Engineering

E-ISSN No : 2581-6195 | Volume : 9 | Special Issue | May 2026

PREDICTIVE MODELING OF URBAN SPRAWL USING QGIS SOFTWARE: A CASE STUDY OF CHANDAPURA, BANGALORE

***Shaamlie Devi T R[1], Maithili K L[1], Prema T[2], Saran[3]**

[1] Assistant Professor, Civil Engineering, AMC Engineering College, Bengaluru, India
[2] Associate Professor, Civil Engineering, AMC Engineering College, Bengaluru, India
[3] Final Year Student, Civil Engineering, AMC Engineering College, Bengaluru, India

ABSTRACT

Urban sprawl—the unplanned and uncontrolled expansion of urban areas—poses significant challenges to sustainable development, infrastructure planning, and environmental management. This paper presents a study on predictive modeling of urban growth in the Chandapura suburban region of Bangalore using open-source geospatial tools. By integrating multi-temporal Landsat satellite imagery (2015 and 2025) with the MOLUSCE (Modules for Land Use Change Evaluation) plugin in QGIS, the study employs change detection analysis, Artificial Neural Network (ANN)-based transition potential modeling, and Cellular Automata (CA) simulation to forecast future Land Use/Land Cover (LULC) patterns. The results reveal significant built-up area expansion along transport corridors, declining vegetation cover, and emerging growth hotspots. Findings support evidence-based policy recommendations including urban growth boundaries, green belt protection, and transit-oriented development to promote sustainable and compact urban growth.

KEYWORDS: Urban Sprawl, QGIS, MOLUSCE Plugin, Cellular Automata, LULC, Remote Sensing, Predictive Modeling, Land Use Change, Bangalore, Chandapura

How to Cite:
Shaamlie Devi T R, Maithili K L, Prema T & Saran (2026), Predictive Modeling of Urban Sprawl Using Qgis Software: A Case Study of Chandapura, Bangalore, International Educational Journal of Science & Engineering (IEJSE),Vol: 9, Special Issue, May 2026 499-503

I. INTRODUCTION

Urban sprawl refers to the unplanned, uncontrolled, and low-density expansion of urban areas into the surrounding rural or semi-rural landscape. Rapid urbanization in developing nations has intensified sprawl, leading to adverse consequences including loss of agricultural and forest land, degradation of ecosystems, increased infrastructure costs, and challenges to sustainable governance [1]. Cities across South Asia, particularly in India, have experienced extraordinary spatial growth over the last two decades, driven by population pressure, economic growth, and inadequate urban planning frameworks [2].

Bangalore, one of India's fastest-growing metropolitan cities, has witnessed exponential urban expansion in its peripheral regions. The Chandapura zone, located in the southeastern suburban corridor along the Hosur Road and Chandapura–Anekal Road, exemplifies this rapid transformation. Historically a semi-rural agricultural area, Chandapura has experienced dramatic land-use conversion driven by proximity to industrial estates, information technology corridors, and growing residential demand [3].

The ability to forecast urban growth using geospatial modeling tools has emerged as a key instrument for urban planners and decision-makers. Geographic Information Systems (GIS) and remote sensing have proven to be powerful platforms for monitoring, analyzing, and simulating spatial changes in land cover [4]. Among predictive modeling approaches, Cellular Automata (CA) models have gained prominence due to their capacity to simulate complex spatial dynamics through simple local interaction rules [5].

Research Paper

When combined with machine learning algorithms such as Artificial Neural Networks (ANN), CA-based models offer high predictive accuracy and spatial fidelity [6].

The MOLUSCE plugin, an open-source extension for QGIS, integrates change detection, correlation analysis, transition potential modeling, and Cellular Automata simulation in a unified workflow [7]. This tool provides an accessible, cost-effective alternative to commercial software for LULC change prediction, making it suitable for academic and planning applications.

Previous studies have applied similar approaches in diverse global contexts. Mohammady (2016) demonstrated CA-based urban growth modeling in Tehran using Landsat imagery [8]. Islam (2023) employed remote sensing data to forecast sprawl in Sylhet, Bangladesh, finding strong alignment between predicted and observed growth [9]. Tavares (2025) examined the socio-spatial consequences of sprawl in Brazilian cities and emphasized the need for regulatory interventions [10]. While such studies validate the methodology, localized case studies are essential due to region-specific land-use dynamics, cultural patterns, and planning frameworks.

This paper addresses the gap by presenting a comprehensive GIS-based predictive study for the Chandapura region. The objectives of this study are: (i) to analyze historical LULC changes between 2015 and 2025; (ii) to model urban growth transition potential using ANN within the MOLUSCE environment; (iii) to simulate future LULC scenarios using Cellular Automata; and (iv) to develop evidence-based policy recommendations for sustainable urban planning.

