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RESEARCH ARTICLE

Modelling Future Urban Growth in Ibadan Metropolis Using CA-Markov and Geospatial Techniques.

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Abstract

Ibadan Metropolis, the largest city by geographical area in sub-Saharan Africa and the third most populous in Nigeria, is experiencing rapid, largely unregulated urban expansion that threatens environmental sustainability, infrastructure integrity, and social equity. This study models future urban growth in Ibadan for 2034 using the Cellular Automata–Markov (CA-Markov) framework, implemented via the MOLUSCE plugin in QGIS, and calibrated with multi-temporal Landsat imagery acquired in 2004, 2014, and 2024 at 30-metre resolution. Supervised classification using the maximum likelihood algorithm identified four land cover classes, built-up, vegetation, bare land, and water body, across the study area of approximately 13,592 hectares. Classification accuracy, validated through the Kappa coefficient, yielded values of 0.66 (2004), 0.77 (2014), and 0.84 (2024), indicating good to very good agreement. Historical results reveal that built-up land expanded from 5,109 ha (38.03%) in 2004 to 10,948 ha (80.55%) in 2024, an increase of 111.8% over twenty years, while vegetation declined by 61.8% and bare land by 76.7%. The Urban Expansion Intensity Index (UEII) rose from 0.98% per annum (2004–2014, medium speed) to 1.12% per annum (2014–2024, high speed), confirming the acceleration of urbanization. Shannon entropy analysis showed a decline from 0.837 (2004) to 0.434 (2024) in relative entropy, indicating a transition from a dispersed to an increasingly compact urban form driven by land scarcity and infill pressure. CA-Markov projections for 2034 forecast built-up areas expanding to 13,295 ha, while vegetation and bare land are projected to decline catastrophically to 270 ha and 25 ha, respectively, with water bodies facing near-complete disappearance. These findings underscore the urgency of integrating geospatial monitoring systems, evidence-based land use master plans, and predictive modelling into metropolitan governance frameworks to achieve sustainable urban development in Ibadan and analogous African cities.

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1. INTRODUCTION

Sub-Saharan Africa is experiencing the most rapid pace of urbanization in the world. Projections indicate that the urban population in the region will be more than double by 2050, placing extraordinary pressure on land resources, physical infrastructure, and governance frameworks (United Nations, 2022). Within this context of accelerating urban transformation, Ibadan Metropolis represents one of the most consequential yet analytically underserved case studies on the continent. As the largest city by geographical extent in sub-Saharan Africa, Ibadan has undergone sustained and substantial spatial expansion since the colonial era, growing from a predominantly Yoruba settlement occupying approximately 103.8 km² in 1952 to an estimated 400 km² by 2000, with documented continued expansion into surrounding Local Government Areas (LGAs) in subsequent decades (Areola, 1994; Adelekan et al., 2021). This trajectory of growth has fundamentally reshaped the spatial structure of the city, the ecological footprint, and the socioeconomic geography.

The consequences of unregulated urban expansion in Ibadan have been well documented and are severe. The proliferation of informal settlements in environmentally hazardous locations, chronic deficits in water supply, sanitation, and transportation infrastructure, progressive loss of agricultural land and natural vegetation cover, mounting vulnerability to climate-related hazards, and deepening spatial inequalities collectively characterise the urban development challenge confronting the metropolis (Agbola *et al.,* 2012; Coker *et al.,* 2021; Adeyemi *et al.,* 2024). The August 2011 Ogunpa River flood, which resulted in over one hundred fatalities, is a defining illustration of the catastrophic human cost of uncontrolled encroachment into ecologically sensitive riparian zones (Agbola *et al.,* 2012). Despite the scale and urgency of these challenges, formal planning responses in Ibadan have remained fragmented, chronically under-resourced, and insufficiently informed by spatially explicit evidence. This disconnects between urban growth dynamics and planning capacity underscores the critical need for robust, data-driven analytical frameworks capable of both diagnosing historical land use change and projecting credible future spatial scenarios.

Geospatial technologies, principally remote sensing, Geographic Information Systems (GIS), and spatial simulation modelling, have demonstrated considerable analytical utility in characterising urban growth trajectories in rapidly expanding cities across the Global South (Aburas *et al.,* 2021; Henderson & Turner, 2020). Among the available modelling frameworks, the Cellular Automata–Markov (CA-Markov) model has emerged as a methodologically robust and widely validated approach for simulating urban land use/land cover (LULC) change. By integrating the spatial neighbourhood dynamics of Cellular Automata with transition probability matrices derived from historical land cover data through Markov chain analysis, CA-Markov enables dynamic, spatially explicit simulation of future urban expansion under business-as-usual conditions (Aburas *et al.,* 2021; Elangovan & Krishnaraaju, 2023). The model has been successfully applied across comparable urban contexts in sub-Saharan Africa, including Lagos (Makinde & Oyelade, 2022), Kaduna (Usman *et al.,* 2024), and Addis Ababa (Girma *et al.,* 2020), consistently demonstrating high predictive validity when calibrated against multi-temporal satellite data.

In the Ibadan context specifically, prior studies have documented the progressive conversion of peri-urban agricultural land to built-up uses (Oyeleke & Chukwujindu, 2021; Adebayo *et al.,* 2023), and systematic reviews have identified CA-Markov as among the most frequently employed and validated predictive frameworks in Nigerian urban land change research (Akinbobola *et al.,* 2024). However, these studies collectively exhibit three significant limitations that constrain their policy relevance. First, none extends their predictive horizons beyond 2024, leaving future spatial trajectories for Ibadan analytically uncharted at a moment of intensifying urban pressure. Second, existing work has not integrated complementary intensity-based metrics, specifically the Urban Expansion Intensity Index (UEII) and Shannon entropy analysis with CA-Markov simulation, thereby limiting the capacity to assess the pace, magnitude, and spatial character of urban growth within a unified methodological framework. Third, the analytical coverage of multi-decadal change spanning the 2004–2024 period, which encompasses critical phases of peri-urban transformation in Ibadan, remains incomplete in the published literature.

