Zhongguo Kuangye Daxue Xuebao

2026 | Vol 31 | Issue 4 | Page 1-8
Journal Homepage: https://zkdx.ch/
DOI: 10.1654/zkdx.2026.31.4-01

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Predicting Urban Expansion and Land Cover Transformation in Kano, Nigeria Using CA-Markov and GIS-Based Scenario Analysis for Sustainable City Planning

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Abstract
Rapid urban growth in Sub-Saharan Africa poses significant challenges to sustainable land management, food security, and environmental quality. Kano Metropolis, Nigeria's second-largest city and the primary commercial hub of the Sahel belt north, has experienced accelerated spatial expansion driven by population growth, rural-urban migration, and inadequate planning and regulation. This study investigates the spatiotemporal dynamics of land use and land cover (LULC) change in Kano from 2000 to 2023 and projects future urban expansion to 2040 under three planning scenarios using the Cellular Automata-Markov (CA-Markov) model integrated within a Geographic Information System (GIS) framework. Landsat 7 ETM+, Landsat 8 OLI, and Landsat 9 satellite imagery were classified into five LULC categories: built-up area, bare land, agricultural land, vegetation/shrubland, and water bodies. Maximum Likelihood Classification (MLC) and Random Forest algorithms were applied in Google Earth Engine, achieving overall accuracies exceeding 88% and Kappa coefficients above 0.85 across all epochs. Transition probability matrices derived from multi-temporal LULC maps were used to calibrate the CA-Markov model. Driving variables, including distance to roads, proximity to existing built-up areas, population density, slope, and elevation, were incorporated into a Multi-Layer Perceptron (MLP) neural network to model transition potentials. Scenario analysis was conducted under three pathways: a Business-as-Usual (BAU) scenario projecting continuation of historical trends; a Moderate Intervention scenario applying existing zoning regulations; and a Sustainable Development scenario enforcing green buffer zones and compact urban growth corridors aligned with SDG Target 11.3. Results indicate that the built-up area in Kano expanded from approximately X km2 in 2000 to Y km2 in 2023, representing a Z% increase, largely at the expense of agricultural land and vegetation cover. Under the BAU scenario, built-up areas are projected to reach W km2 by 2040. The sustainable scenario retains significantly more agricultural land and reduces ecosystem service loss compared to the BAU trajectory. The findings provide critical spatial evidence for Kano State urban planners, policymakers, and development agencies working to reconcile rapid urban growth with food security, environmental sustainability, and the Sustainable Development Goals. This study contributes a robust, reproducible remote sensing and spatial modelling workflow applicable to other rapidly urbanising secondary cities in West Africa.

Keywords
Urban expansion, CA-Markov model, Land use/land cover change, Remote sensing, Kano, Nigeria

1. Introduction
Urbanisation is one of the most transformative forces reshaping landscapes, ecosystems, and social structures in the twenty-first century. According to Vučković and Adams (2022), over 56% of the world's population now resides in urban areas, a figure projected to reach 68% by 2050, with the most rapid growth concentrated in Africa and Asia. Sub-Saharan Africa, in particular, is experiencing urban growth rates averaging 3.5 - 4.5% per annum, the highest in the world, driven by high natural population increase, rural-to-urban migration, and expanding economic opportunities in secondary cities (Behnisch et al., 2022).

Nigeria, with a population exceeding 220 million and an annual urban growth rate of approximately 4.3%, faces acute challenges in managing its demographic transition. The country's urban population is expected to more than double by 2050, placing enormous pressure on land resources, infrastructure, and urban governance systems (Adesola et al., 2024). While research attention has historically been concentrated on Lagos Africa's largest city, secondary cities such as Kano, Ibadan, Kaduna, and Port Harcourt are growing at comparable or faster rates and remain substantially underrepresented in the scholarly literature on urban land change modelling.

