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FORECASTING LONG-TERM URBAN GROWTH PATTERNS AND DRIVERS IN WEST AFRICAN SECONDARY CITIES: A CASE STUDY OF UYO, NIGERIA (2025–2050)

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Abstract

Secondary cities in West Africa are the new frontiers of global urbanization, yet they often lack the long-term spatial foresight needed for sustainable growth. In Uyo, Nigeria, rapid demographic shifts are putting unprecedented pressure on land resources, necessitating a shift toward predictive urban modeling. This study utilizes an integrated MLP-Markov chain model to simulate urban growth for the years 2035 and 2050. A Logistic Regression model was first employed to identify spatial drivers, revealing that proximity to major roads and elevation were the primary determinants of expansion. The resulting projections were then evaluated using the SDG 11.3.1 (Land Use Efficiency) framework, comparing projected built-up expansion against a UN-validated population growth rate of 4.32%. The simulation predicts that Built-up areas will expand to 106.58 km² (58.06%) by 2035 and 118.47 km² (64.54%) by 2050. The LCRPGR ratio is projected to drop to 0.20 by 2050, indicating that while land use is "efficient" in per-capita terms, the city is facing extreme hyper-densification. The findings serve as a spatial early-warning system, advocating for a transition from horizontal sprawl management to inclusive vertical densification and the preservation of remaining ecological corridors to ensure Uyo's long-term resilience.

Keywords

Urban Forecasting; MLP-Markov; Land Use Efficiency; Logistic Regression; Hyper-densification

Introduction

While global attention often focuses on megacities, the most significant urban transformations in the 21st century are occurring in secondary cities across the Global South. In Nigeria, cities like Uyo are experiencing rapid lateral expansion that often outpaces institutional planning capacity. This "unseen" urbanization leads to the fragmentation of ecological corridors and inefficient land use, directly threatening the targets set by Sustainable Development Goal (SDG) 11 [1]. SDG Target 11.3 aims to enhance inclusive and sustainable urbanization. A critical indicator for this is Indicator 11.3.1: the ratio of land consumption rate (LCR) to the population growth rate (PGR). Historically, monitoring this has been retrospective, looking at what happened in the past. However, to be effective, urban planners require foresight as there is a pressing need for models that not only quantify past growth but also simulate future scenarios to predict when and where land consumption will become unsustainable [2] [3].

Traditional urban growth models like Cellular Automata (CA) often struggle with the non-linear complexities of African urbanism. Traditional urban growth models such as Cellular Automata (CA) often face limitations in capturing the highly dynamic, non-linear, and heterogeneous patterns that characterise urban expansion in many African cities [4] [5]. This research utilized an integrated MLP-Markov (Multi-Layer Perceptron-Markov Chain) approach to spatially and temporally model and forecast land use change for the city of Uyo. By using an MLP neural network to determine transition potentials based on spatial "drivers" (such as topography and proximity to infrastructure) and a Markov chain to simulate the temporal change, the study provide a high-fidelity forecast of Uyo's footprint through 2050. This paper aims to identify the primary spatial drivers (topographic and socio-economic) of urban expansion in Uyo using Logistic Regression, simulate urban growth for the years 2035 and 2050 using the MLP-Markov framework and evaluate the implications of these projections for Land Use Efficiency and regional sustainability.

Study Area

Uyo, the capital of Akwa Ibom State, serves as a critical administrative and commercial nexus in Nigeria's South-South geopolitical zone. The study area, covering approximately 183.56 km², has transitioned from a modest provincial town into a rapidly expanding metropolis since the late

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1990s. Its strategic location within the oil-rich Niger Delta has catalyzed significant population influx and infrastructural investment, making it a representative model for secondary city growth in West Africa [6] [7].

The physical landscape of Uyo is characterized by a low-lying plain with elevations ranging from 38 m to 105 m [8]. This subtle topographic variation plays a decisive role in urban morphology. Historically, development has gravitated toward higher elevations to mitigate the risks associated with the region's high annual rainfall and potential flooding. The urban form of Uyo is heavily influenced by a "radial-concentric" road network. Major arteries, such as the Ring Roads and highways connecting to neighboring commercial hubs, act as magnets for development. The presence of institutional landmarks, including the University of Uyo and various government secretariats, creates "nodes of attraction" that drive land-use conversion [9] [10].