This study addresses these gaps directly. Using multi-temporal Landsat satellite imagery spanning 2004 to 2024, this paper applies a CA-Markov modelling framework, implemented via the MOLUSCE plugin in QGIS, to simulate LULC patterns for Ibadan Metropolis in 2034. This predictive analysis is embedded within a comprehensive methodological suite comprising supervised image classification, UEII computation, and Shannon entropy analysis, enabling an integrated account of the pace, intensity, spatial structure, and future trajectory of urbanization in Ibadan over twenty years. The findings are intended to provide spatially explicit, empirically grounded evidence to inform urban planning, land use governance, and environmental management in one of sub-Saharan Africa's most rapidly evolving metropolitan regions.

2. MATERIALS AND METHODS

2.1 Study Area

Ibadan, the capital of Oyo State, Nigeria, is geographically situated in the southwestern region of the country between latitudes 7° 22' and 7° 30', and longitudes 3° 50' and 4° 00'. Located approximately 128 km northeast of Lagos and 530 km southwest of Abuja, Ibadan stands as the largest indigenous metropolis in West Africa by spatial extent, encompassing a total regional administrative area of 3,080km. Demographically, it stands as Nigeria's third most populous urban agglomeration, with a core metropolitan population estimated at 3.64 million in 2021 and a wider metropolitan footprint exceeding six million inhabitants (Adelekan *et al.,* 2024). Topographically, the city occupies a predominantly undulating lowland terrain punctuated by prominent granitic inselbergs. The hydrologic network is driven by three primary channels, the Ogunpa, Ona, and Ogbere rivers, which converge within a terrain highly susceptible to severe flash flooding when natural drainage pathways are constrained by anthropogenic development.

The spatial morphology of Ibadan exhibits structural characteristics typical of rapidly expanding metropolises in developing economies. This includes unregulated, population-driven horizontal expansion that consistently outpaces formal spatial planning and development controls, giving rise to sprawling informal settlements in ecologically sensitive zones. This rapid landscape modification is further complicated by institutional fragmentation among planning authorities and a distinct dual morphology featuring a high-density historic core contrasted against a rapidly sprawling peri-urban fringe (Coker *et al.,* 2021; Adeyemi *et al.,* 2024).

Administratively, the metropolitan structure comprises eleven Local Government Areas (LGAs), divided into five core urban units, namely, Ibadan North, Ibadan North-East, Ibadan North-West, Ibadan South-East, and Ibadan South-West, and six peripheral LGAs. Although the five urban LGAs form a statutory administrative boundary spanning approximately 463.33km (46,333 ha), this legal delineation does not align with the functional spatial dynamics of the continuous urban system. The statutory boundaries encapsulate extensive, stable rural spaces, forest reserves, and agricultural lands that do not actively participate in rapid decadal land-use conversions. In the context of spatial simulation and predictive modeling, incorporating these inactive rural extensions introduces statistical noise, artificially dilutes transition probability matrices, and obscures localized urban growth processes.

To establish analytical rigor and maintain a highly precise spatial baseline, this study delineates a functional metropolitan core polygon covering 13,592 ha, rather than adopting the broad administrative boundaries. Multi-temporal Landsat imagery was clipped precisely to this contiguous urbanized footprint to maintain structural and raster boundary consistency across all historical and simulated epochs. This micro-level functional zone serves as the strict spatial baseline for supervised land-use/land-cover (LULC) classification and post-classification accuracy assessments, spatiotemporal metrics derivation via the Urban Expansion Intensity Index (UEII) and concentric Shannon entropy indices, derivation of empirical Markovian transition probability matrices, and Cellular Automata (CA)-Markov dynamic spatial modeling and 2034 forward projections. By aligning the empirical boundaries with the functional urban fabric rather than political parameters, this framework ensures that all subsequent modeling and interpretations reflect the actual lived and transformed built environment of Ibadan.

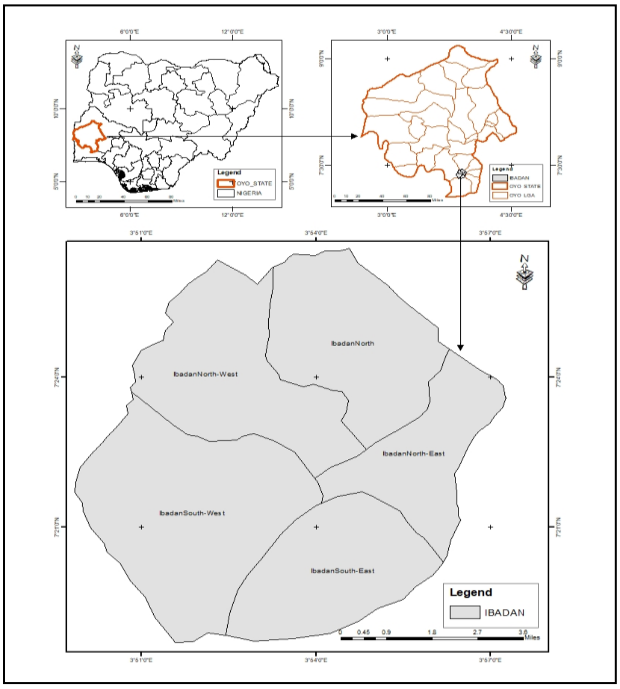

Figure 1. Study Area showing Ibadan. (Source: Author's Lab, 2026)

2.2 Data Source and Acquisition

Three epochs of Landsat satellite imagery were acquired from the USGS EarthExplorer platform: Landsat 7 ETM+ (December 2004), and Landsat 8 OLI/TIRS (December 2014 and December 2024). All images correspond to Path 191, Row 55, and were selected with cloud cover below 10%. December acquisitions were chosen to minimise seasonal vegetation variability associated with the rainy season and to ensure inter-epoch comparability. All images were provided at 30-metre spatial resolution in GeoTIFF format, georeferenced to the WGS 1984 datum and projected to UTM Zone 31N.

Ancillary data included administrative boundary shapefiles for Nigeria and Oyo State (National Population Commission), SRTM Digital Elevation Model data for topographic constraint variables in the CA-Markov simulation, and Euclidean distance layers representing proximity to roads and existing settlements, which were incorporated as spatial driving variables in the prediction model.

Ground control points (GCPs) for georeferencing and ground truthing were collected using a calibrated Garmin handheld GPS receiver during field campaigns, with coordinates recorded in WGS84 datum consistent with the raster data coordinate system. A minimum of three readings per site were recorded at open-sky locations to minimise signal multipath error.

