent the extent to which one lies within or outside the simulation boundary in an urban development framework.

Category	Data	Year	Data Ressource
Satellite data	LU Dataset (5.8 m)	2012, 2014, 2018 & 2023	Bhoonidhi
Socioeconomic	Road Network Distance	2024	OpenStreetMap
	Settlement Distance	2023	Derived from the LU maps
	Population	2023	BBMP ward-wise data
	GDDP	2023	Government of Karnataka Economic Survey Reports
Environmental	Slope & DEM (30 m)	2014	USGS-SRTM
	Waterbody distance	2023	Derived from the LU maps
Constraint	Open water layer	2023	Derived from the LU maps

Table 1. Spatial driving factors of land use changes in this data



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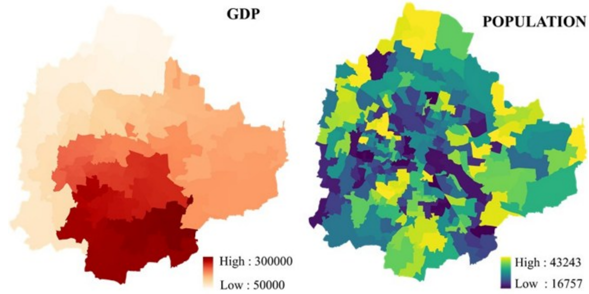

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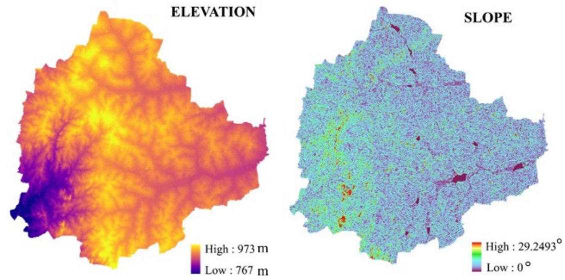

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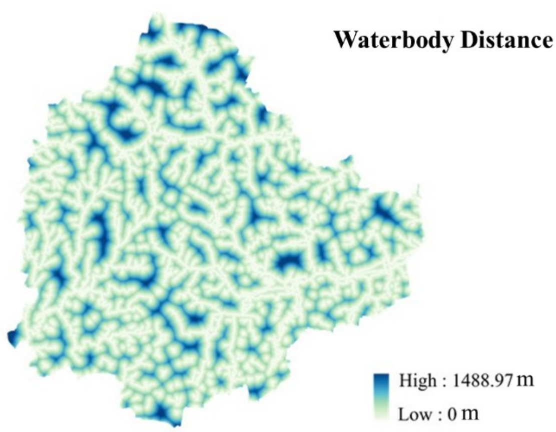


(d)

Figure 2. Key driving factors utilized for land use simulation in the CA-PLUS: (a) proximity of road and settlement, (b)Gross Domestic Product (GDP) and population density, (c)elevation and slope, (d) proximity to water bodies.

3.2 Methodology

3.2.1 Land Use Classification: The multi-temporal Resourcesat-2A (LISS-IV) imagery was preprocessed to classify land use by georeferencing and projecting the datasets to the WGS 84 datum in UTM zone 43 N. Using NIR, red, and green spectral bands, a false color composite (FCC) was generated to increase visually separability of the land use classes. Administrative boundaries were overlaid onto the FCC to define the spatial coverage of the study area, as shown in Figure 4. This preprocessing generated training sets for four primary land use classes: urban, water, and vegetation. Based on heterogeneous spectral reflectance, polygons were digitized to capture the intra-class variability of each land use category. Corresponding class labels were assigned, and the extracted spectral signatures were used to construct the training dataset for classification. Each sample was critically evaluated to ensure high-class purity and minimize spectral confusion, particularly in transitional regions. Subsequently, the Gaussian Maximum Likelihood Classifier (GMLC) was used to classify land use, using a supervised classification technique based on the probability theory of Bayesian statistics. GMLC uses the assumption that a multivariate normal distribution can define the spectral response of each land use type. It deals with each pixel and estimates a probability that its spectral signature belongs to one land use based on a mean vector and a covariance matrix estimated in training data. When the probabilities of classes were not known in advance, equal likelihood is assumed. The pixel is then allocated to the highest probable class, where differentiation is robust even in similar spectra. This is especially effective in classifying heterogeneous and spectrally complex urban landscapes.