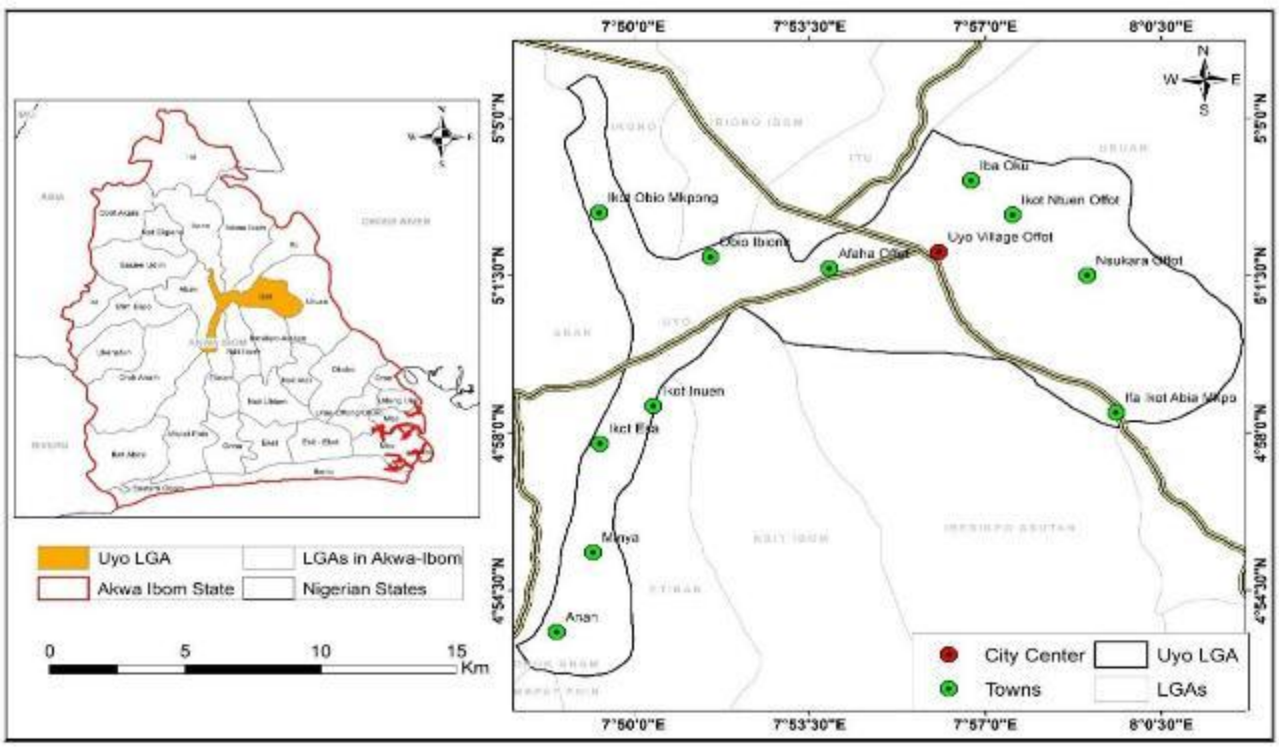

Figure 1: Map showing the location of Uyo city in Akwa Ibom State

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Methodology

Research Design, Data Acquisition and Sources

This study employs a three-stage workflow: (i) Retrospective Analysis, where historical LULC transitions are quantified; (ii) Explanatory Modeling, using Logistic Regression to identify growth drivers; and (iii) Scenario Simulation, applying an MLP-Markov chain to forecast future urban footprints for 2035 and 2050. This design allows for a seamless transition from historical observation to policy-relevant foresight. The study integrated multi-source geospatial data, categorized into primary LULC data and auxiliary spatial drivers (Table 1). All spatial data were projected to the WGS 1984 UTM Zone 32N coordinate system to ensure spatial overlay accuracy.

Table 1: Data Types and Sources

Data Category	Data Type	Source	Purpose
LULC (2010, 2020 and 2025)	Raster (30m)	Derived from Landsat 7, 8, & 9	Input for Markov Chain & MLP training
Topography	DEM (30m)	SRTM (USGS Earth Explorer)	Elevation & Slope drivers for Logistic Regression
Infrastructure	Vector (Shapefile)	OpenStreetMap	Proximity drivers (Roads, CBD, Institutions)
Population	Tabular/Census	National Population Commission	Calculating PGR for SDG 11.3.1

Software and Computational Framework

The forecasting architecture was implemented using a suite of advanced geospatial and statistical tools:

i. TerrSet (IDRISI): Used specifically for the MLP-Markov simulation and the generation of transition potential maps.

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ii. ArcGIS 10.8: Utilized for spatial proximity analysis (Euclidean distance calculations for roads/CBD) and final cartographic visualization.

iii. SPSS / Python (SciPy): Employed for the Logistic Regression analysis to determine the statistical significance and coefficients of the growth drivers.

iv. Microsoft Excel: Used for the mathematical computation of the SDG 11.3.1 (LCRPGR) ratios.

Identification of Growth Drivers via Logistic Regression

To understand the spatial logic of Uyo's expansion, a Logistic Regression (LR) model was employed. The LR model treats "Built-up" expansion as a binary dependent variable (Change vs. No Change) and tests it against a set of independent spatial variables (drivers). The study utilized spatially measurable GIS proxy variables that have been widely validated in urban growth research [11]. These include distance to major roads, distance to existing built-up areas, proximity to the city center, slope, elevation, and proximity to major urban infrastructure (Table 2). Logistic regression is suitable for modeling binary outcomes and is widely applied in urban growth studies. The logistic regression model is expressed in Equation 1 and 2.

$$P = \frac{1}{1 + e^{-Z}} \qquad (Eq. 1)$$

Where:

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \ldots \ldots \beta_n X_n + \varepsilon \qquad (Eq. 2)$$

and:

- P = probability of urban expansion
- β_0 = intercept
- β_n = regression coefficients/ coefficients indicating the strength of each driver
- X_n = explanatory spatial variables: Elevation, Slope, Distance to Major Roads, Distance to the Central Business District (CBD), and Distance to Educational Institutions
- e = base of natural logarithm

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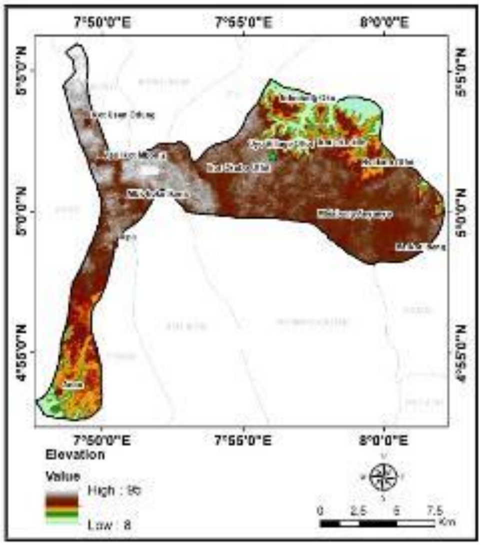
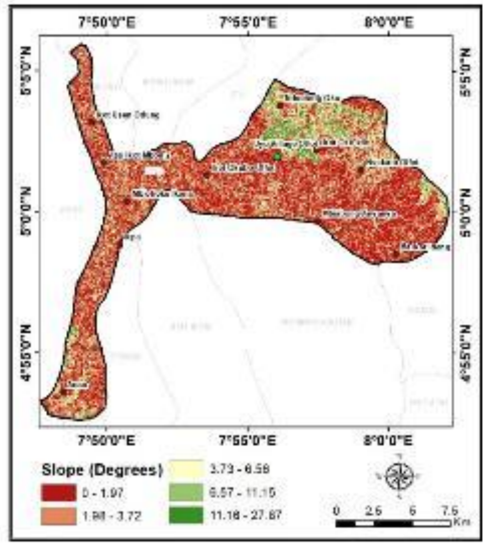
Table 2: Variables Influencing Urban growth