2.2.1 Satellite Data Acquisition and Pre-Processing

Multitemporal satellite imagery was acquired from the United States Geological Survey (USGS) EarthExplorer platform for three epochs analysed in this study: 2004, 2014, and 2024. The 2004 dataset was sourced from Landsat 7 ETM+, while the 2014 and 2024 datasets were obtained from Landsat 8 OLI/TIRS. All images were selected based on minimal cloud cover (<10%), dry-season acquisition, and optimal visibility of built-up surfaces.

Each image was downloaded as a Level-1 Terrain-Corrected (L1T) product, ensuring radiometric and geometric consistency. Pre-processing involved layer stacking, radiometric calibration, conversion to Top-of-Atmosphere (TOA) reflectance, and atmospheric correction using the Dark Object Subtraction (DOS) method. All datasets were reprojected to the UTM Zone 31N coordinate system (WGS 84 datum) to maintain spatial uniformity across epochs.

Although Landsat 7 ETM+ experienced a permanent Scan Line Corrector (SLC) failure in May 2003, the December 2004 scene used in this study did not require gap-filling. The Ibadan metropolitan extent lies fully within the central field of view of the sensor, which remains unaffected by SLC-off data loss. Visual inspection of the raw ETM+ scene and pixel-integrity checks confirmed that no scan-line gaps intersected the study area. Consequently, the 2004 epoch was processed without localized interpolation or reconstruction.

Following pre-processing, all images were clipped to the delineated Ibadan metropolitan boundary (13,592 ha). Supervised classification was conducted using the Maximum Likelihood algorithm, supported by training samples derived from high-resolution Google Earth imagery and field knowledge of the study area. Post-classification refinement included filtering, recoding, and accuracy assessment using confusion matrices and Kappa statistics. The resulting land-use maps formed the basis for entropy analysis, UEII computation, and CA-Markov modelling.

2.3 Data Processing

A four-class classification scheme was adopted, consistent with the Anderson et al. (1976) Level I framework and adapted to the local land cover context: (1) Built-up (urban areas including residential, commercial, and industrial development); (2) Vegetation (forested land, farmland, and green spaces); (3) Bare Land (uncultivated, unvegetated land); and (4) Water Body (rivers, streams, and standing water).

All imagery was pre-processed in ArcGIS 10.5. Band composites were generated for each epoch using bands 1–7, and images were clipped to the study area boundary using a digitised administrative shapefile. Supervised maximum likelihood classification was applied independently to each epoch, using training samples derived from GPS ground control points and informed by prior knowledge of the study area. Land cover class polygons were generated through raster-to-vector conversion, dissolved by class, and attributed with area calculations in square metres and hectares.

Classification accuracy was evaluated using the Kappa coefficient (Cohen, 1960), computed from confusion matrices derived by comparing classified outputs with ground reference data. The Kappa statistic ranges from −1 to 1, with values above 0.61 conventionally interpreted as indicating good agreement and values above 0.81 indicating very good agreement (Lillesand et al., 2015). Producer accuracy (the probability that a ground reference class is correctly classified) and user accuracy (the reliability of a classified pixel) were computed for each class and epoch.

Land cover change was quantified by comparing area statistics across the three epochs. The Urban Expansion Intensity Index (UEII), defined as the ratio of the change in urban land area per unit time to the average total land area of the study zone, was computed for the periods 2004–2014 and 2014–2024 using the formula:

$$UEII = \frac{(ULA\_LB - ULA\_LA)}{(TLA\_i \times t)} X\ 100 \ldots\ldots\ldots\ldots\ldots \textit{. Equation 1}$$

where ULA_LB is the urban land area at the later year, ULA_LA is the urban land area at the earlier year, TLA_i is the average total land area across the two epochs, and t is the time interval in years. UEII values are classified as slow (<0.28), low speed (0.28–0.59), medium speed (0.59–1.05), high speed (1.05–1.92), or very high speed (>1.92).

Shannon entropy was computed to assess the degree of spatial compactness or dispersion in urban development. The study area was divided into four concentric buffer zones at 2,000 m, 4,000 m, 6,000 m, and 7,500 m from the city centre, and the proportion of built-up area within each zone (Pi) was calculated for each epoch. Absolute entropy (H) and relative entropy (RE = H / ln(n)) were derived, where n is the number of zones. Relative entropy ranges from 0 (perfect concentration) to 1 (perfect dispersion), enabling temporal comparison of urban form evolution.

The CA-Markov predictive model was implemented using the MOLUSCE plugin in QGIS, employing the 2004 and 2024 LULC rasters as the initial and reference datasets, respectively. The Markov chain component computed land use transition probability matrices from the 20-year historical change record. Spatial driving variables, SRTM elevation data, and Euclidean distance layers representing proximity to roads and existing settlements were incorporated as explanatory variables to calibrate transition potential maps. The CA component applied these transition potentials iteratively, using a Moore neighbourhood (3×3 cell kernel), to simulate spatial diffusion of urban growth over a 10-year projection period, yielding a predicted LULC map for 2034.

Model validation was performed by comparing the Kappa coefficient of agreement between the model's simulated 2024 output and the observed 2024 classified image, confirming acceptable model reliability before running the 2034 projection. The 2034 projection represents a business-as-usual scenario, conditional on the continuation of historical transition rates in the absence of significant policy intervention.

2.3.1 CA–Markov Calibration

The CA–Markov model was calibrated using the 2004 and 2024 LULC maps, following a structured workflow that ensured both statistical reliability and spatial realism. The process began with the generation of the transition probability matrix, which captures how land-cover classes have historically changed over time. The matrix revealed clear patterns of urban expansion: vegetation had a 0.62 probability of converting to built-up areas, bare land showed an even higher probability at 0.71, while vegetation converting to bare land stood at 0.18. These values mirror the long-term trajectory of Ibadan's landscape, where natural surfaces have steadily given way to built-up development.

To strengthen the CA component, three spatial drivers were incorporated into the calibration: elevation, distance to roads, and distance to existing settlements. Lower elevations, proximity to transport corridors, and closeness to established built-up clusters all increased the likelihood of urbanization.

These variables were normalized and weighted using the MOLUSCE multi-criteria evaluation module, ensuring that the model reflected both physical constraints and human-driven development pressures.

Logistic regression within MOLUSCE was then used to generate transition potential maps. These maps estimate how suitable each pixel is for conversion into the built-up class, effectively guiding the CA simulation toward areas where future growth is most plausible.