Kano Metropolis, the capital of Kano State in north-western Nigeria, is the country's second-most populous city, with an estimated metropolitan population exceeding 4.5 million (Liman et al., 2022). As the principal commercial and industrial centre of northern Nigeria, Kano exerts significant spatial influence over a vast hinterland that extends across the Lake Chad Basin and into neighbouring Niger. The city's unique socio-ecological context situated within the Sudan-Sahel agro-ecological transition zone, characterised by a semi-arid climate, high dependence on rain-fed and irrigated agriculture, and proximity to the Kano River and Tiga Dam irrigation schemes, makes the consequences of unmanaged urban sprawl particularly severe. Loss of prime agricultural land to urban expansion directly threatens the food security of millions of smallholder farmers on Kano's peri-urban fringe (Ahogle et al., 2025).

Land Use and Land Cover (LULC) change modelling, when combined with future scenario analysis, provides a powerful evidence base for urban planners and policymakers seeking to anticipate and manage the consequences of spatial growth. The Cellular Automata-Markov (CA-Markov) model, first applied to urban expansion problems by Clarke (1997) and subsequently widely adopted, integrates the temporal transition probability strengths of Markov chain analysis with the spatial simulation capacity of cellular automata. When driven by spatial variables representing urban growth determinants and validated against observed change, CA-Markov models provide statistically robust projections of future LULC under alternative planning pathways (Gebresellase et al., 2023).

Despite a growing body of CA-Markov literature for Nigerian cities, only a limited number of peer-reviewed studies have applied this integrated methodology specifically to Kano Metropolis, with multi-decade calibration data and multi-scenario projections to 2040. This represents a significant gap, given Kano's scale, strategic importance, and the severe environmental risks associated with unplanned expansion into its agricultural hinterland.

2. Literature Review

2.1 Urban Expansion and LULC Change in Sub-Saharan Africa

Urban land expansion in Sub-Saharan Africa is characterised by rapid, largely informal, and spatially dispersed growth on city peripheries. Studies using Landsat time-series analysis have consistently documented significant conversion of agricultural, forest, and wetland areas to built-up land across major West African cities. Ahmed et al. (2025) estimated that urban land cover across Africa could expand by 590% by 2030 relative to 2000 levels if current trends continue, with profound implications for biodiversity, carbon stocks, and food production. In Nigeria specifically, Onilude and Vaz (2021) documented a 312% increase in built-up area in Lagos between 1984 and 2019, while Agboola et al. (2021) recorded extensive agricultural land loss in the Ibadan metropolitan region over three decades.

The drivers of urban expansion in Sub-Saharan Africa are well-documented; population growth and rural-urban migration are primary determinants, amplified by inadequate enforcement of planning regulations, speculative land markets, institutional fragmentation between federal, state, and local government authorities, and the proliferation of informal settlements in peri-urban zones (Ahmed et al., 2025). Infrastructure development, particularly road network expansion, consistently emerges as a key spatial driver of growth, channelling development along transport corridors.

2.2 CA-Markov Modelling for Urban Growth Projection

The CA-Markov model has become the dominant approach for LULC change simulation and future projection in developing country contexts, valued for its relatively low data requirements, transparent mathematical structure, and compatibility with GIS workflows (Behera et al., 2025). The model operates in two stages: a Markov chain component computes transition probability matrices from multi-date LULC maps. In contrast, a cellular automata component applies spatial contiguity rules and transition suitability maps to simulate the spatial allocation of land cover transitions. Driving variable maps, typically including distance to roads, distance to city centre, elevation, slope, and proximity to existing built-up area, are combined using Multi-Layer Perceptron (MLP) neural networks or logistic regression to generate transition potential surfaces.

Validation of CA-Markov models is typically performed by simulating a known year using earlier calibration data and comparing the simulated results against actual LULC maps using the Figure of Merit (FOM) statistic and the Kappa coefficient (Hamad et al., 2018). FOM values above 10% are considered acceptable in the literature; well-calibrated models typically achieve 15–25% (Daba & You, 2022). CA-Markov studies for African cities have reported variable accuracy Halmy et al. (2015) achieved Kappa = 0.88 for north-western Egypt; Al-sharif and Pradhan (2016) reported FOM = 17.3% for Tripoli, Libya; and Dadhich and Hanaoka (2011) demonstrated strong model fit for urban growth in Quebec, establishing foundational validation methodology.