3.2.2 Accuracy Assessment: The accuracy of the classified land use maps was evaluated with standard statistical measures based on a confusion matrix, like overall accuracy, kappa coefficient. Three central reference point locations (350 in total) were chosen randomly and evenly deployed in the study area to cover all major classes of land use

3.2.3 Spatial Metrics: This study used spatial metrics to help quantitatively describe land use patterns' spatial arrangement, structure, and temporal characteristics. The zonal analysis was implemented by creating concentric buffers within the central business district (CBD) as the urban center and further dividing each circle into four directional zones, including northwest (NW), northeast (NE), southeast (SE), and southwest (SW), as indicated in Figure 3.

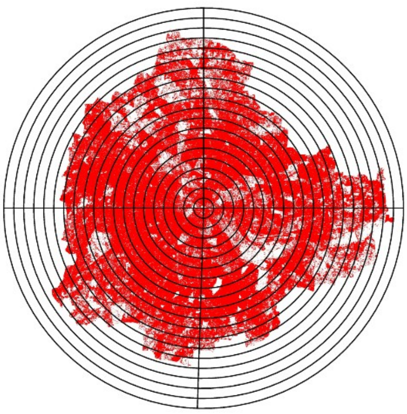


Figure 3. Gradient and Zone-wise Analysis.

Thus, reflecting the directional imbalance of urban growth caused by infrastructure, socio-economic factors, and planning policies (Ramachandra et al., 2014). These metrics were calculated at three analytical levels: patch, class, and landscape. Also, these metrics were divided into functional groups: area and edge measure (edge density); shape complexity measures (e.g., perimeter-area fractal dimension, landscape shape Index); Aggregation and cohesion measures (e.g., patch density, clumpiness, splitting index, adequate mesh size). To deal with these metrics' high dependency and redundancy, Spearman's rank correlation was utilized to select a non-collinear set appropriate for the non-parametric and non-linear relationships. These metrics were classified into five major spatial dimensions: area and aggregation, fragmentation, shape and edge complexity, spatial cohesion, and shape irregularity. A single measure representative of each cluster was retained based on its uniqueness and minimal redundancy, leading to the identification of five priority metrics, namely aggregation index (AI), Land shape index (LSI), Splitting index (SPLIT), Clumpiness (CLUMPY), and Effective Mesh size (MESH) as measures of spatial cohesion, perimeter compelexity, degree of fragmentation, spatial clustering and structural continuity, respectively. The selected metrics collectively provide an integrative, non-overlapping, and thematically comprehensive framework to quantify spatial heterogeneity and morphological changes in urban landscapes over time.

3.2.4 Implementation of Patch-Generating Land Use Simulation (PLUS) Model: The CA-PLUS model was utilized to simulate the future dynamics of land use in Bangalore, incorporating land expansion detection, modelling land suitability, and spatial allocation with three major components: (i) Land expansion extraction, (ii) Land Expansion Analysis Strategy (LEAS), and (iii) Cellular Automata with multi-type random patch Seeds (CARS) (Liang et al., 2021). A land expansion map for a specific time interval was extracted from two phases of land use changes between 2012 and 2023. These maps were provided as input into the LEAS model to simulate the influence of the driving factors on the expansion of each land use type, which were then fed into a random forest regression (RFR) algorithm that estimated the development potential maps of each land use class. The probability of the potential development $\boldsymbol{P_{i,k}^{d}}$ Of cell i and type of land use k is given as:

$$P_{i,k}^{d}(x) = \frac{1}{M}\sum_{n=1}^{M} I\ (h_n\ (x) = d) \qquad (1)$$

Where M denotes the number of decision trees, $h_n(x)$ indicates the n-th tree prediction utilizing the input vector x of driving factors, and I is the indicator function that takes the value 1 when the prediction matches the converted class d, with the remainder of the class k.