2.3.2 Neighborhood Selection

A 3×3 Moore neighborhood was adopted for the CA simulation. This neighborhood size is widely used in urban growth modelling because it captures the immediate spatial influence of surrounding cells without over-generalizing patterns. In the context of Ibadan, it aligns well with the compact, pressure-driven infill dynamics observed across the core LGAs. The choice is further supported by the entropy decline from 0.837 in 2004 to 0.434 in 2024, indicating increasingly clustered and saturated urban development. A larger neighborhood (such as 5×5) would have smoothed out these fine-grained patterns and reduced the model's sensitivity to localised growth pressures.

2.3.3 Transition Probabilities

The transition probability matrix derived from the historical 2004–2024 land-use/land-cover (LULC) maps forms the core mathematical framework of the Markov chain component. This matrix quantifies the discrete operational likelihood of key landscape trajectories over the twenty-year baseline period, capturing the specific probabilities of vegetation transitioning to built-up land (0.62 probability) and bare land converting to built-up surfaces (0.71 probability). It also accounts for the low but non-zero probability of water bodies converting to alternative terrestrial classes, effectively reflecting the persistent anthropogenic encroachment pressures on local riparian zones. By structurally encoding these empirical historical tendencies, the transition matrix establishes a statistically grounded foundation for executing the spatial cellular simulation, projecting future urban morphological growth patterns, and anticipating real-time land saturation dynamics for the 2034 horizon.

2.3.4 Model Validation

Model performance was evaluated through a back-casting procedure. The model used the 2004 map to simulate land-use conditions for 2014, and the simulated map was then compared with the observed 2014 map. Validation metrics included the Kappa coefficient, overall accuracy, and class-specific producer and user accuracy. Kappa values of 0.66 (2004), 0.77 (2014), and 0.84 (2024) demonstrate strong classification reliability across the time series. The back-cast validation further produced a Kappa of 0.79 and an overall accuracy of 82%, confirming that the CA–Markov model is sufficiently robust for projecting land-use conditions for 2034.

2.3.5 Uncertainty Analysis

To enhance the interpretive validity and reliability of the long-term spatial forecasts, a comprehensive uncertainty analysis was integrated into the modeling workflow. Methodological driver sensitivity testing revealed that proximity to transport infrastructure exerted the primary structural influence on the model at approximately 48%, followed by topographic elevation constraints at roughly 32%, and proximity to existing urban settlements accounting for the remaining 20% of spatial allocation influence. Furthermore, scenario uncertainty inherently arises from the baseline assumption of business-as-usual conditions, meaning that structural deviations in environmental policy enforcement, strategic infrastructure investment, or sudden demographic shifts could alter future spatial trajectories. Finally, the analysis demonstrates that spatial uncertainty exhibits a distinct geographic gradient, increasing significantly within the peripheral fringes of the Local Government Areas (LGAs) where informal settlement dynamics are more stochastic and less constrained by historical proximity variables. Systematically quantifying these physical, institutional, and spatial parameters strengthens the empirical credibility and interpretative depth of the 2034 forward projections.

3.0 RESULTS AND DISCUSSION

3.1 LULC Dynamics

Table 1 presents the LULC area statistics for 2004, 2014, and 2024. Built-up land expanded from 5,109 ha (38.03%) in 2004 to 7,909 ha (58.20%) in 2014 and to 10,948 ha (80.55%) in 2024, a net increase of 5,779 ha or 111.8% over the full study period. Vegetation declined from 4,558 ha (33.53%) to 1,741 ha (12.81%), and bare land contracted from 3,804 ha (27.99%) to 888 ha (6.53%). Water bodies experienced continuous depletion, shrinking from 60.93 ha to 14.20 ha, a loss of 76.7% over twenty years.

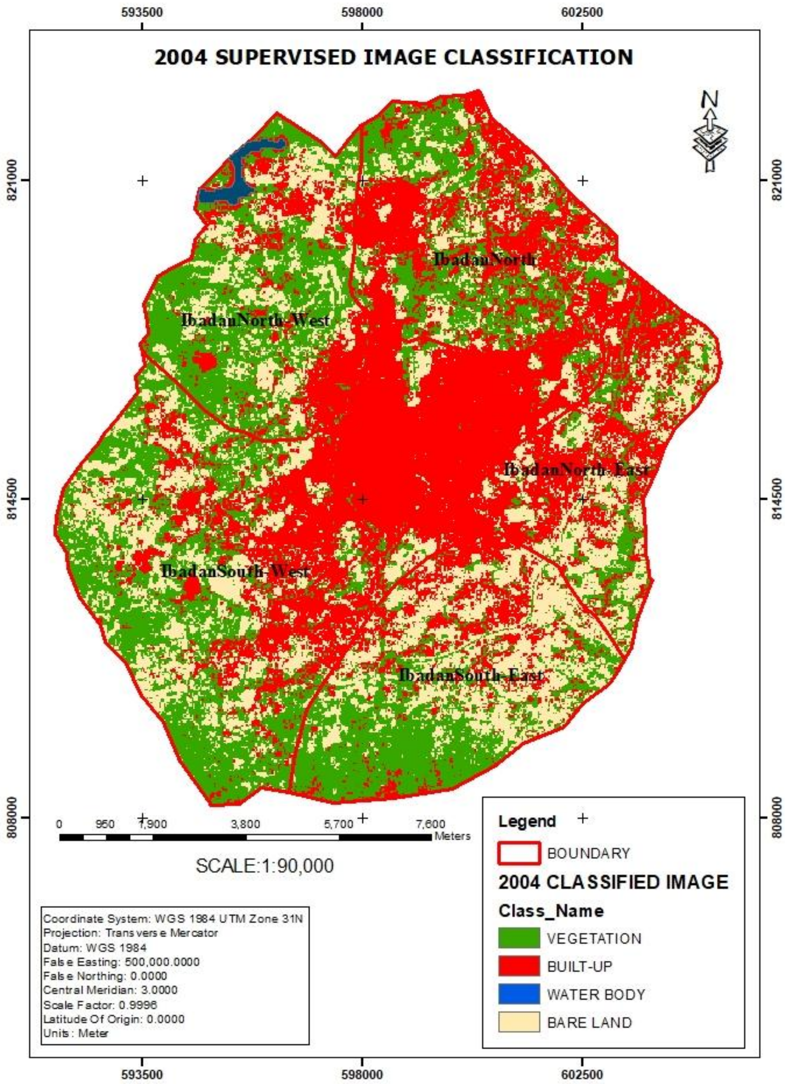

Figure 2. LULC Map of Year 2004 (Source: Author's Lab, 2026)