<table>
<tr><th>Variable group</th><th colspan="2">Factors</th></tr>
<tr><td>Topographic Factors</td><td>
</td><td>
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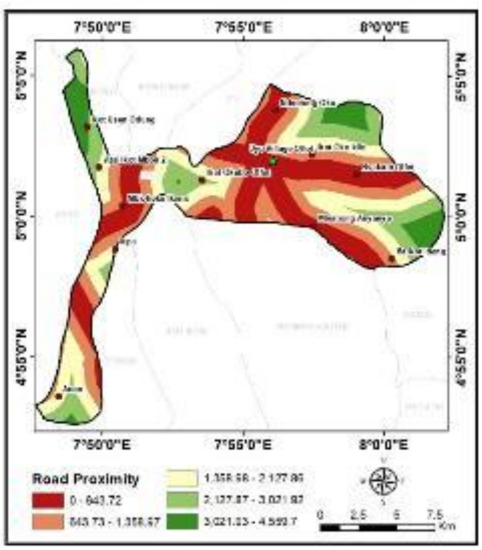
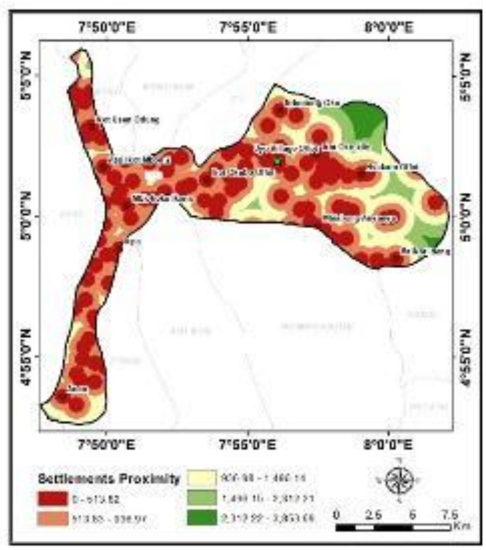
<tr><td>Connectivity and Agglomeration</td><td>
</td><td>
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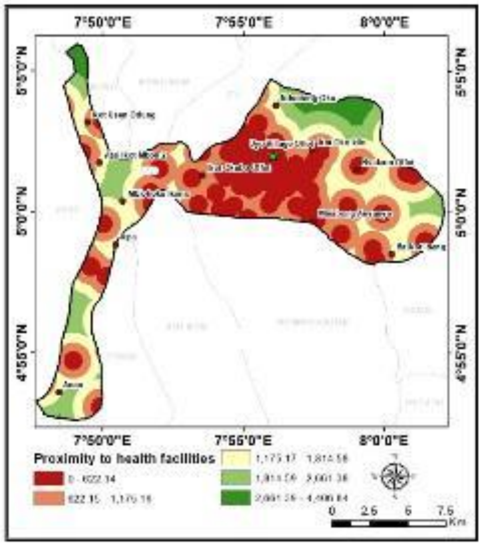
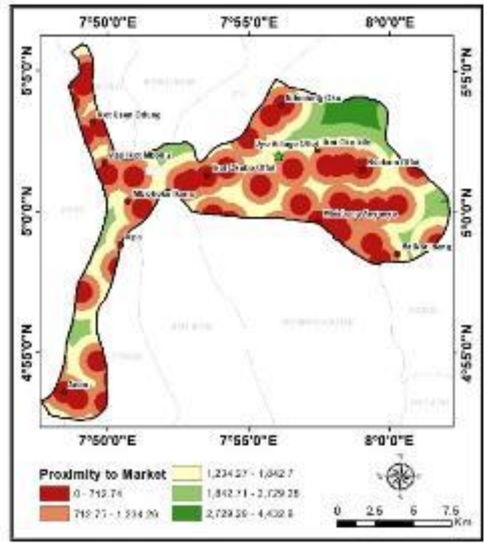
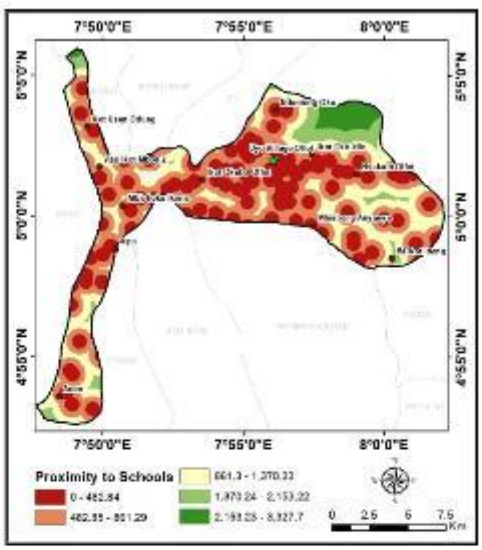
Socio-Economic Pull: Proximity to Markets, Schools, and Hospitals







Sample points were randomly extracted from the raster datasets and divided into training (70%) and validation (30%) datasets. Model calibration was performed using the training dataset, while predictive accuracy was evaluated using the validation dataset [12] [13]. Model performance was assessed using overall classification accuracy, Receiver Operating Characteristic (ROC) curve and Area Under Curve (AUC) statistic computed in Equation 3 below –

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$$\int_0^1 TPR(FPR)\, d(FPR) \qquad (Eq. 3)$$

where:

- TPR = true positive rate
- FPR = false positive rate

The regression coefficients (β) were interpreted to assess the magnitude and direction of influence of each spatial variable. Positive coefficients indicate a higher likelihood of urban expansion, while negative coefficients suggest inhibitory effects. The statistical significance of each variable was evaluated at $p < 0.05$, enabling identification of the most influential drivers of urban growth in Uyo. To complement the logistic regression analysis and to measure nonlinear relationships among the spatial drivers, a multilayer perceptron (MLP) neural network was implemented. Rather than using a linear approach, this study utilizes a Multi-Layer Perceptron (MLP) neural network to generate a Transition Potential Map. The model was trained using existing land use and land cover change of 2020 and 2025.