In addition to the development potential given by LEAS, the CARS module simulates the spatial pattern of area allocations of different land use types via a patch-based CA process. This method uses random seeding, area-dependent patch thresholds, conversion constraints to achieve spatial realism, and land use demand, transition matrix, and neighbourhood weights were assigned as parameters to the model. The approach for measuring the overall probability (OP) for each land use type is given by:

$$\mathrm{OP}_{i,k}^{d=1,t} = P_{i,k}^{d=1} \times \Omega_{i,k}^{t} \times D_k^t \qquad (2)$$

Where $p_{i,k}^{d=1}$ represents the Potential Development of type *k* and *I*, $\Omega_{i,k}^{t}$ represent the domain effect of land use type *k* influenced by neighbours around unit *I*, and D_k^t represent the impact of future land use demand of type *k,* which depends on the gap between the present amount of land at *t* and the land use target land demand *k*, calculated as:

$$\Omega_{i,k}^{t} = \frac{con\ (C_i^{t-1}=k)}{n \times (\mathrm{n}-1)} \times \omega_k \qquad (3)$$

Where*,* $\Omega_{i,k}^{t}$ depends on the effect of the land use type (ω_k), ($C_i^{t-1} = k$) represent the last iteration and ($n \times n$) represent the neighborhood region (refer to equation 3). The adaptation approach is illustrated below.

$$D_k^t = \begin{cases} D_k^{t-1} & \text{if } \left|G_k^{t-1}\right| \le \left|G_k^t\right| \\ D_k^{t-1} \times \frac{G_k^{t-2}}{G_k^{t-1}} & \text{if } 0 > G_k^{t-2} > G_k^{t-1} \\ D_k^{t-1} \times \frac{G_k^{t-1}}{G_k^{t-2}} & \text{if } G_k^{t-1} > G_k^{t-2} > 0 \end{cases} \qquad (4)$$

Iterations $G_k^{t-1}$and G_k^{t-2} denotes the sum of the difference between the number of land use types k for future demand (refer to equation 4).

Using this Overall probability, the spatial distribution of land use in any iteration is determined. It can be updated and constantly changed to respond to local suitability and global demand. The Markov Chain model estimates future land demand in 2042 based on past transition probabilities to calculate the magnitude of each type of land use required. The CA-PLUS framework sequentially improves the land use structure by incorporating the development potential, neighborhood effects, and demand limit. It also helps simulate land use of a patch at various levels simultaneously and captures complicated spatiotemporal dynamics. Furthermore, the model performance was assessed by comparing actual and simulated land use maps for 2023, with the help of overall accuracy and the kappa coefficient. Assuring both spatial reliability and consistency of simulated results.