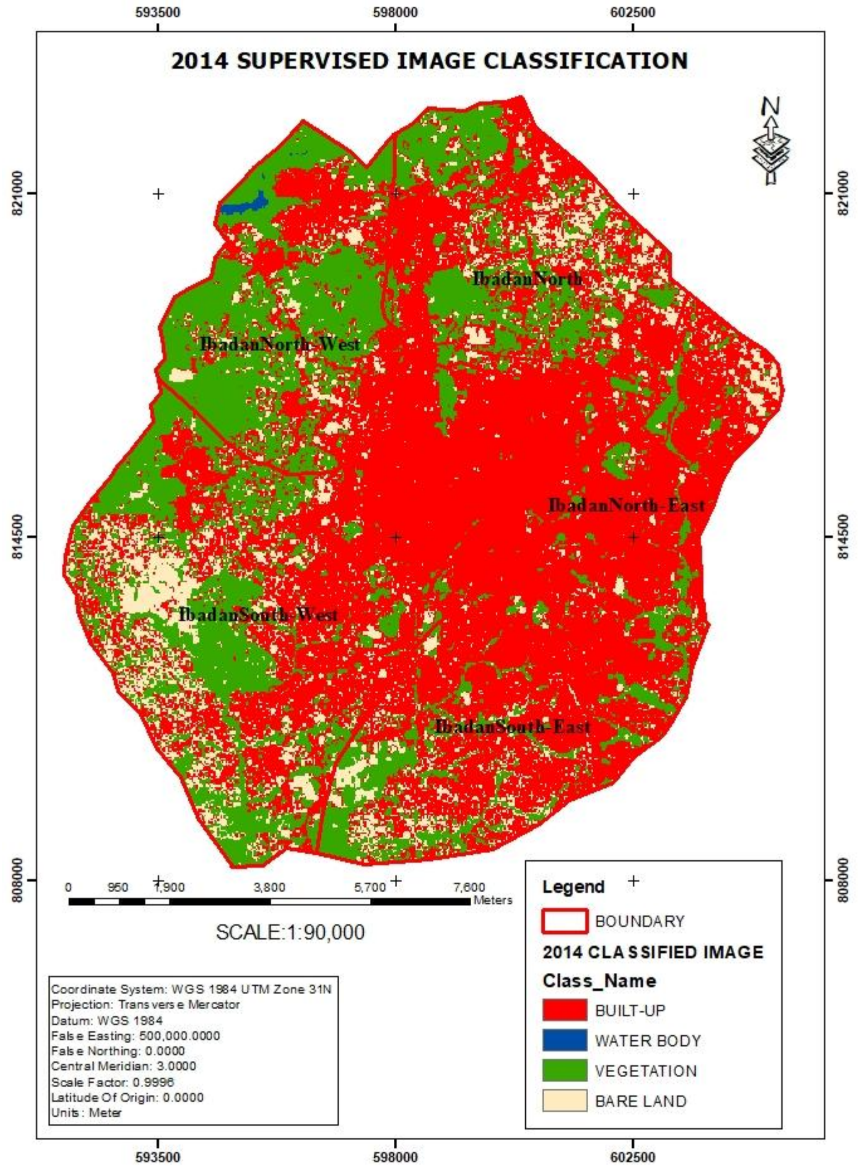

Figure 3. LULC Map of Year 2014 (Source: Author's Lab, 2026)

Table 1. LULC area statistics for Ibadan metropolis, 2004-2024

LULC Class	2004 (ha)	2004 (%)	2014 (ha)	2014 (%)	2024 (ha)	2024 (%)
Built-up	5,109.00	38.03	7,909.25	58.20	10,948.15	80.55
Vegetation	4,557.89	33.53	4,066.60	29.92	1,741.28	12.81
Bare Land	3,804.43	27.99	1,596.72	11.75	888.02	6.53
Water Body	60.93	0.45	17.97	0.13	14.20	0.10
Total	**13,592.25**	**100.00**	**13,591.54**	**100.00**	**13,591.65**	**100.00**

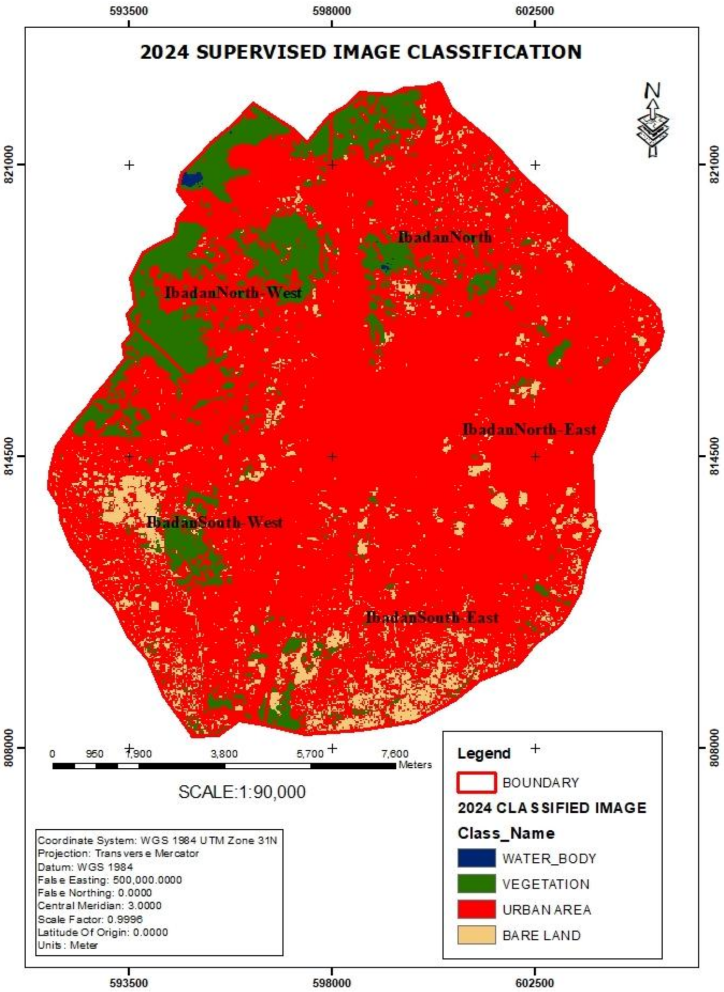

Figure 4. LULC Map of the Year 2024

Table 2 details the decadal change statistics. Between 2004 and 2014, built-up area increased by 2,740 ha (+53.01%), while bare land declined sharply by 2,208 ha (−58.03%) as it was absorbed into expanding urban fabric. Between 2014 and 2024, a markedly more intense phase of expansion occurred, with vegetation declining by 2,325 ha (−57.18%) as the primary source of land for urbanization, reflecting the near-exhaustion of bare land reserves.