II. MATERIALS AND METHODS

A. Study Area

The study area encompasses the Chandapura region located in the southeastern suburban fringe of Bangalore, Karnataka, India. Situated along the Chandapura–Anekal Road and Hosur Road transport corridors, this zone has undergone rapid urban transformation owing to its strategic proximity to Electronic City, industrial estates, and expanding residential developments. The study area coordinates fall approximately within 12°50'N to 12°56'N latitude and 77°38'E to 77°44'E longitude.

B. Data Collection

Multi-temporal satellite data were acquired from the USGS Earth Explorer platform. Landsat 8 Operational Land Imager (OLI) imagery for the years 2015 and 2025 was used as the primary data source. Images were selected based on minimal cloud cover (< 10%) and consistent seasonal conditions to reduce atmospheric variability. Ancillary spatial data including administrative shapefiles, road network layers, and population statistics were obtained from the Bruhat Bengaluru Mahanagara Palike (BBMP) and Census of India records.

C. Data Pre-Processing

All imagery was pre-processed in QGIS 3.x to ensure radiometric correction, geometric alignment, and coordinate system standardization (WGS 84, Zone 43N). A supervised classification technique was applied using the Semi-Automatic Classification Plugin (SCP) to generate LULC maps for both epochs. The land-use classification scheme comprised five classes: Built-up, Vegetation, Open Land, Agriculture, and Water Bodies. Band compositing was performed using standard band combinations: True Colour (Band 4-3-2), False Colour Vegetation (Band 5-4-3), and Urban/Built-up view (Band 7-6-4) as detailed in Table I.

Table I: Landsat 8 Band Combination Summary

View Type	Red Channel	Green Channel	Blue Channel	Purpose
True Colour (Natural)	Band 4	Band 3	Band 2	Natural visual appearance
False Colour Vegetation	Band 5	Band 4	Band 3	Highlights healthy vegetation
Urban / Built-up	Band 7	Band 6	Band 4	Identifies built-up surfaces
Agriculture / Vegetation Health	Band 6	Band 5	Band 2	Crop and vegetation health
Geology / Minerals	Band 7	Band 5	Band 3	Rock and soil variation

D. MOLUSCE Plugin Framework

The MOLUSCE plugin for QGIS was employed as the primary modeling environment. The plugin provides an integrated workflow comprising four analytical stages: (i) Change Detection Analysis, (ii) Correlation

Analysis of Driving Factors, (iii) Transition Potential Modeling using ANN, and (iv) Cellular Automata Simulation. The LULC rasters from 2015 and 2025 were input as base and reference layers respectively. Driving factors for model calibration included: proximity to built-up areas, distance to major road networks, slope derived from SRTM DEM, and population density layers.

E. Transition Potential Modeling

An Artificial Neural Network (ANN) with a multi-layer perceptron architecture was used to learn the spatial patterns of LULC transitions between 2015 and 2025. The ANN was trained on transition matrices derived from the change detection module. The Neural Network Learning Curve was monitored to assess model convergence and avoid overfitting. Training iterations were continued until the error function reached a stable minimum, confirming model readiness for spatial extrapolation. Resulting transition potential maps provided pixel-wise probability scores for each land-use class conversion.

F. Cellular Automata Simulation and Validation

Cellular Automata (CA) simulation was applied to project future LULC scenarios using the trained transition potential maps. The CA model operated on a neighbourhood configuration where each cell's future state was determined by its current state and the spatial conditions of surrounding cells. Multiple simulation iterations were executed to produce a predicted LULC map representing the urban footprint for the projected period. Model validation was performed using the Kappa Index and Fuzzy Similarity metrics by comparing the simulated 2025 LULC output against the actual 2025 reference map.

III. RESULTS

A. LULC Change Detection (2015–2025)

The change detection analysis revealed substantial LULC transformation in the Chandapura region over the ten-year study period. Built-up areas exhibited significant expansion, particularly in the northwestern and central zones, driven by residential and commercial development. Vegetation cover declined considerably due to urban encroachment at settlement boundaries. Open and agricultural land parcels showed progressive conversion into built-up uses. Water bodies remained relatively stable but showed minor encroachment at peripheral extents. Table II summarizes the estimated LULC class distribution for 2015 and 2025.

Table II: LULC Class Distribution – 2015 and 2025 Comparison

LULC Class	Area 2015 (%)	Area 2025 (%)	Change (%)
Built-up	28.4	46.7	+18.3
Vegetation	34.2	20.8	-13.4
Open Land	22.5	17.1	-5.4
Agriculture	12.6	13.2	-1.9 (approx.)
Water Bodies	2.3	2.2	-0.1

B. Transition Potential Modeling Results

The ANN-based transition potential model successfully converged after training, as evidenced by the stabilization of the Neural Network Learning Curve. Transition probability maps indicated that regions adjacent to the Chandapura–Anekal Road and Hosur Road corridors exhibited the highest built-up transition potential, consistent with observed growth trends. Areas with steep terrain or existing dense vegetation showed low conversion probability, confirming model sensitivity to physical constraints. The model demonstrated an overall training accuracy exceeding 85%, with the Kappa Index for simulated versus actual 2025 LULC maps indicating strong agreement.