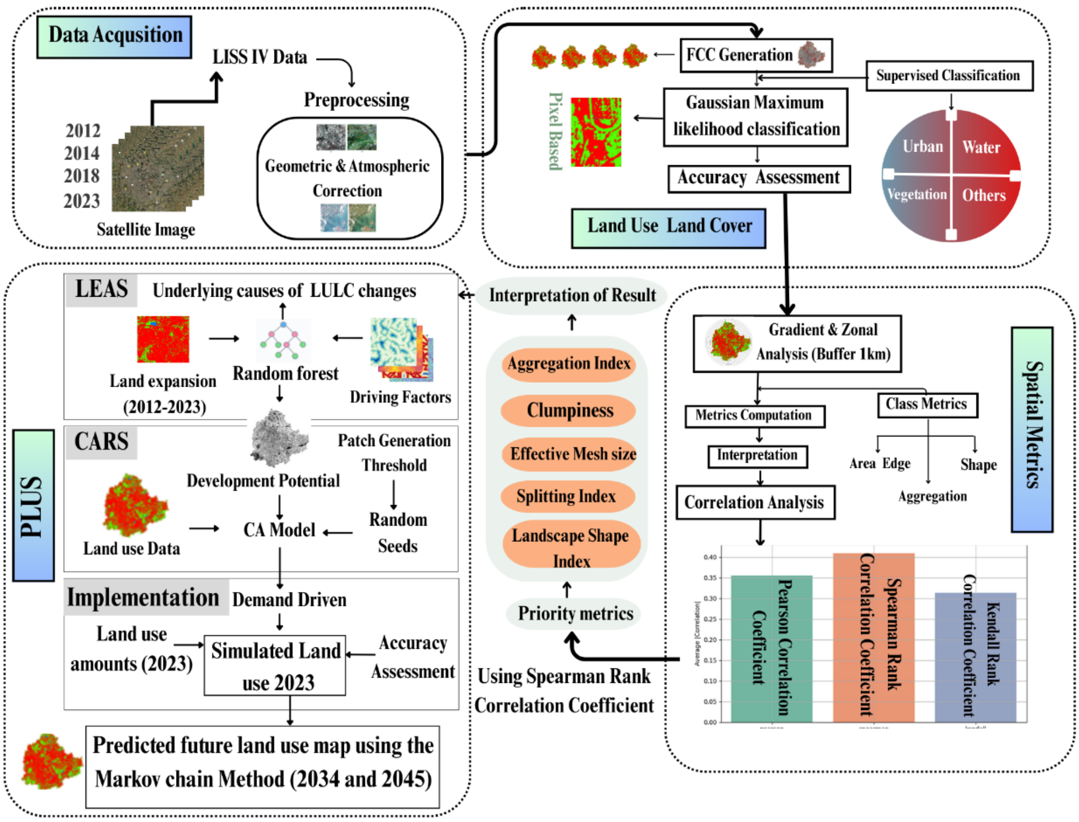


Figure 4. Methodology Framework for Urban Growth Patterns.

Results and Discussion

Land Use Pattern Detection

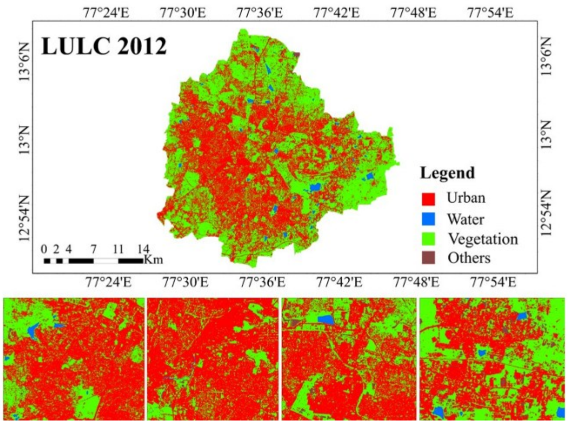
The spatio-temporal LU evaluation of the years (2012, 2014, 2018, and 2023) in Bangalore provides quite an explicit and increasing trend of urban growth and loss of vegetation in the four directional regions, which include NW, SW, SE, and NE, as indicated in Figure 5. In 2012, built-up areas were significantly concentrated in the city centre, with a total area of about 292.89 km^2 (42.81%), whereas the vegetation remained the predominant landscape, occupying 361.17 km^2 (52.79%). The NW and NE zones were predominantly covered with vegetation with no substantial urban development, unlike the SW and SE zones, which have experienced initial urban development along with industrial corridors and near the outer ring road, which reflected early peripheral urban sprawl. By 2014, urban cover increased to 335.48 km^2 (49%), and vegetation declined to 323.87 km^2(47.31%). It was observed that NW experienced incremental growth in residential areas, the SW was characterized by rapid spread of housing and enhanced connectivity, and the SE demonstrated a high growth rate due to the spread of IT hubs. The NE has started transformation under the pressure of expansion by neighbouring commercial hubs and emerging urban infrastructure, which has led to a peri-urban to urban LU structure. Continuing this trend of urban development in 2018, it has increased at a denser level across the entire city, approximately 387.84 km^2 (56.6%), with a corresponding drastic reduction in vegetation cover to 273.60 km^2 (39.97%). In the NW zone, already fragmented settlements were consolidated; the SW had a significant infill development and the loss of scattered green spaces; in the SE, the focus created a compact urban core with high population density. During this time, the NE lost significant vegetation, mainly through activities such as metro expansions and institutional encroachments. This led to an exacerbation of the shift to a built-up form. This trend has been followed up to 2023, where the built-up areas have increased further to 433.81 km^2 (63.40 %), the city's highest level of urbanization. This growth can be characterized by the continued infill and densification of urban centers and gradual encroachment out toward the peri-urban expanses, in line with high-resolution LISS-IV-based urban footprint analysis of Bengaluru (Aithal & Ramachandra, 2016; Sharma et al., 2021). The vegetation further deteriorated to 222.53 km^2 (32.52%), highlighting continued conversion of natural land use to developed areas, as shown in Table 2 (Venkatesh et al., 2020). The remaining green edges of the NW were almost buried in urban patterns, the SW was highly saturated, and the SE and NE were rapidly becoming the most urbanized areas. Conversely, the water bodies were relatively stable over the years (e.g., 1.29% in 2012 and 1.58% in 2023 (Table 3), which the environmental regulations and zoning policies have probably preserved (Kumar et al., 2022). The accuracy evaluation of the GMLC classification reveals a gradual increase from 2012 to 2023, as illustrated in Table 4. The overall accuracy in 2012 was 80.00 % (kappa: 0.70), meaning there was considerable consistency between the classified and reference data. Its precision was stable in 2014 with an accuracy of 80.08% (kappa: 0.71). However, it slightly increased in 2018 to 82.08% (kappa: 0.73) because the classes are now more separated and the quality of training data has improved. In 2023, the most accurate, with an 88.01 % (kappa: 0.81), was achieved, indicating a high classification reliability and the minimum misclassification within the land use class. The metrics emphasize the reliability of the GMLC technique in reflecting the spatio-temporal dynamics of land use patterns, especially the proliferation of built-up areas and the reduction of vegetation cover. Thus, it increases the accuracy of LU across four temporal periods.