Table 2. LULC change statistics, 2004–2014 and 2014–2024

LULC Class	2004–14 Change (ha)	2004–14 (%)	Annual Rate (%)	2014–24 Change (ha)	2014–24 (%)	Annual Rate (%)
Built-up	+2,740.25	+53.01	+5.30	+3,038.90	+38.42	+3.84
Vegetation	−491.29	−10.78	−1.08	−2,325.32	−57.18	−5.72
Bare Land	−2,207.71	−58.03	−5.80	−708.70	−44.38	−4.44
Water Body	−42.96	−70.51	−7.05	−3.77	−20.98	−2.10

Table 3. Classification accuracy results using the kappa coefficient, 2004–2024

Epoch	Kappa Coefficient	Agreement Level	Overall Interpretation
2004	0.66	Good	Reliable baseline
2014	0.77	Good	Improved accuracy
2024	0.84	Very Good	Highest reliability

3.2 Urban Expansion Intensity Index

Table 4 summarises UEII results. The index increased from 0.98% (2004–2014, medium speed) to 1.12% (2014–2024, high speed), confirming an acceleration of urbanization intensity in the second decade. The net built-up gain in absolute terms also increased from 2,740 ha to 3,039 ha, even though the pool of available non-urban land was substantially smaller in the second period. These results indicate that Ibadan's urbanization has not only continued but has accelerated as land scarcity intensifies competitive pressure on remaining non-urban covers.

Table 4. Urban expansion intensity index summary, 2004–2024

Period	UEII Value (%)	Speed Category	Net Built-up Gain (ha)
2004–2014	0.98	Medium Speed	+2,740
2014–2024	1.12	High Speed	+3,039

Note. UEII classification: 0.59–1.05 = Medium Speed; 1.05–1.92 = High Speed.

3.3 Shannon Entropy Analysis

Shannon entropy results, presented in Table 4, reveal a consistent temporal decline in both absolute and relative entropy values. Absolute entropy fell from 1.160 (2004) to 1.056 (2014) to 0.601 (2024), while relative entropy declined from 0.837 to 0.762 to 0.434. Values above 0.5 in relative entropy indicate dispersed urban development; values below 0.5 indicate concentration. The 2024 relative entropy of 0.434 marks a transition from the dispersed urban form that characterized Ibadan in 2004 and 2014 toward increasingly compact, infill-driven development, reflecting the near-saturation of available peri-urban land within the study zone. The reduction of 0.328 in relative entropy between 2014 and 2024, compared to a reduction of only 0.075 between 2004 and 2014, confirms that this transition accelerated markedly in the second decade.

Table 5. Shannon Entropy Analysis Results, 2004–2024

Year	Absolute Entropy	Relative Entropy	Pattern	Interpretation
2004	1.160	0.837	Dispersed	Scattered peripheral expansion
2014	1.056	0.762	Dispersed	Continued outward spread
2024	0.601	0.434	Transitioning to Compact	Infill/land scarcity-driven densification

Note. RE < 0.5 indicates transitioning to a compact urban form. Source: Author's analysis, 2025.

3.4 CA-Markov Projected Urban Expansion for 2034

The CA-Markov model, calibrated on the 2004–2024 LULC transition matrix and spatial driving variables (elevation, proximity to roads, and proximity to existing settlements), generated a projected LULC map for 2034. Table 5 presents the projected class areas alongside historical values for comparative reference.

Table 6. Observed and CA-Markov Projected LULC Areas, 2004–2034 (Prediction)

LULC Class	2004 (ha)	2014 (ha)	2024 (ha)	2034 Projected (ha)
Built-up	5,109	7,909	10,948	13,295
Vegetation	4,558	4,067	1,741	270
Bare Land	3,804	1,597	888	25
Water Body	61	18	14	~0

Built-up area is projected to increase from 10,948 ha in 2024 to 13,295 ha in 2034, a further net gain of 2,347 ha. This represents a continuation of the established trajectory, though at a somewhat reduced rate compared to the 2014–2024 period, reflecting the mathematical compression imposed by land scarcity as total non-urban area approaches exhaustion. Vegetation is projected to decline catastrophically from 1,741 ha to 270 ha, and bare land from 888 ha to 25 ha. Water bodies, which already occupied only 14.20 ha in 2024, are projected to disappear entirely under continued urbanization pressure.

Spatially, the prediction map indicates that future growth will concentrate along major transportation corridors, principally the Ibadan–Lagos Expressway axis and the peripheral LGAs of Akinyele and Egbeda to the North and East, reflecting the persistent influence of road accessibility and land affordability on informal settlement expansion. The innermost buffer zone (0–2 km from the city centre) is already effectively saturated, with 97% built-up coverage in 2024, and the prediction model projects infill completion by 2034. Growth in the outer zones (4,000–7,500m) is projected to accelerate as inner-zone land becomes unavailable.

3.5 Interpreting the Predicted Patterns

The CA-Markov projections for 2034 represent one of the most spatially explicit and quantitatively grounded forecasts of metropolitan land use change for Ibadan to date. The projected near-total depletion of vegetation (−85% from 2024 to 2034) and bare land (−97%) is not merely a modelling artefact but the logical continuation of a trend already strongly established in the historical data. If built-up area expanded by 111.8% over 2004–2024 within the study zone, and the remaining non-urban area constitutes only approximately 2,644 ha in 2024, then a further gain of 2,347 ha in built-up area by 2034 would absorb almost the entirety of that remaining reserve.