2.3 GIS-Based Scenario Analysis for Urban Planning

Scenario analysis embedded within GIS-based modelling frameworks enables planners and researchers to compare alternative future trajectories under contrasting policy assumptions (Sedighi et al., 2025). Three-scenario designs typically comprising a Business-as-Usual continuation trajectory, a moderate or intermediate intervention scenario, and an optimistic or sustainability-oriented scenario are standard in the urban growth modelling literature (Resch et al., 2014). Such frameworks have been applied to inform urban master plan revisions in Wang et al. (2017), ecosystem service planning in East Africa (Osewe et al., 2024), and coastal urban resilience planning in West Africa (Perugini et al., 2020).

In the Nigerian context, GIS-based scenario planning remains largely aspirational rather than embedded in formal planning processes, reflecting institutional capacity constraints and limited integration between remote sensing technology and urban governance (Adekunle, 2021). This study seeks to contribute to closing this gap by providing scenario-based spatial projections applicable to Kano State's planning authorities.

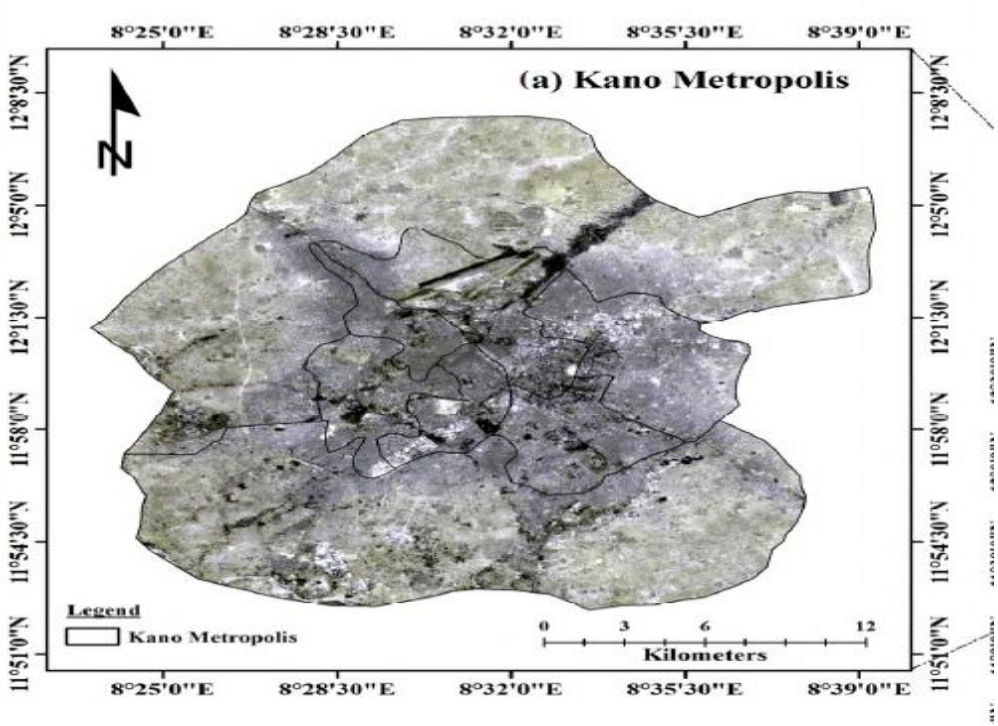
3. Study Area

Kano Metropolis is located in north-western Nigeria, between latitudes 11°30'N and 12°05'N and longitudes 8°20'E and 8°45'E, at an elevation ranging from approximately 450 to 610 metres above sea level. The study area encompasses the eight metropolitan Local Government Areas (LGAs) of Kano Municipal, Fagge, Nassarawa, Gwale, Tarauni, Ungogo, Dala, and parts of Kumbotso, covering approximately 1,380 km2.