Land Use Classes	2012	2014	2018	2023
	Area in sq km	Area in sq km	Area in sq km	Area in sq km
Urban	292.888	335.484	387.844	433.812
Water	8.832	7.872	10.893	10.822
Vegetation	361.166	323.874	273.601	222.532
Others	21.319	17.363	12.219	17.064

Table 2. Temporal land use Statistics in (km^2)

Land Use Classes	2012	2014	2018	2023
	(%)	(%)	(%)	(%)
Urban	42.81	49	56.66	63.40
Water	1.29	1.15	1.59	1.58
Vegetation	52.79	47.31	39.97	32.52
Others	3.12	2.54	1.78	2.49

Table 3: Temporal land use Statistics in (%)



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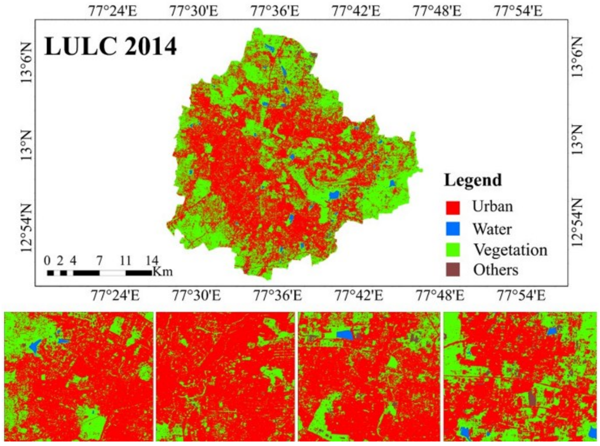

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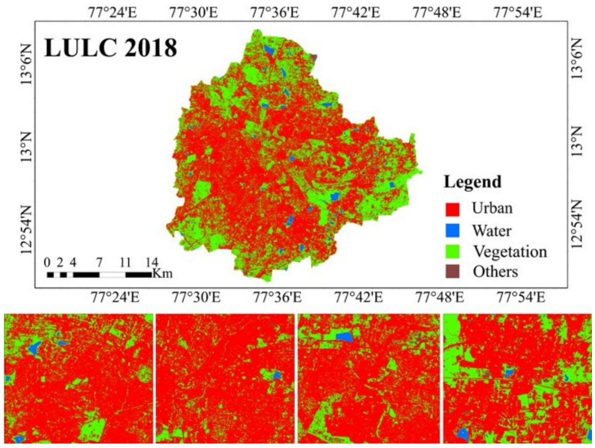