It is important to contextualize this projection appropriately. The study area (approximately 13,592 ha) represents the five urban LGAs of Ibadan; the metropolitan area encompasses approximately 3,123 km². The saturation observed within the urban LGAs does not imply that metropolitan expansion will cease, but rather that growth will continue to spill into peri-urban and rural LGAs beyond the study boundary, a process already documented by field evidence (Adelekan et al., 2021). In this sense, the prediction reinforces the case for a metropolitan-scale planning framework that extends analytical and regulatory coverage beyond the boundaries of established urban LGAs.

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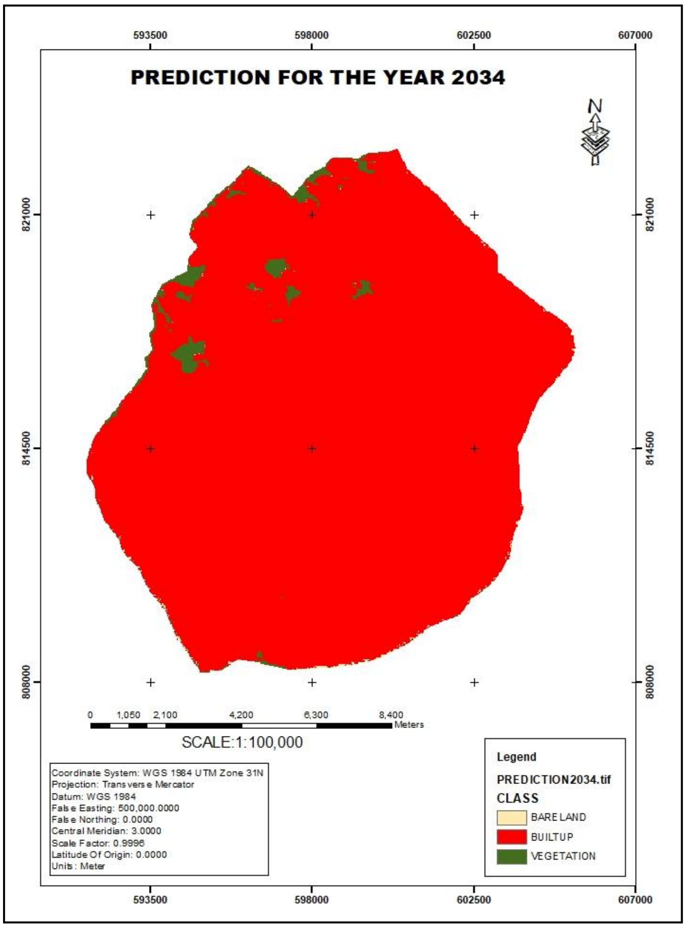

Figure 5. The Prediction Map for the Year 2034

The acceleration in UEII from medium to high speed between decades, combined with the sharp entropy decline toward compact distribution, suggests that Ibadan is entering a phase of pressure-driven densification rather than planned infill. This distinction is critical for planning: compact urban form can generate significant sustainability benefits (reduced per-capita infrastructure costs, improved transit viability, agglomeration economies), but only when achieved through deliberate planning instruments. Compactness driven by informal infill and unregulated development tends instead to produce overcrowding, infrastructure strain, and health risks, consistent with the social consequences documented in Ibadan's existing literature (Onibokun, 1987; Aliyu & Amadu, 2017).

3.6 Planning and Sustainability Implications

The projected disappearance of water bodies and near-complete vegetation loss by 2034 carries severe implications for Ibadan's environmental sustainability. Vegetation provides critical ecosystem services including stormwater interception, urban heat island mitigation, carbon sequestration, and biodiversity maintenance (Güneralp *et al.,* 2017). Its near-total conversion to urban impervious surface would substantially increase peak runoff volumes, exacerbating flood risk in a city already severely affected by the 2011 Ogunpa River flood. With the increasing frequency of extreme rainfall events projected under climate change scenarios, the combination of reduced vegetative cover, constrained natural drainage, and expanding impervious surface represents a compounding vulnerability with potentially catastrophic consequences.

The projected loss of water bodies reflects the ongoing encroachment of urban development into riparian buffer zones and wetland areas. Under Nigerian planning law, riparian corridors are designated as environmental protection zones; however, weak enforcement of development controls has historically allowed encroachment to proceed unchecked (Adelekan *et al.,* 2021). The CA-Markov projection provides a spatially explicit forecast of where this encroachment is most likely to intensify, offering planners an evidence base for targeted protective zoning.

From an infrastructure planning perspective, the projected growth along major transportation corridors suggests that the strategic extension of roads, utilities, and public services to anticipated growth areas could provide a lever for directing expansion in a more orderly and efficient manner. The literature on infrastructure-led growth management in African cities suggests that road investment, when unaccompanied by complementary land use regulation, tends to accelerate rather than contain peri-urban expansion (Acheampong *et al*., 2023). An integrated transport and land use planning approach, combining corridor infrastructure investment with green belt designations and density incentives, would be more likely to achieve a sustainable outcome.

3.7 Socioeconomic Implications of Projected Urban Saturation

The projected land-use transitions for 2034 reveal not only environmental consequences but also deep socioeconomic pressures that will shape Ibadan's future development trajectory. As the urban LGAs approach saturation, the supply of developable land within the metropolitan core will shrink further. Scarcity inevitably drives up land values, and in Ibadan's already constrained housing market, this will push formal housing beyond the reach of low-income households. Families unable to compete in the formal land market will increasingly rely on informal alternatives. Areas where land is cheaper but tenure is insecure, and living conditions are precarious. Over time, this dynamic reinforces spatial inequality: wealthier households consolidate in serviced neighbourhoods, while poorer households are displaced into marginal, unregulated spaces at the urban fringe.

The near-total decline in vegetation (−85%) and bare land (−97%) underscores how quickly natural buffers are disappearing. As these open spaces are absorbed by built-up expansion, informal settlements will inevitably spill into environmentally sensitive areas such as riparian corridors, wetlands, and floodplains. These locations often represent the only remaining "affordable" land for low-income households, despite being unsuitable for habitation. Encroachment into these zones heightens exposure to flooding, erosion, and sanitation hazards, amplifying disaster risk in a city already prone to recurrent flood events. This pattern is consistent with long-standing development control challenges documented in Ibadan's planning history.