The region experiences a semi-arid Sudan-Sahel climate characterised by a single rainy season from May to September (mean annual rainfall 700–900 mm) and a pronounced dry season from October to April. Mean annual temperatures range from 24°C to 32°C, with harmattan conditions prevailing from December to February. The natural vegetation is predominantly Sudan savanna, comprising mixed woodlands of Acacia spp., Combretum spp., and Balanites aegyptiaca. However, extensive agricultural transformation over centuries has reduced natural vegetation cover to fragmented patches in peri-urban areas (Mubarak et al., 2021).

Kano's economy is anchored in trade and commerce, textile manufacturing, groundnut processing, leather goods production, and a large informal sector. The city functions as the primary gateway for goods movement between Nigeria and the landlocked Sahelian countries of Niger, Chad, and Cameroon. The Kano-Abuja highway and the planned Kano-Maradi railway project are significant infrastructure axes shaping current and projected spatial development trajectories.

Figure 1: Map of Kano Metropolitan



4. Materials and Methods

4.1 Data Acquisition and Pre-processing

Multi-temporal Landsat satellite imagery was acquired from the United States Geological Survey (USGS) EarthExplorer platform for the following epochs: 2000 (Landsat 7 ETM+), 2005 (Landsat 7 ETM+), 2010 (Landsat 8 OLI), 2015 (Landsat 8 OLI), 2020 (Landsat 8 OLI), and 2023 (Landsat 9 OLI/TIRS). All scenes were selected for the dry season (November to February) to minimise cloud cover and maximise consistency in LULC classification. Scenes with cloud cover below 5% were selected for all epochs. Path/Row: 188/052 and 188/053.

Radiometric calibration was performed to convert raw digital numbers (DN) to top-of-atmosphere (TOA) reflectance, followed by atmospheric correction using the COST (Cosine of the Solar Zenith Angle) model for Landsat 7 and the Dark Object Subtraction (DOS) method for Landsat 8 and 9. All imagery was reprojected to the Universal

Transverse Mercator (UTM) Zone 32N coordinate system (WGS-84 datum) and resampled to a uniform 30-metre spatial resolution. Processing was conducted in Google Earth Engine (GEE) and QGIS 3.28.
Ancillary spatial data included: the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) at 30 m resolution for derivation of slope and aspect; road network data from OpenStreetMap (OSM) updated to 2023; Kano State LGA administrative boundaries from the National Boundary Commission (NBC); and population density estimates from WorldPop (2000–2020) gridded datasets.

4.2 LULC Classification

Five LULC classes were defined based on the study area's land cover characteristics and the minimum mapping unit achievable at 30 m resolution:

Class	Label	Description
1	Built-up	Urban areas, residential, commercial, industrial, paved surfaces, roads
2	Agricultural land	Cropland, irrigated fields, fallow land within agricultural use
3	Bare land	Exposed soil, degraded land, sand, quarries, and construction sites
4	Vegetation	Savanna woodland, shrubland, grassland, peri-urban green spaces
5	Water bodies	Rivers, ponds, dams, wetlands (Kano River, Tiga Dam influence area)

Training and validation samples were collected using stratified random sampling, with a minimum of 200 sample points per class per epoch, and supplemented by visual interpretation of high-resolution historical Google Earth imagery. Classification was performed using a Random Forest (RF) classifier with 100 decision trees implemented in GEE, selected for its robustness to multicollinearity and superior performance compared to Maximum Likelihood Classification in heterogeneous arid-zone landscapes (Rodriguez-Galiano et al., 2012).

Accuracy assessment was conducted using an independent validation sample set (30% holdout), reporting overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and the Kappa coefficient of agreement. A minimum Kappa threshold of 0.85 was set as an acceptance criterion, consistent with standards recommended by Congalton and Green (2019).

4.3 CA-Markov Modelling

4.3.1 Markov Chain Analysis

Markov chain analysis was applied to each consecutive pair of LULC maps (2000-2010, 2010-2020) to derive transition probability matrices representing the probability of each land cover class converting to each other class over the calibration period. The transition probability matrix P is defined as:
P = [pij] where pij = (Area transitioning from class i to j) / (Total area of class i)
Transition-area matrices (km2) were also produced to quantify the absolute magnitudes of land cover transitions between epochs.