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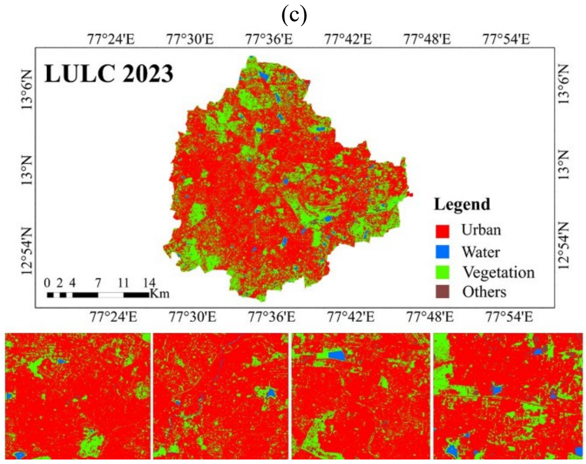

(d)

Figure 5. Land Use maps of Bangalore city represented the view of four directional zones (NW, SW, SE, and NE) (a) 2012, (b) 2014, (c) 2018, and (d) 2023.

Land use Year	Gaussian Maximum Likelihood Classification	
	Overall Accuracy (%)	Kappa
2012	80	0.70
2014	80.08	0.71
2018	82.08	0.73
2023	88.01	0.81

Table 3: Accuracy Assessment

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Spatial Metric Analysis

The spatial measurement of the period from 2012 to 2023 exhibits prominent changes in the urban morphology of Bangalore, characterized by the simultaneous processes of spatial consolidation in the core city and fragmentation of the urban fringe. Prior to the analysis, Spearman's rank correlation indicated the strongest average absolute value on correlation (0.41), which was used to determine non-collinear measures to be utilized in the evaluation process. AI, PLADJ, SPLIT, DIVISION, and PLAND were highly intercorrelated, with the lowest interdependence with NP, LSI, ED, CA, PAFRAC, and CLUMPY, with NLSI and IJI the least intercorrelated. The AI has shown a persistent growth, with higher values of more than 93 in the NE and SE zones, which means an enormous potential in enhancing the spatial integrity of urban land use by 2023. This denotes the consolidation of non-contiguous built-up areas into better-connected and more continuous urban structures defined through the growth of infrastructure connectivity and densification. In line with this trend, CLUMPY increased 0.78 in 2012 to above 0.90 in the NE, NW, and SE, indicating that the degree of spatial dispersion has significantly decreased, resulting in compact and homogenous urban agglomerations as shown in Figure 6. This implies the intensification of urban core regions, with the pattern of development transforming to aggregation with continued infill development and dense residential and commercial developments.

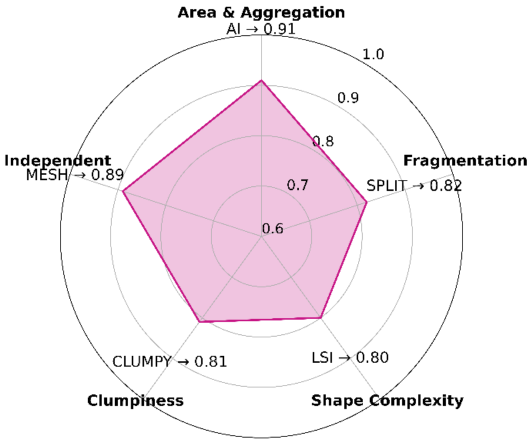

Figure 6. Gradient and Zonal Analysis.

Conversely, the SPLIT metric exhibited significantly increased values, especially in the case of NE and SW, which implies ongoing fragmentation of land into smaller, disconnected spatial units, reflecting the continual fragmentation pressure at the urban expansion. Such spatial disintegration reflects uncontrolled edge growth, in which informal settlements, peri-urban sprawl, and unregulated growth precede planned zoning regulation and infrastructure. Complementing this shift, the LSI exceeded 35 ha in the NE, NW, and SE, measuring urban patch edges' geometric complexity and irregularity. These discontinuous morphologies have been generally linked to infrastructure-driven and non-linear encroachment and fragmented land conversion at the urban edges, which implies a pattern of organic growth that is not compact and planned urban development. Additionally, the most profound change was demonstrated in the MESH, which increased from (< 30ha) in 2012 to (> 90 ha) in 2023 in the NW and SE zones. This growth represents a high degree of land concentration in urban areas, with previously fragmented patches developing into large, uninterrupted blocks of urban land, providing enhanced spatial continuity and land use efficiency. These changes have been commonly linked to intense activity development corridors and strategic zoning involving large-scale integrated developments. Collectively, these trends in metrics, taken as a combination, characterize a spatially imbalanced city building plan of action- in-filled densification in core areas supported by policy-driven compaction and deployment in infrastructure, and outward subdivision in the periphery, a result of decentralized growth and poor land-use management. Such spatial processes provide vital information on the disproportional structural change of Bangalore, and this aspect is pertinent to future urban sustainability, planning interventions, and the potential resilience of the landscape.