Deep Learning Forecasting Models (MLP-Markov for 2035 and 2050)

Deep learning–based forecasting models were employed to predict future urban growth patterns in Uyo based on historical land use/land cover changes and spatial transition dynamics for the future (2035 and 2050). The rationale behind the selection of these years was that it represented a strategic blend of medium- and long-term planning horizons that align with local, regional, and global sustainable development milestones. Specifically, the 10-year forward horizon to 2035 serves as a crucial mid-term benchmark to evaluate post-2030 local urban master plans and the implementation phases of the African Union (AU) Agenda 2063. Meanwhile, the 25-year forward horizon to 2050 captures the long-term macro-temporal impacts of rapid demographic shifts and urban population doubling in West African secondary cities, aligning perfectly with the definitive global urbanization forecasting targets established by United Nations (UN-Habitat) demographic frameworks [14] [15].

The forecasting process builds on the classified multi-temporal LULC datasets generated for the period 2000–2025. The deep learning model was trained using sequences of historical land-use maps to learn spatial and temporal transition patterns between land cover classes, particularly

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transitions from non-built-up to built-up areas [16] [17]. Let the land-use state at time t be represented in Equation 4:

$$L_t = f(X_t) \qquad (Eq. 4)$$

where:

- Lt = land-use state at time t
- Xt = spatial feature representation extracted from satellite imagery

The deep learning model learns a temporal transition function expressed in Equation 5:

$$L_{t+1} = f(L_t, L_{t-1}, \dots\dots, \theta) \qquad (Eq. 5)$$

where:

- Lt+1 = predicted land-use state at future time t+1
- θ = learned model parameters

The trained model was applied iteratively to forecast urban growth for selected future periods (2035 and 2050). The resulting outputs represent predicted spatial distributions of built-up areas and other land cover classes.

SDG 11.3.1 Framework: Land Use Efficiency (LUE)

To evaluate the implications of Uyo's projected expansion, this study adopts the Sustainable Development Goal (SDG) 11.3.1 indicator. While traditional urban studies focus solely on the magnitude of growth, the SDG 11.3.1 framework assesses Land Use Efficiency (LUE) by calculating the relationship between the rate at which land is consumed and the rate at which the population grows [1]. The indicator is derived from the ratio of the Land Consumption Rate (LCR) to the Population Growth Rate (PGR). For the forecast periods (2025–2035 and 2035–2050), these rates are calculated as follows:

i. **Land Consumption Rate (LCR):** measures the annual percentage increase in built-up area, representing how quickly cities expand into surrounding land as shown in Equation 6.

$$LCR = \frac{\ln(Urb_{t2} - Urb_{t1})}{n} \qquad (Eq. 6)$$

Where Urb{t_2} and Urb{t_1} are the total built-up areas at the final and initial years of the simulation, and n is the number of years in the interval.

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ii. **Population Growth Rate (PGR):** Population growth rate (PGR) is the change of a population in a defined area (country, city, etc) during a period, usually one year, expressed as a percentage of the population at the start of that period (Equation 7)

$$PGR = \frac{ln\left({Pop_{t+n}}/{Pop_t}\right)}{n} \qquad (Eq.7)$$

Where Pop_t represents the projected population figures for the Uyo metropolis.

iii. **LCRPGR Ratio (The Efficiency Metric)**: This is computed by the ratio of both metrics in Equation 8

$$LCRPGR = {LCR}/{PGR} \qquad (Eq.8)$$

The resulting ratio serves as the primary benchmark for the 2050 sustainability forecast:

i. Ratio < 1: Indicates efficient, compact growth (population is growing faster than land consumption).

ii. Ratio > 1: Indicates Urban Sprawl (land is being consumed faster than the population is growing), signaling a move toward unsustainable land use.

Results and Discussion

Analysis of Urban Growth Drivers (Logistic Regression)

Logistic Regression achieved an accuracy of 0.773 and an AUC of 0.861 (Figure 2). This indicates a strong ability to explain the general direction of growth. MLP Neural Network achieved a higher accuracy of 0.813 and an AUC of 0.906 (Figure 3). The superior performance of the MLP suggests that urban expansion in Uyo is not a simple linear process; rather, drivers interact in complex ways (e.g., the influence of roads might change depending on the elevation).

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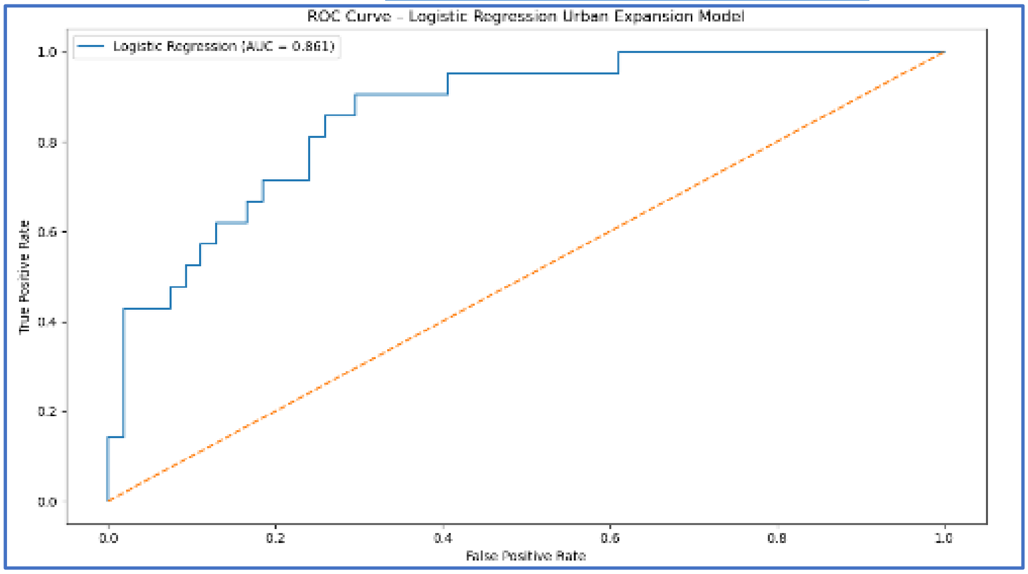