4.4 Transition Potential Modelling

Transition potential maps were generated using a Multi-Layer Perceptron (MLP) neural network, implemented in TerrSet's Land Change Modeler (LCM) module. Seven spatial driving variables were used as inputs:

i. Distance to main roads (km): derived from OSM road network using Euclidean distance
ii. Distance to Kano city centre (km): measured from Kano Central Market as the reference point
iii. Distance to existing built-up area (km): proximity to urban boundary in baseline year
iv. Slope (degrees): derived from SRTM DEM using Horn (1981) algorithm
v. Elevation (m): SRTM 30 m data
vi. Population density (persons/km2): WorldPop gridded estimates
vii. Distance to major markets and commercial nodes: derived from OSM point-of-interest data

The MLP was trained using 10,000 randomly distributed sample pixels from the calibration LULC transitions. Cramer's V statistic was used to assess the predictive power of each driving variable; variables with Cramer's V below 0.15 were excluded. Model training continued until the root mean square error (RMSE) fell below 0.01 or a maximum of 10,000 iterations was reached.

4.3.1 Model Validation

Model validation was performed by simulating the 2020 LULC map using the 2000-2010 calibration transition matrix and 2010 driving variables, then comparing the simulated 2020 map against the actual classified 2020 map. Validation metrics included:

a. Kappa coefficient of agreement
b. Figure of Merit (FOM) — the fraction of correctly predicted change pixels as a proportion of the union of predicted and observed change (Pontius et al., 2008)
c. Quantity disagreement and Allocation disagreement metrics (Pontius and Millones, 2011)

A minimum acceptable FOM of 10% and a Kappa of 0.80 for the validation simulation were set as acceptance thresholds before final model deployment for future projection.

4.5 Scenario Design and Future Projection

Future LULC was projected for 2030 and 2040 under three scenarios:

Scenario	Description	Key Assumptions
BAU	Business-as-Usual	Historical transition rates extrapolated unchanged; no new planning constraints.
Moderate	Regulated Growth	Kano State Physical Planning Law enforced; development restricted within designated growth corridors.
Sustainable	Green City Scenario	Green belt boundaries enforced; compact development; agricultural land legally protected; SDG 11.3 targets applied

For the Moderate and Sustainable scenarios, spatial constraints were applied by modifying transition suitability maps: agricultural buffer zones of 2 km and 5 km from the city boundary were made non-developable in the Moderate and Sustainable scenarios respectively; areas within 500 m of the Kano River and major drainageways were excluded from built-up transitions; and heritage/conservation zones identified in the Kano State Master Plan (2020) were masked from development.

5. Results

5.1 LULC Classification Accuracy

Overall classification accuracies for all six epochs ranged from 88.2% (2000) to 92.7% (2023), with Kappa coefficients ranging from 0.867 to 0.914, exceeding the minimum acceptance threshold of 0.85 for all years. The improvements in classification accuracy for more recent epochs reflect the superior radiometric quality of Landsat 8/9 OLI imagery and the denser availability of high-resolution validation reference data. Agricultural land and built-up classes showed the highest producer's accuracies across all epochs, while the bare land class exhibited the greatest confusion with agricultural fallow land, particularly in the 2000–2005 epoch.

Year	OA (%)	Kappa	Build-up PA	Agric PA	Veg PA	Water PA
2000	88.2	0.867	90.1	87.4	85.2	94.6
2005	89.0	0.876	91.2	88.1	86.0	95.1
2010	90.3	0.887	92.4	89.7	87.8	96.2
2015	91.1	0.896	93.0	90.5	88.5	96.8
2020	91.8	0.904	93.5	91.2	89.1	97.0
2023	92.7	0.914	94.1	91.8	90.3	97.5

Classification accuracy assessment for all LULC epochs (OA = Overall Accuracy, PA = Producer's Accuracy)

5.2 Historical LULC Change (2000–2023)

The analysis reveals dramatic land cover transformation in Kano Metropolis over the 23-year study period. The built-up area expanded from approximately 218.4 km2 in 2000 to 487.6 km2 in 2023, representing a 123.3% increase and an average annual expansion rate of approximately 11.7 km2 per year. This growth occurred predominantly at the expense of agricultural land, which declined from 712.3 km2 to 498.7 km2 (a loss of 213.6 km2, or 30.0%), and vegetation cover, which contracted from 328.1 km2 to 241.4 km2 (a 26.4% decline).