C. Cellular Automata Simulation Outputs

The CA simulation generated a predictive LULC map for the future planning horizon. Key spatial patterns emerging from the simulation include: (i) ribbon development extending along primary transport corridors, (ii) clustered expansion around existing residential nodes, (iii) leapfrog development in peripheral semi-urban zones, and (iv) encroachment into current vegetation and open land areas. Table III presents the model performance validation metrics.

Table III: Model Validation Metrics

Validation Metric	Value	Interpretation
Overall Classification Accuracy	> 85%	Good model performance
Kappa Coefficient	> 0.78	Strong spatial agreement
Fuzzy Similarity Index	High	Realistic spatial pattern replication
ANN Training Error (final)	< 0.05	Converged, no overfitting observed

IV. DISCUSSION

The results of this study confirm that the Chandapura region is undergoing rapid and spatially extensive urban transformation driven primarily by its proximity to major employment centers, transport infrastructure, and the broader metropolitan influence of Bangalore. The 18.3 percentage-point increase in built-up area between 2015 and 2025 aligns with documented trends of peri-urban sprawl in South Asian cities [11][12], where outer suburban zones absorb the overspill of metropolitan growth under conditions of inadequate land-use regulation.

The dominance of ribbon development patterns along the Chandapura–Anekal and Hosur Road corridors is consistent with findings from Ansar & de Vries (2024), who observed similar transport-led sprawl dynamics in Indonesian suburban areas [13]. The strong correlation between proximity to road networks and high transition potential supports the established urban growth theory that infrastructure provision acts as a primary catalyst for peri-urban land conversion [14]. The linear spread observed in Chandapura also reflects the concentrated investment in road-side commercial and residential development typical of areas lacking urban growth boundaries.

The declining vegetation cover identified in this study — a 13.4% reduction between 2015 and 2025 — has significant environmental implications. Fragmentation of green patches near settlement edges increases exposure to urban heat island effects, reduces biodiversity connectivity, and diminishes the ecological services provided by vegetative buffers [15]. The spatial concentration of vegetation loss near built-up expansion fronts suggests that without regulatory intervention, the remaining green cover will continue to erode in future growth cycles. This observation is consistent with findings by Saouli (2021), who documented similar vegetation degradation under sprawl conditions in the Annaba metropolitan area [16].

The effectiveness of the MOLUSCE-based CA-ANN approach in replicating observed spatial growth patterns validates its applicability for planning-oriented studies. The Kappa coefficient exceeding 0.78 indicates strong predictive agreement with actual LULC observations, comparable to accuracy levels reported in similar regional studies [8][9]. The method's reliance entirely on open-source tools (QGIS, MOLUSCE, SCP) makes it particularly appropriate for resource-constrained urban planning agencies in developing countries, where access to commercial modeling software may be limited.

One limitation of the current study is the reliance on pixel-based supervised classification, which may introduce class confusion between spectrally similar land-cover types such as open land and fallow agricultural areas. Future work should incorporate object-based image analysis (OBIA) and higher-resolution satellite data such as Sentinel-2 to improve classification accuracy. Additionally, the integration of socioeconomic variables — including household income distribution, property values, and employment accessibility indices — as additional driving factors would enhance the explanatory power of the transition potential model [17].

V. CONCLUSIONS

This study presents a robust, GIS-based predictive framework for analyzing and forecasting urban sprawl in the Chandapura suburban region of Bangalore using freely available satellite imagery and open-source QGIS tools. The key findings demonstrate that the region experienced substantial built-up area expansion and concurrent vegetation loss between 2015 and 2025, with growth strongly aligned along major transport corridors. The MOLUSCE-based CA-ANN model successfully captured these spatial dynamics and produced validated predictive LULC maps that identify future high-growth zones.

Based on the predictive analysis, the following planning interventions are recommended: (i) establishment of defined urban growth boundaries to contain outward sprawl; (ii) declaration of remaining vegetation patches as eco-sensitive conservation zones; (iii) promotion of transit-oriented development and compact vertical growth; (iv) periodic remote sensing-based monitoring of LULC changes to enable adaptive planning; and (v) integration of scientifically derived LULC predictions into municipal master planning frameworks.

The methodology presented is transferable to other rapidly urbanizing regions in South Asia and other developing contexts, offering a scalable, cost-effective tool for evidence-based urban governance.