Simulation-Based Assessment of Urban Expansion

In order to evaluate the measure and predict the spatial development of Bangalore's urban structure, the CA-PLUS simulation model with land use data from 2012 to 2018 was implemented to calibrate the data for 2023. The calibration was employed to produce landscape forecasts for 2036 and 2042, which provide explicit information about the future dynamics of urban expansion and projected land use configuration over time. The model was validated against the classified land use map (2023), reaching an overall accuracy of approximately 88.01% (kappa: 0.81). To support the correctness of the CA-PLUS model, a simulated map of land use in 2023 was tested and compared to the actual land use. The validation outcomes showed high accuracy with user accuracy of 0.88, producer accuracy of 0.97, and a figure of merit (FoM) of 0.86, which indicates that the model is highly efficient in predicting the existing land use change. To examine further the spatial dynamics derived from the model, Figure 8 demonstrates the development potential maps concerning key land use classes during the transition period of 2012 and 2018. Such maps define the geographical probability of change according to past trends and socio-economic dynamics. It is also notable that regions of high development potential have been focused along the urban periphery, especially those with low planning implementation and land parcels that are easily serviced. This spatial agglomeration of development hotspots indicates growing pressure on vegetated and low-density areas. In order to further explain the socio-economic factors leading to these transitions, the LEAS model was employed. The analysis identified that the most significant factors that led to urban growth were population density (influence score: 0.20) and GDP (influence score: 0.80), as illustrated in Figure 7. These are key influential metrics of anthropogenic pressure, as rising population density directly increases the residential and infrastructure land use. In contrast, GDP growth represents the expansion of economic activity, which leads to commercial and industrial land transformations. Spatial transformation in these fringe areas, where regulatory land-use controls are insufficiently enforced, permits unplanned development of accessible parcels in response to demographic expansion and intensifying urban pressures. The absolute growth of urban areas is projected to increase by 43,381.15 ha from 2023 to 48,698.1 ha in 2036 and eventually achieve 49705.8 ha by 2042. This acceleration in the development of built-up land is associated with a substantial decline in vegetation cover, which is estimated to decrease from 25.97% in 2036 to 24.58% in 2042, as compared to 32.58% in 2023, as shown in Figure 9. These changes highlight a significant trade-off between city growth and preservation of natural resources. The high decline in the vegetative land use shows how urban development is taking place at the detriment of the green infrastructure. Such a city-wide shift in land use trends requires long-term, ecosystem-specific planning initiatives to support a resilient environmental condition, streamline spatial development, and limit unplanned urban sprawl through the Bangalore metropolitan area. Specifically, the CA-PLUS was forecasted to have a distinct spatial configuration of land use, in which built-up areas became more spatially cohesive rather than dispersed by 2042. At the same time, the simulated exhibits a marked loss of vegetative cover and open land, which reflects decreased ecological connectivity and increased environmental uncertainty.

Conclusion

This study extensively evaluates Bangalore's spatio-temporal urban transformation from 2012 to 2023, including projections of land use changes by 2042 using high-resolution classification, spatial metrics, and CA-PLUS simulation modelling. The results indicate that built-up areas have significantly increased primarily due to decreased vegetation cover, particularly in peri-urban areas with fewer regulations. The spatial metrics reveal competing densification trends in urban cores and fragmentation at the edges, suggesting an uneven and structurally unbalanced growth trajectory. The CA-PLUS model had high simulation accuracy, producing transitions from poorer states of fragmented patches and spatially aggregated forms. It also identified key anthropogenic drivers of population density and GDP, causing land transformation. The projected development potential maps highlight the implications of ecological assets from unplanned urban growth.