Figure 2: Accuracy for logistic regression model

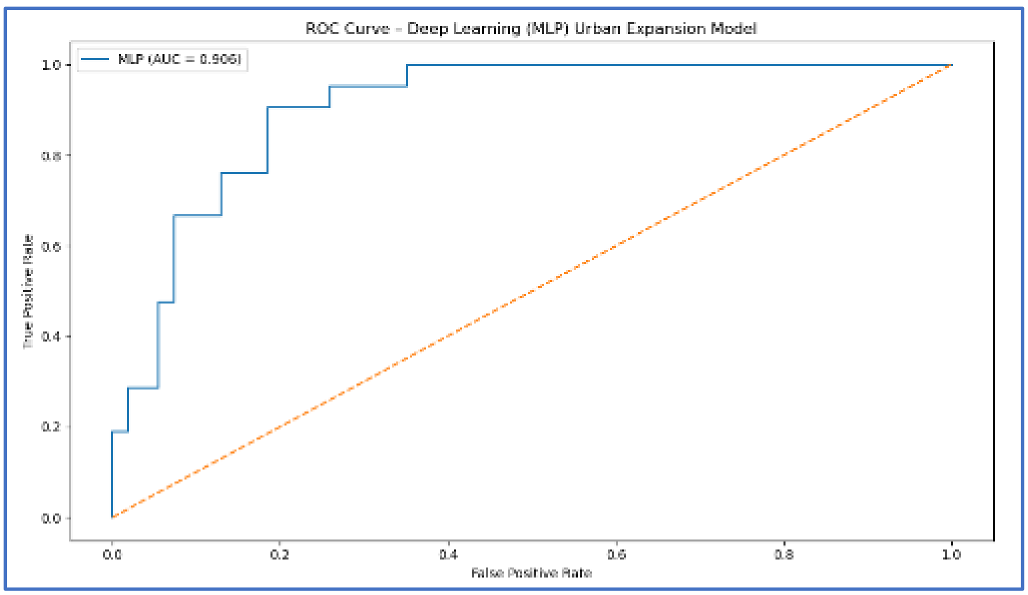

Figure 3: ROC Curve for accuracy (MLP model)

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Table 3: Statistical Analysis of Drivers (Logistic Regression)

Feature	Coefficient	Odds Ratio
Elevation	0.9521	2.591
Proximity to Markets	0.3271	1.387
Distance to Roads	-0.6799	0.506
Distance to Settlements	-0.6864	0.503
Slope	-0.2074	0.812

Elevation is the most dominant driver in Uyo (Odds Ratio: 2.59) as shown in Table 3. Developers are actively seeking higher ground, likely to mitigate the risks of seasonal flooding prevalent in the region. The negative coefficient for slope (-0.207) further confirms that flat, high-plateau areas are the "gold mine" for new housing. The analysis confirms a "Corridor-based" growth pattern [7]. The negative coefficient for distance to roads (-0.679) means that for every kilometer moved away from a road, the chance of urban development is cut in half. Similarly, proximity to markets (1.386) shows that economic centers are primary nodes for sprawl (Table 3).

Interestingly, proximity to hospitals and schools showed negative coefficients. This suggests that in Uyo, residential sprawl often precedes the government's provision of social infrastructure. People are building in new areas first, and schools/hospitals are lagging behind the residential frontier [18] [19]. The jump in AUC from 0.861 (Regression) to 0.906 (MLP) is significant. It proves that urban drivers do not act in isolation. For example, a road might be a strong driver at high elevation but a weak driver in a swampy (low elevation) area.

Simulation and Forecasting (2035 and 2050)

Using the MLP-Markov trained model, the urban growth patterns for the year 2035 and 2050 were analyzed. It analyzed potential transitions from one class to another, with respect to the proximity to road development as an independent variable. Figure 4 – 6 showed the potential transitions used

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in training the MLP-Markov sub models. Each land cover class was trained under a sub-model to measure the potential for transition before the final predictions were made.

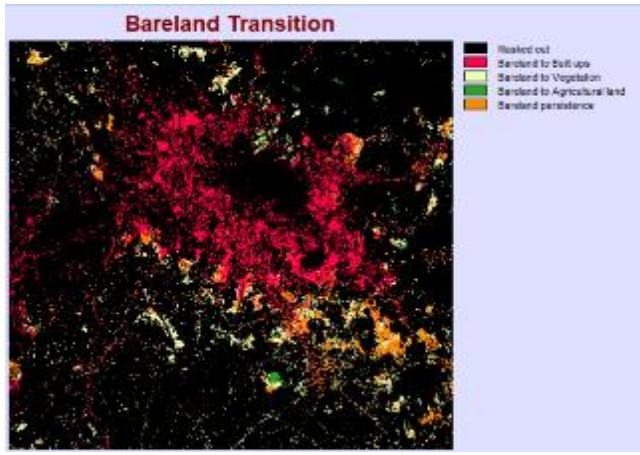

Figure 4 Transition sub-model for bareland

Table 4: Transition sub model areas for Bareland

Category	Square kilometers	Legend
1	53.274600	Bareland to Built ups
2	25.746300	Bareland to Vegetation
3	1.632600	Bareland to Agricultural land
4	18.733500	Bareland persistence