VII. REFERENCES

1. United Nations Human Settlements Programme (UN-Habitat), 'World Cities Report 2022: Envisioning the Future of Cities,' Nairobi: UN-Habitat, 2022.
2. A. Shaw and M. K. Satish, "Metropolitan restructuring in post-liberalized India: Separate towns for the rich, Environment and Urbanization, vol. 19, no. 1, pp. 33–55, 2007.
3. Government of Karnataka, "Revised Master Plan 2031 for Bruhat Bengaluru Mahanagara Palike, Bangalore: BBMP, 2015.
4. P. A. Longley, M. F. Goodchild, D. J. Maguire, and D. W. Rhind, Geographic Information Systems and Science. Chichester: Wiley, 2015.
5. K. C. Clarke and L. Gaydos, "Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore, International Journal of Geographical Information Science, vol. 12, no. 7, pp. 699–714, 1998.
6. X. Li and A. G.-O. Yeh, "Neural-network-based cellular automata for simulating multiple land use changes using GIS, International Journal of Geographical Information Science, vol. 16, no. 4, pp. 323–343, 2002.
7. A. Samusev, "MOLUSCE Plugin: Modules for Land Use Change Evaluation in QGIS, NEXTGIS, Technical Documentation, 2015.
8. S. Mohammady and M. Delavar, "Urban sprawl assessment and modelling using Landsat images and GIS, Modeling Earth Systems and Environment, vol. 2, no. 3, pp. 1–10, 2016.
9. M. A. Islam, "Modelling and forecasting urban sprawl in Sylhet Sadar using remote sensing data, Applied Geomatics, vol. 15, pp. 521–537, 2023.
10. J. Tavares, "Urban sprawl and transformations in the urban fabric: contemporary challenges for Brazilian cities, Urban Science, vol. 9, no. 2, pp. 45–63, 2025.
11. A. Shuaibu, "Urban sprawl pattern and its implications for urban management: Zaria Urban Area, Nigeria, African Geographical Review, vol. 41, no. 4, pp. 398–415, 2022.
12. A. Adhikari and B. T. K. Ghosh, "Urban sprawl in Rangpur City Corporation from 2003 to 2023: a spatiotemporal exploration using geospatial techniques, Urban Climate, vol. 54, p. 101826, 2025.
13. Z. Ansar and W. T. de Vries, "Urban sprawl symptoms in Bandar Lampung suburban area, Indonesia, Land Use Policy, vol. 138, p. 107032, 2024.
14. E. L. Glaeser and M. E. Kahn, "Sprawl and urban growth, Handbook of Regional and Urban Economics, vol. 4, pp. 2481–2527, 2004.
15. K. McGarigal, A. Compton, E. Plunkett, W. Deluca, J. Grand, E. Ene, and S. D. Jackson, "A landscape index of ecological integrity to inform landscape conservation, Landscape Ecology, vol. 33, pp. 1029–1048, 2018.
16. R. A. Saouli, "Modelling the urban sprawl effect on vegetation cover in Annaba, Remote Sensing Applications: Society and Environment, vol. 23, p. 100548, 2021.
17. G. Fordjour and J. Anthony, "Urban sprawl in sub-Saharan Africa: a case study of the Greater Kumasi Metropolitan Area, Ghana, Cities, vol. 148, p. 104869, 2025.
18. N. Hildebrand and S. Kummer, "Exploring urban environment heterogeneity: impact of urban sprawl on charging infrastructure demand over time, Sustainability, vol. 16, no. 4, p. 1523, 2024.
19. M. Hajilou, "Identifying the financial and economic consequences of urban sprawl on urban management, Journal of Urban Management, vol. 12, no. 3, pp. 211–224, 2023.
20. M. Muwafaq, "Cities urban resilience in the face of urban sprawl challenges, IOP Conference Series: Earth and Environmental Science, vol. 1006, p. 012004, 2022.
21. T. Yu, X. Liao, and S. Yang, "Unearthing the impact of urban sprawl on transport carbon dioxide emissions: fresh evidence from 274 Chinese cities, Environment International, vol. 185, p. 108538, 2024.
22. M. Schaffert, C. Sahinkaya, and C. Wolff, "Visualizing urban sprawl to raise local awareness, Urban Informatics, vol. 4, no. 1, pp. 1–14, 2025.
23. P. Rizkiya, N. Haikal, and Z. Hasan, "Urban sprawl typology and the urban growth pattern, E3S Web of Conferences, vol. 371, p. 03009, 2023.
24. K. McGarigal and E. B. Plunkett, "Modelling non-stationary urban growth: the SPRAWL model and the ecological impacts of development, Landscape and Urban Planning, vol. 177, pp. 179–190, 2018.
25. E. F. Lambin, H. J. Geist, and E. Lepers, "Dynamics of land-use and land-cover change in tropical regions, Annual Review of Environment and Resources, vol. 28, pp. 205–241, 2003.