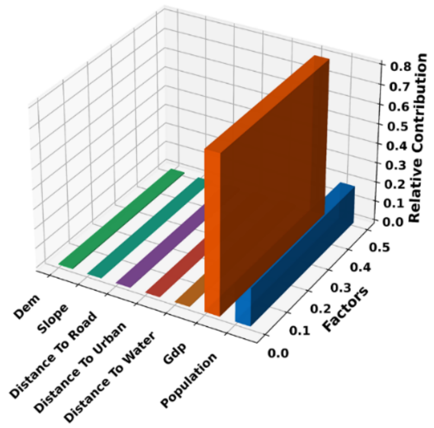

Figure 7. Relative Influence of Socio-Economic Drivers on Simulated Urban Expansion.

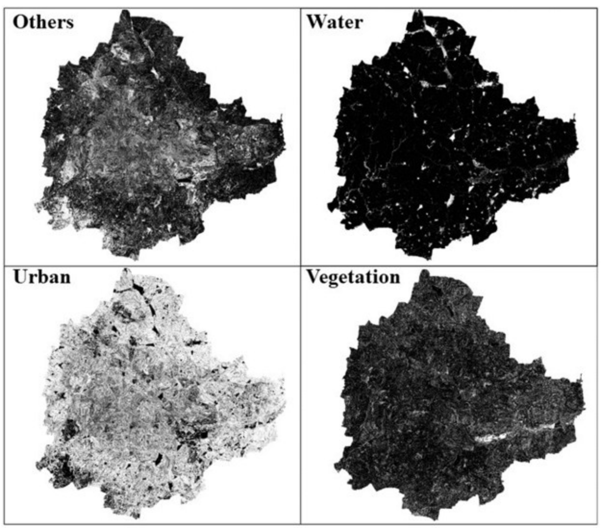

Figure 8. Development Potential maps (band-wise) for each land use class for 2012- 2018

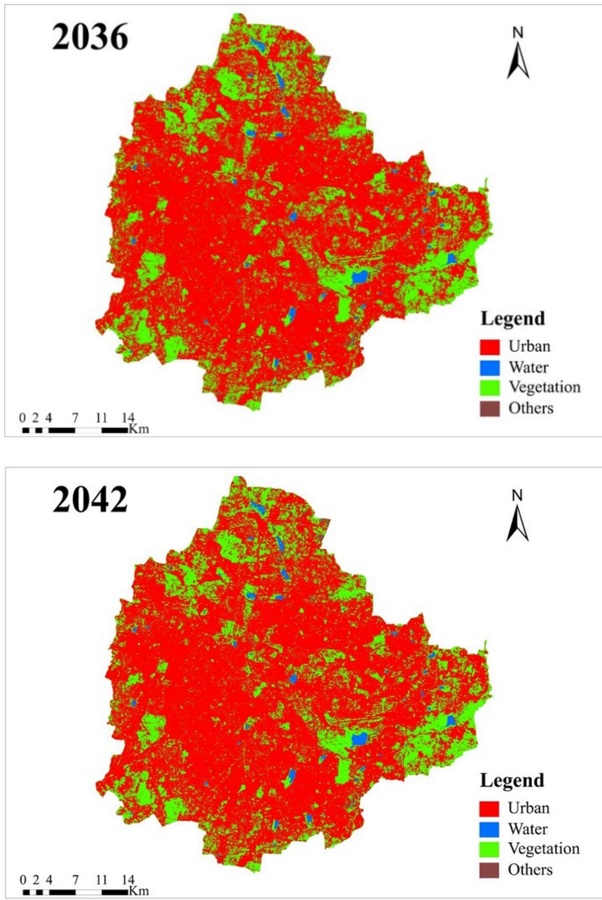

Figure 9. Simulated land use map using the PLUS Model for 2036 and 2042

Land Use Classes	Actual Land Use (%)	CA-PLUS Markov Chain Model (%)		
	2023	2023	2036	2042
Urban	63.40	64.75	71.77	73.26
Water	1.58	1.05	1.05	1.05
Vegetation	32.52	32.58	25.96	24.58
Others	2.49	1.62	1.21	1.11

Table 4.Simulated Land Use Area Statistics using CA

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