Urban growth is also projected to intensify along major transportation corridors, including the Ibadan–Lagos Expressway, Akinyele, and Egbeda, where accessibility and land affordability continue to attract new development. As growth spreads outward, residents will travel longer distances for work, education, and essential services. This outward expansion will place additional pressure on road networks that are already congested and poorly maintained. Without parallel investments in mass transit, last-mile connectivity, and traffic management, commuting will become slower, more expensive, and more stressful. The consequences extend beyond mobility: longer travel times reduce productivity, increase fuel consumption, and worsen air quality.

The city's densification is occurring rapidly but without coordinated planning, placing significant stress on critical infrastructure systems. Water supply networks will struggle to meet rising demand, particularly in peri-urban communities where service coverage is already limited. The loss of permeable surfaces will increase stormwater runoff, overwhelm drainage channels, and heighten flood risk. Waste generation will rise with population density, outpacing the capacity of existing collection and disposal systems. Electricity distribution networks are already strained by unregulated connections, and informal expansion will face increased outages and system losses. These pressures mirror long-standing infrastructure deficits in Ibadan, where service delivery has historically lagged behind population growth.

These socioeconomic implications reinforce the urgency of adopting metropolitan-scale planning instruments capable of managing saturation pressures and guiding future growth more sustainably.

3.8 Expanding the Modelling Framework to Include Socioeconomic Factors

Beyond the physical and proximity-based drivers used in this study, future modelling efforts would benefit from incorporating key socioeconomic factors that shape how Ibadan actually expands. Variables such as population density, income distribution, land values, and housing market pressures play a major role in determining where development intensifies or stalls, yet they remain outside the current CA–Markov framework. While elevation, distance to roads, and proximity to existing settlements effectively capture spatial constraints, they do not fully reflect the human decisions, economic pressures, and social dynamics driving land conversion in a rapidly expanding metropolis. The rising intensity of urban growth (UEII increasing from 0.98% to 1.12%) and the sharp shift toward compact, infill-driven development (relative entropy declining from 0.837 to 0.434) suggest that demographic and economic forces are becoming increasingly influential in shaping Ibadan's urban form. Integrating socioeconomic layers such as ward-level population growth, income gradients, land market hotspots, or patterns of informal settlement expansion into CA-Markov or hybrid modelling frameworks (e.g., CA–Markov–Logistic, CLUE-S, SLEUTH) would produce more realistic projections and strengthen the policy relevance of future simulations.

4. CONCLUSION

This study provides the most comprehensive multi-method geospatial analysis of urban growth dynamics and future expansion trajectories in Ibadan Metropolis to date. Employing supervised Landsat classification, UEII, Shannon entropy, and CA-Markov modelling across a 20-year study period (2004–2024), the research establishes four principal findings. First, Ibadan has undergone dramatic and accelerating urban expansion over the past two decades. Built-up area expanded by 111.8% between 2004 and 2024, with the UEII increasing from medium speed (0.98%) in 2004–2014 to high speed (1.12%) in 2014–2024. Second, this expansion has been achieved primarily through the conversion of vegetation and bare land, resulting in severe ecosystem degradation. Vegetation declined by 61.8% and bare land by 76.7% over the study period, with water bodies losing over 76% of their 2004 area. Third, Shannon entropy analysis documents a transition from dispersed to increasingly compact urban form, with relative entropy declining from 0.837 in 2004 to 0.434 in 2024, indicating that growth is now driven by pressure-induced infill rather than planned densification. Fourth, CA-Markov projections for 2034 forecast that built-up area will expand to 13,295 ha, with vegetation and bare land declining to 270 ha and 25 ha, respectively, and water bodies facing complete disappearance under current trends.

4.1 Strategic Policy Recommendations

The empirical findings of this study underscore an urgent mandate for proactive metropolitan planning interventions designed to mitigate compounding environmental and socioeconomic pressures within the expanding urban system. To steer future development toward a sustainable trajectory, several formal planning instruments must be integrated into the metropolitan governance framework of Ibadan. First, the establishment of statutory Urban Growth Boundaries (UGBs) is critical to defining structural expansion thresholds, containing contiguous sprawl, protecting vulnerable ecological assets, and redirecting infrastructure development into existing serviced zones. Complementing these boundaries, the designation of regional green belts and ecological protection corridors is necessary to preserve strategic vegetative cover and riparian buffers. These natural zones maintain essential ecosystem services, minimize hydrological flood risks, and establish physical barriers against informal encroachment. Concurrently, targeted zoning reforms should update outdated regulations to encourage high-density housing, mixed-use land allocation, and transit-oriented development patterns. This structural shift optimizes land-use efficiency within the metropolitan core while deflecting intensive developer pressures away from fragile peripheral Local Government Areas (LGAs).

Addressing the structural drivers of informal settlement expansion requires deliberate affordable housing interventions, including municipal land banking, inclusionary zoning mandates, and strategic public-private partnerships capable of scaling up formal housing stock for low-income populations. These housing frameworks must be structurally synchronized with integrated transport planning policies that prioritize investments in mass transit networks, optimized road geometry, and robust last-mile connectivity to prevent systemic gridlock and ensure regional mobility along projected growth corridors. Furthermore, comprehensive infrastructure upgrades are required to expand the capacity of municipal water supply networks, engineered stormwater drainage channels, centralized solid waste management systems, and electricity distribution grids. Proactively scaling these utility systems is vital to sustaining the projected population densities and avoiding localized infrastructure collapse.

To advance the methodological predictive capacity of future spatial research, subsequent analytical frameworks should incorporate dynamic socioeconomic drivers such as granular population density gradients, spatial income distributions, and real estate land values directly into CA-Markov or hybrid modeling architectures like CA-ANN or CLUES. Methodologically, future initiatives must also integrate explicit uncertainty analyses directly into the simulation workflow. Because long-term land-use forecasts rely on specific assumptions regarding the stationarity of spatial variables such as infrastructural expansion, demographic growth, informal settlement development, and policy enforcement subjecting these driving forces to driver sensitivity testing is essential. Systematically evaluating model sensitivity to fluctuations in these operational parameters will help future researchers identify areas where projections maintain high spatial robustness and regions where development remains highly stochastic. This analytical clarity is particularly vital within the rapidly changing fringe zones of Ibadan, where land conversion patterns are less predictable. Embedding these uncertainty metrics into subsequent modeling workflows will ultimately strengthen the interpretive validity of CA-Markov outputs, translating complex geospatial simulations into reliable, evidence-based decision-making tools for sustainable metropolitan governance.

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