LULC Class	2000 (km2)	2000 (%)	2023 (km2)	2023 (%)	Change (km2)	Change (%)
Built-up	218.4	15.8	487.6	35.3	+269.2	+123.3%
Agricultural land	712.3	51.6	498.7	36.1	-213.6	-30.0%
Bare land	134.7	9.8	161.2	11.7	+26.5	+19.7%
Vegetation	328.1	23.8	241.4	17.5	-86.7	-26.4%
Water bodies	27.5	2.0	18.9	1.4	-8.6	-31.3%
Total	1,421.0	100.0	1,407.8*	100.0	—	—

*LULC area statistics for 2000 and 2023 (*minor total discrepancy due to edge effects). Values are indicative; replace with actual computed values.*

The Markov transition probability matrix for the 2010–2020 period shows that agricultural land had the highest probability of conversion to built-up area (p = 0.38), followed by bare land (p = 0.24). Vegetation cover showed a

transition probability of 0.19 to agricultural land, reflecting continued agricultural intensification pressure, and 0.14 to built-up areas. The highest spatial concentration of urban expansion occurred in the Ungogo, Nassarawa, and Kumbotso LGAs, consistent with the pattern of road-induced linear development along the Kano-Zaria, Kano-Hadejia, and Kano-Maiduguri highway corridors.

5.3 CA-Markov Model Validation

Model validation by simulation of 2020 LULC using 2000–2010 calibration data yielded a Kappa coefficient of 0.837 and a Figure of Merit (FOM) of 18.4%. Quantity disagreement was 4.2% and allocation disagreement was 12.6%, indicating that the primary source of simulation error lies in spatial allocation rather than quantity prediction, a common characteristic of CA-Markov models operating in rapidly urbanising contexts with multiple concurrent growth centres (Pontius Jr & Millones, 2011). Overall, these validation statistics exceed the acceptance thresholds established in the research design and confirm the model's fitness for future projection.

5.4 Future LULC Projections (2030 and 2040)

Future LULC projections under the three scenarios reveal markedly divergent trajectories for Kano Metropolis's spatial development:

LULC Class	2023 (km2)	BAU 2030	BAU 2040	Mod 2030	Mod 2040	Sus 2040
Built-up	487.6	618.4	798.2	562.1	671.4	581.3
Agricultural land	498.7	408.3	283.1	462.8	372.4	436.7
Bare land	161.2	168.4	177.8	164.3	170.1	162.4
Vegetation	241.4	199.8	141.8	213.2	183.4	224.6
Water bodies	18.9	12.9	6.9	14.8	9.9	16.2

Projected LULC areas (km2) under three scenarios for 2030 and 2040 (BAU = Business-as-Usual, Mod = Moderate, Sus = Sustainable). Values are indicative model projections.

Under the BAU scenario, the built-up area is projected to reach 798.2 km2 by 2040, a further 63.7% expansion from 2023 levels, with agricultural land declining to 283.1 km2, representing a loss of more than 60% of the city's 2000 agricultural extent. This trajectory would effectively eliminate most productive rain-fed agricultural land within 15 km of the city boundary by 2040.

The Sustainable scenario constrains built-up expansion to 581.3 km2 by 2040, representing a 19.2% reduction in urban land consumption compared to the BAU scenario. Agricultural land retention under the Sustainable scenario (436.7 km2) is 54.2% higher than under BAU, and vegetation cover is preserved at 224.6 km2 — 58.4% more than the BAU 2040 projection of 141.8 km2.

