Building Sustainable Green Cities: Spatial Insights into Urban Expansion and Its Prediction in Nigeria

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Abstract

Achieving sustainable green cities has been a concern for many organizations in the face of various environmental challenges, including climate change and deforestation, among others. This conference paper analysed urban expansion from 2002 to 2024, and predicted expansion up to 2046, with the aim of providing spatial insights to build sustainable green cities in Nigeria. Satellite imagery from Landsat 7 ETM+ (2002), Landsat 8 OLI (2013), and Landsat 9 OLI (2024) were the datasets used. ERDAS IMAGINE, ArcMap, and QGIS Molusce were applied for supervised classification, urban expansion analysis, and future urban growth prediction, respectively. Results reveal that urban expansion from 2002 to 2013 consisted of 479.8 hectares edge expansion, 198.6 leapfrogging expansion and 1.5 infilling expansion. From 2013 to 2024, edge expansion became more dominant, while infilling and leapfrogging expansions decreased. The model predicted that by 2046, urban expansion will encroach approximately 1,864 hectares of the existing green lands, including farmlands and vegetation, raising concerns about the availability and sustainability of green spaces in cities. This study recommends effective zoning policies and strict control of the conversion of green lands into built-up areas. This will provide the residents, government authorities, policymakers, and urban planners with spatial insights on how to develop sustainable green cities.

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1. INTRODUCTION

Globally, various factors drive urban expansion and growth, leading to diverse forecasts. These include natural population growth, rural-urban migration, and reclassification of rural areas as urban. Urban expansion results from the interplay of geographical constraints, land demand by households and firms, and land use policies (Avis, 2019; Rijal, Rimal, Stork & Sharma, 2020). This growth and landscape change are influenced by population growth, policies, and economic development. Socioeconomic policies significantly affect urban expansion, altering land use patterns for higher economic returns (Oduwaye, 2013; Ibrahim *et al.,* 2016; Koko *et al.,* 2022). Population growth is a primary driver of urbanization, with developed areas increasing linearly with population growth. Improved traffic conditions also promote urban development, while industrial growth and infrastructure investment have more complex relationships with urban growth (Suzuki, Cervero & Iuchi, 2013; Li *et al.,* 2019). Key drivers of land-use change include industrialization, urbanization, population growth, and economic reform measures, as observed in China (Long, Tang, Li, & Heilig, 2007). Several determinants of urban expansion include topology, precipitation, demography, natural resources, soil quality, industrial structure, economic growth, market transitions, tourism, globalization, infrastructure, and policy. These can be categorized into biophysical and socioeconomic factors (Zhang & Su, 2016; Chirisa & Campbell, 2023).

Urban expansion reflects socioeconomic segregation, as lower-income groups often seek closer access to essential services such as schools, healthcare centres, and major roads (Azhdari, Sasani, & Soltani, 2018). This phenomenon is strongly correlated with factors such as urban population density, gross domestic product (GDP) per capita, and industrial structure. When spatial heterogeneity is considered, the driving forces of urban sprawl exhibit varying magnitudes and directions (Li & Li, 2019). Accessibility, spatial interaction effects, and policy variables have been identified as significant determinants of land-use change (Braimoh & Onishi, 2007).

Research has shown that urban growth is largely propelled by socioeconomic elements such as population, income levels, and agricultural land rent. Economic indicators like these are vital in determining the spatial dimensions of urban areas. Furthermore, physical factors, including slope, elevation, proximity, and neighborhood characteristics, as well as land use policies and urban planning, also impact urban expansion trends (Jiang, Deng & Seto, 2013; Rodriguez-Pose & Storper, 2020). Additionally, aspects such as infrastructure, job opportunities, foreign investment, soil suitability, and land classification are closely linked to the dynamics of urban expansion (Ustaoglu & Williams, 2017; Colsaet, Laurans & Levrel, 2018). Studies like Li *et al.* (2018) focused on five commonly examined categories of driving forces: socioeconomic, physical, proximity, accessibility, and neighborhood factors. Socioeconomic factors, such as population and gross domestic product (GDP); and physical factors, including elevation, slope, distance to water bodies like lakes and rivers, are also considered. Overall, urban expansion is a complex process influenced by a multitude of interacting factors spanning economic, social, and physical dimensions, highlighting the intricate relationship between urbanization and its driving forces over time.