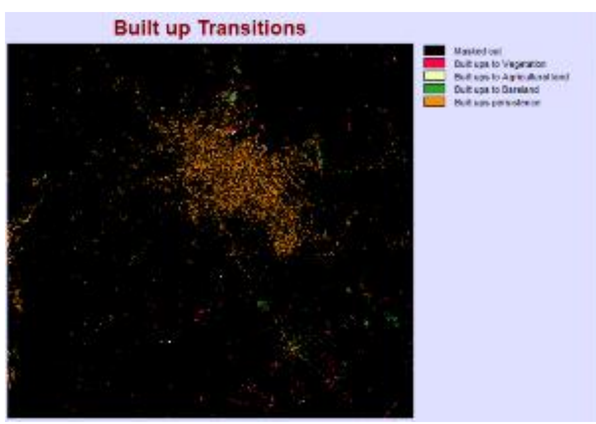

Figure 5: Transition sub-model for built ups

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Table 5: Transition sub model areas for Built ups

Category	Square kilometers	Legend
1	1.953900	Built ups to Vegetation
2	0.207000	Built ups to Agricultural land
3	2.247300	Built ups to Bareland
4	18.120600	Built ups persistence

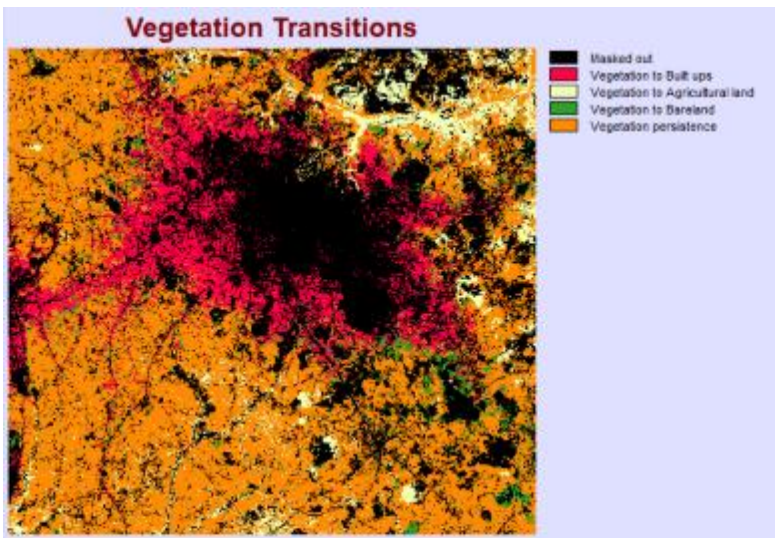

Figure 6: Transition sub-model for vegetation

Table 6: Transition sub model areas for vegetation

Category	Square kilometers	Legend
1	76.225500	Vegetation to Built ups
2	37.915200	Vegetation to Agricultural land
3	22.013100	Vegetation to Bareland
4	295.571700	Vegetation persistence

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From these sub-models, it is seen that the vegetation sub-model confirms that forest and green areas are the most significant victims of sprawl. Approximately 76.23 km² of vegetation is transitioning directly to built-up areas. Despite heavy losses, 295.57 km² of vegetation remains persistent, primarily in the outskirts. This transition represents the "frontier" of expansion where natural landscapes are being cleared for new residential developments (Table 4). The built-up sub-model showed the highest level of stability. 18.12 km² of the urban core remained unchanged (persistent). Bareland acts as a critical intermediate stage in the urbanizing process. 53.27 km² of bareland is transitioning to built-up areas. Interestingly, 25.75 km² reverted to vegetation, due to land abandonment or fallow periods. The high conversion of bareland to built-up areas suggests that "Infilling" will occur, where previously cleared lots within the city are finally being developed with structures (Table 7).

Table 7; Land Use Transition Contributions to Built-up Expansion

Source Class	Area Converted to Built-up (km2)	Percentage Contribution
Vegetation	76.23	53.8%
Bareland	53.27	37.6%
Agricultural Land	12.21	8.6%
Total New Built-up	141.71	100%

The MLP-Markov simulation reveals that Uyo is entering a phase of sustained urban dominance. By 2035, Built-up areas are projected to cover 106.58 km² (58.06%) of the study area, and by 2050, this figure will rise to 118.47 km² (64.54%) (table 9). The forecast indicates that the urban footprint will expand by an additional 25.7% between 2025 and 2050. Most of this growth is expected to occur through the conversion of Vegetation, which is projected to decline from 38.27% to 29.21%. A critical observation is the continued depletion of Agricultural Land, which drops to just 4.06% by 2050 (Table 10). This suggests that the agricultural land of Uyo is at risk of being completely absorbed by residential and commercial structures.

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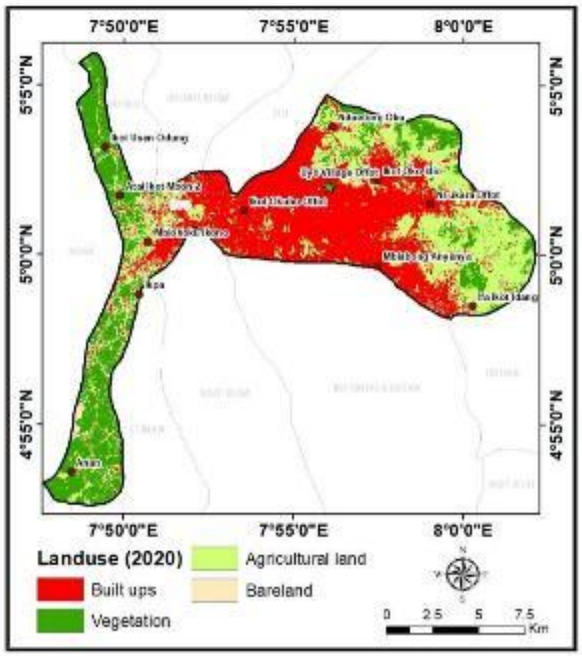
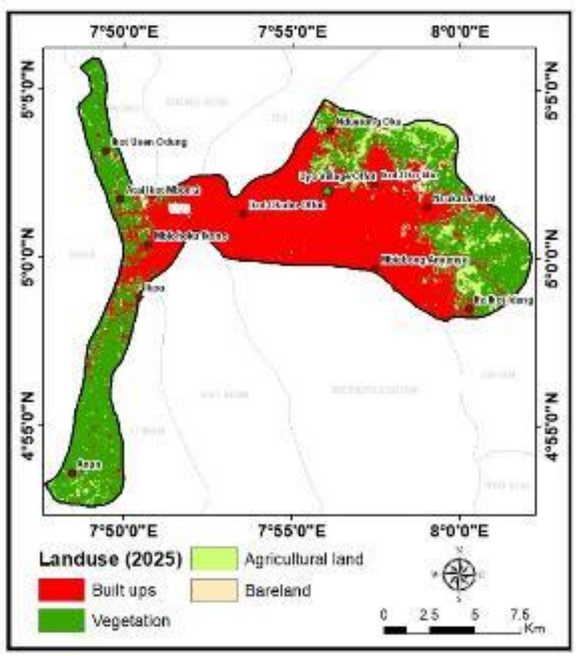
Table 8: Land use projection from 2020 - 2050