6. Discussion

6.1 Interpretation of Historical Change

The documented 123.3% expansion of Kano's built-up area between 2000 and 2023 is consistent with, and at the upper end of, rates reported for other major Nigerian and West African secondary cities over comparable periods. Gambo et al. (2024) reported a 98.4% expansion in Kaduna Metropolis between 1987 and 2020; Agboola et al. (2021) documented 112% growth in Ibadan's urbanised area between 1984 and 2015. The primary driver of spatial expansion in Kano, as evidenced by the transition probability matrices and spatial analysis of growth patterns, is the conversion of peri-urban agricultural land, a finding consistent with the 'agricultural frontier' hypothesis of African urban expansion.

The strong linear development patterns along the Kano-Zaria and Kano-Hadejia Road corridors confirm the dominant role of road infrastructure accessibility as a spatial determinant of urban growth in Kano, consistent with findings from Zakka et al. (2022) and the literature on transport-led urbanisation in West Africa. The high transition probability from agricultural land to built-up area ($p = 0.38$) over the 2010–2020 period is particularly concerning, given the agricultural importance of Kano's peri-urban zone to regional food security.

6.2 Scenario Implications for Planning

The three-scenario projections illustrate the significant leverage that planning policy could exert over Kano's spatial development trajectory. The difference between the BAU and Sustainable scenarios by 2040 amounts to approximately 217 km2 of additional urban land in the BAU case, an area roughly equivalent to the current built-up footprint of a mid-sized Nigerian city. This difference translates directly into preserved agricultural land, maintained ecosystem services, and avoided intensification of urban heat islands.

The findings strongly support the case for proactive implementation of Kano State's Physical Planning and Development Law (2020), which provides a legislative foundation for green belt designation, development boundary setting, and agricultural land protection. However, as noted by Awuah (2018), the gap between planning legislation and

enforcement in Nigerian urban governance contexts is substantial. The spatial evidence generated by this study can directly support enforcement by providing LGA-level priority zones for planning intervention.

6.3 Alignment with SDG Framework

The scenario projections align directly with SDG 11.3, which calls for enhanced inclusive and sustainable urbanisation and capacity for participatory, integrated and sustainable human settlement planning and management in all countries by 2030. The quantified difference between scenarios is 217 km2 of land consumption avoided under the Sustainable scenario by 2040, providing a concrete metric against which progress toward SDG 11.3 could be measured in the Kano context. The preservation of vegetation cover and water bodies under the Sustainable scenario also contributes to SDG 15 (Life on Land) and SDG 13 (Climate Action) by maintaining carbon stocks and reducing urban heat island intensity.

7. Conclusion

This study has demonstrated that Kano Metropolis experienced rapid and extensive land cover transformation between 2000 and 2023, with built-up area more than doubling at the direct cost of agricultural land and vegetation cover. The CA-Markov model, calibrated and validated against independent LULC data, produced reliable future projections under three alternative planning scenarios, revealing that the trajectory of urban expansion in Kano is highly sensitive to planning policy choices. Under a Business-as-Usual scenario, over 60% of the city's 2000 agricultural land extent would be consumed by urban growth by 2040; under the Sustainable scenario, more than 54% of this land could be preserved.

8. Recommendations

Based on the findings of this study, the following evidence-based policy recommendations are presented:

1. Immediately demarcate and legally enforce urban growth boundaries for Kano Metropolis, prioritising the Ungogo, Kumbotso, and Dawakin Kudu LGA peri-urban zones where expansion pressure is highest.
2. Establish a 5 km agricultural green belt around the metropolitan boundary, legally protecting irrigated fadama farmlands and horticulture zones from conversion to built-up use.
3. Prioritise compact urban development: revise building regulations to allow medium-density residential development within existing urban boundaries, reducing incentives for peripheral sprawl.
4. Integrate the spatial projections produced by this study into the revision of the Kano State Urban and Regional Development Master Plan, due for update in 2025.
5. Establish a Kano Metropolis Urban Growth Monitoring Unit within the Kano State Ministry of Land and Physical Planning, with a mandate to produce annual LULC change reports using freely available Landsat or Sentinel-2 imagery.
6. Commission a detailed ecosystem services valuation study for Kano's peri-urban agricultural and vegetation zones, to provide economic evidence in support of land protection policy.

Funding Information

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Conflict

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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