Year	Land use land cover
2020	
2025	

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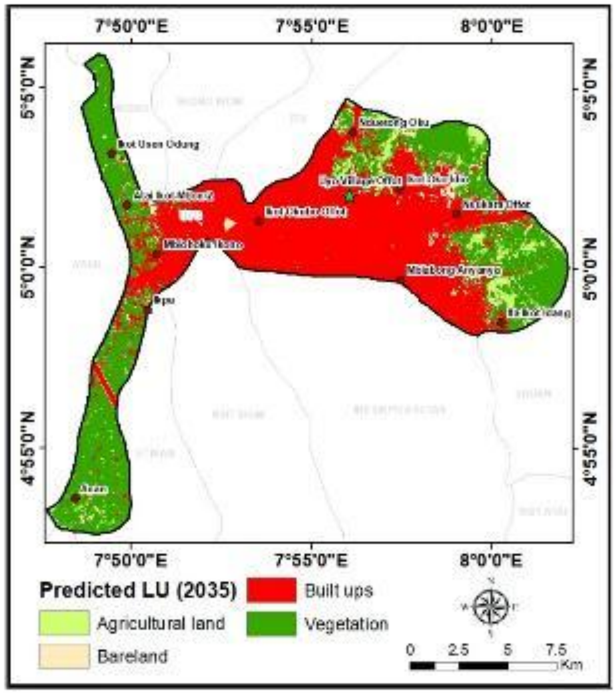
Predicted (2035)



Predicted 2050

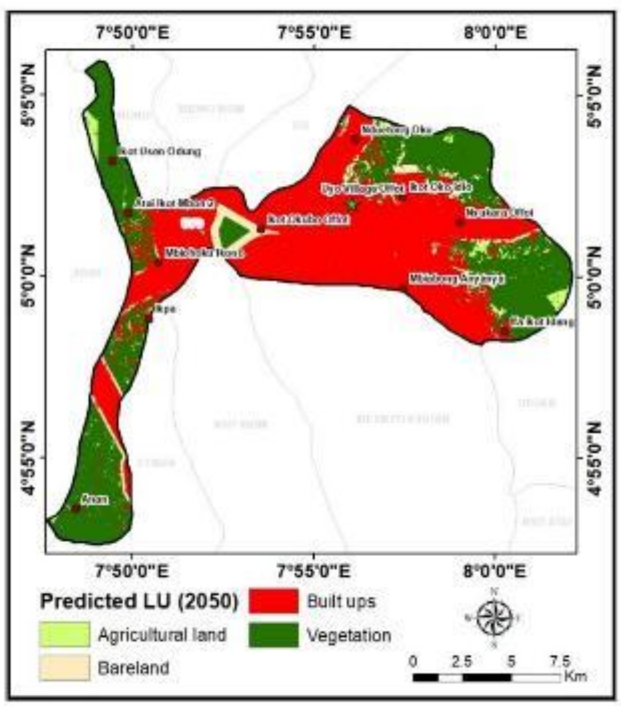


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Table 9: Projected LULC Area (2025 – 2050)

Land Use Class	2025 Area (km²)	2035 Area (km²)	2050 Area (km²)	Net Change (2025-50)
Built-up	94.24	106.58	118.47	**+24.23 km²**
Vegetation	70.25	61.67	53.62	-16.63 km²
Agricultural Land	11.08	9.51	7.45	-3.63 km²
Bareland	7.98	5.80	4.01	-3.97 km²

Table 10: Change Detection and Urban Expansion Statistics (2035–2050)

Variable	2035	2050	Change	% Change
Built-up Area (km²)	106.58	118.47	+11.89	+11.16
Vegetation (km²)	61.67	53.62	−8.05	−13.05
Agricultural Land (km²)	9.51	7.45	−2.06	−21.66
Bareland (km²)	5.80	4.01	−1.79	−30.86

The projected land use scenario indicates continued urban expansion between 2035 and 2050, with built-up land increasing from 106.58 km² to 118.47 km², representing an 11.16% increase (Table 9 and 10). The annual urban expansion rate was estimated at approximately 0.79 km²/year, reflecting sustained urban growth within the study area. In contrast, vegetation, agricultural land, and bareland are projected to decline considerably, suggesting increasing pressure on natural and peri-urban landscapes. Agricultural land experienced a notable reduction of 21.66%, while bareland declined by 30.86% (Table 10), indicating progressive conversion of undeveloped land into urban surfaces. The calculated urban growth intensity of 0.43% per year further highlights the accelerating transformation of the urban landscape toward a more built-up environment.

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Sustainability Assessment and SDG 11.3.1 Projections

The evaluation of Land Use Efficiency (LUE) for the Uyo Metropolis necessitates a robust demographic baseline. According to the UN World Urbanization Prospects (2024–2026), the Uyo urban agglomeration is experiencing a profound demographic surge, with an estimated annual growth rate of 4.32% (United Nations, 2026). This rate significantly exceeds the national average and reflects the city's role as a primary migration destination in the Niger Delta.

For the purpose of this simulation, a Population Growth Rate (PGR) of 0.043 (4.3%) was applied for the 2025–2035 interval, with a slightly moderated rate of 0.035 (3.5%) for the 2035–2050 period as the urban market matures [20] [21]. The Land Consumption Rate (LCR) was derived from the MLP-Markov simulation, which projects a built-up area expansion to 106.58 km² by 2035 and 118.47 km² by 2050. The resulting LCRPGR ratio, the primary metric for SDG 11.3.1, was then calculated.

Table 11: Land Use Efficiency and SDG 11.3.1 Forecast (2025–2050)

Forecast Interval	Land Consumption Rate (LCR)	Population Growth Rate (PGR)	LCRPGR Ratio
2025–2035	0.0123 (1.23%)	0.0430 (4.30%)	0.286
2035–2050	0.0071 (0.71%)	0.0350 (3.50%)	0.202

The calculated LCRPGR ratios of 0.28 and 0.20 are substantially lower than the UN-Habitat sustainability threshold of 1.0 (Table 11). In the context of the SDG 11.3.1 framework, a ratio significantly below unity indicates high land-use efficiency, as population growth is outpacing the physical expansion of the built-up area. However, this statistical efficiency masks a dual-pronged planning crisis:

1. Hyper-Densification and Infrastructure Strain: A ratio of 0.20 implies that the population is growing nearly five times faster than the spatial footprint. While this suggests a "compact" urban form, without corresponding investments in vertical housing and high-

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capacity infrastructure, this trajectory leads to severe overcrowding, increased informal settlements (slums), and the degradation of urban living standards.

2. Irreversible Ecological Attrition: Despite the "efficient" per capita land use, the absolute spatial demand remains aggressive. The simulation predicts that by 2050, the city will have consumed 70% of its baseline vegetation, with Agricultural Land dropping to a critical low of 4.06%.

Discussion

The results from the Logistic Regression and MLP transition potentials indicate that Uyo's urban form is being dictated by a "Radial-Concentric" growth pattern. The high statistical significance of Proximity to Major Roads confirmed that infrastructure acts as the primary catalyst for land conversion. This "ribbon development" is a common characteristic of West African secondary cities, where accessibility to transport corridors outweighs planned zoning [22] [23]. Furthermore, the influence of Elevation reveals a critical "Safety-First" growth logic. The preference for development on higher ground (above 60m) suggests that the urban footprint is naturally avoiding the flood-prone lowland plains [24]. While this is a positive adaptation to the region's high rainfall, it implies that by 2050, as "prime" high-elevation land becomes saturated, lower-income residents may be forced into hazardous, low-lying zones, a trend that planning authorities must proactively address.

The transition from a 19.89% urban footprint in 2000 to a projected 64.54% in 2050 represents a profound environmental transformation. The simulation captured what we term a "Spatio-Temporal Surge", a period of aggressive growth fueled by Uyo's administrative status and its role as a regional economic hub [21]. Also, another important touchpoint of this research is the Efficiency Paradox revealed by the SDG 11.3.1 framework. With an LCRPGR ratio as low as 0.20, Uyo appears to be a "model of efficiency" by UN-Habitat standards (where a ratio < 1.0 is considered compact). However, it is argued that this statistical efficiency is a double-edged sword. In the absence of high-density vertical infrastructure, a ratio this low indicates Hyper-Densification. This is not "compactness by design" but "congestion by necessity." [25] [26] [27]. Without proactive planning, this trajectory leads to:

i. Infrastructure Stress: Overburdened drainage, waste management, and transport systems.

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ii. Social Vulnerability: The proliferation of informal settlements as population influx (4.32% PGR) outpaces the formal housing supply.

iii. Ecosystem Loss: Even "efficient" growth is resulting in the loss of 70% of original vegetation, proving that the SDG 11.3.1 ratio must be used in conjunction with ecological "loss-limits" to be truly effective.

Finally, this research depicts the robustness of the MLP-Markov approach. Unlike traditional linear models, the MLP was able to capture the "surge" between 2020 and 2025, allowing the 2050 forecast to be grounded in recent, high-momentum trends. This confirmed that for rapidly urbanizing tropical cities, non-linear neural network approaches are superior to traditional deterministic models for providing policy-relevant foresight.

Conclusion and Recommendations

This study has transitioned from retrospective mapping to predictive foresight, providing a critical evaluation of Uyo's urban trajectory toward 2050. By integrating an MLP-Markov simulation with Logistic Regression drivers, the research identifies that Uyo's expansion is primarily dictated by infrastructural proximity and topographic safety. The findings project that by 2050, the built-up footprint will encompass 64.54% of the study area, signaling a near-complete transition from a rural-urban mosaic to a dominant metropolitan core.

The application of the SDG 11.3.1 framework revealed a significant "Efficiency Paradox." With an LCRPGR ratio as low as 0.20, Uyo's population is growing significantly faster than its physical boundaries, suggesting a trend toward hyper-densification. While this satisfies the technical criteria for "efficient" land use, it warns of an impending crisis in urban service delivery, housing congestion, and the irreversible loss of peri-urban agriculture. Ultimately, this research provides the empirical evidence required to shift Uyo's planning paradigm from managing sprawl to managing intensity and ecological resilience.

It is recommended that planning authorities should plan vertical residential development to prevent the spread of high-density horizontal slums, with hyper-densification projected for 2050. Strategic zoning should be implemented immediately to preserve the remaining 29% of vegetation, treating these areas as essential carbon sinks and flood-mitigation zones. Since roads were identified as the

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primary growth driver, future arterial road projects should be used as "planning anchors" to pre-define where development is permitted, rather than reacting to unplanned settlement patterns.

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