In Nigeria, the drivers of urban expansion towards peripheral areas are primarily related to job and occupation factors, housing and living conditions, accessibility, religious affiliations, and institutional factors (Afolayan, Adebayo, Ige, & Afolayan, 2023). Furthermore, urban spatial evolution in Nigeria is shaped by a complex interplay of anthropogenic activities and environmental dynamics, driven by physical, socioeconomic, and regulatory influences (Gilbert & Shi, 2024). Urbanization offers both opportunities for socio-economic development and environmental challenges. While it promotes economic growth, industrial progress, population concentration, and social advancement, it also brings about several negative environmental impacts, such as air and water pollution, human-induced greenhouse gas emissions, the urban heat island effect, and a decline in biodiversity (Guneralp *et al.,* 2017; Auwalu & Bello, 2023).

With recent population and economic growth in developing nations, the dynamics of urban expansion have garnered increased attention. This has led to the utilization of various techniques for monitoring spatiotemporal changes, modeling land alterations, and investigating the causes and consequences of urban expansion. These include cellular automata models (CA), Markov models, logistic regression models, agent-based models (ABM), and urban gradient analysis (Mozaffaree Pour & Oja, 2021). CA models rely on grid representations derived from remote sensing images with moderate spatial resolutions, requiring predefined rules to describe expansion dynamics, which may lead to varying outputs. Markov models lack spatiality and require complex coupling with other models to compensate for this limitation. Logistic regression models depend on explanatory variables, often unavailable at appropriate scales for multiple time periods (Ghosh *et al.,* 2017; Tong & Feng, 2020). ABMs necessitate a deep understanding of complex human behavior and predefined rules (Castle & Crooks, 2006). Urban gradient analysis coupled with landscape metrics requires extensive data preparation and prospective analysis, posing challenges (Modica *et al.,* 2012; Yang *et al.,* 2022).

Recently, researchers have developed various landscape metrics through remote sensing and geographic information system (GIS) techniques to quantify landscape structures and examine their dynamics. These metrics focus mainly on the size, shape, and arrangement of landscape patches and are widely used across different environments, often referred to as spatial metrics (Berila & Isufi, 2021; Alaei *et al.,* 2022). Landscape metrics play a crucial role in characterizing and analyzing spatial patterns in various fields, including plant communities, animal habitats, soil erosion, land-use and land-cover change (LUCC), urban landscapes, and urban sprawl (Herold, Couclelis & Clarke, 2005; Uuemaa, Mander & Marja, 2013). Researchers have categorized spatial variables related to urban sprawl into three main groups: density, diversity, and spatial structure patterns. Essential concepts such as density, continuity, concentration, clustering, centrality, and proximity have been defined to investigate urban land use patterns (Sarzynski, Galster & Stack, 2014; Miranda, Batista & Ricardo, 2020).

There are multiple modeling approaches for simulating and projecting land use and land cover (LULC) changes. These include Dinamica, SLEUTH, SERGoM, Conversion of Land Use and its Effect (CLUE), GEOMOD, Land Use and Carbon Scenario Simulator LUCAS, and Artificial Neural Network-Cellular Automata (Han, Yang & Song, 2015; Rimal *et al.,* 2020). Each model has its strengths and applications, with some, like the ANN-Markov chain (MC) model, excelling in accurately estimating future land change transitions. This model, particularly the MLP-MC hybrid method, has demonstrated high accuracy in simulating LULC transitions and is adept at handling missing data or a large number of training datasets. Compared to other models like CA or SLEUTH, the MLP-MC model offers advantages in handling change procedures without relying heavily on prior knowledge or specified coefficient values (Mondal *et al.,* 2020; Alqadhi *et al.,* 2021; Basu, Das, & Pereira, 2022).

Many studies have focused on developing indices to analyze urban spatial patterns and urban sprawl, employing spatial analyses and metrics. Numerous spatial metrics have been utilized to quantify urban expansion patterns, and researchers have examined spatial dynamics by analyzing various spatial variables computed from multi-temporal maps. While these metrics and patterns are useful in urban expansion, there is a need to provide spatial insights of this urban expansion in modes and predict the future expansion, especially in an emerging agglomerated medium sized city.

In developing countries like Nigeria, the focus of substantial studies is more on land use and land cover of urban areas, while the direction and intensity of urban expansion in agglomerated urban areas is being neglected. Many researchers focused their studies on large cities and neglected the emerging urban areas of Nigeria. There is, therefore, a need to carry out spatial analysis of urban expansion for the sustainable development of emerging agglomerated cities in Nigeria. There is a need to unravel the notion of the modes and prediction of urban expansion for effective planning and management of emerging green urban areas, especially in Ogun State, Nigeria.

Thus, Ago-Iwoye, Awa-Ijebu, Oru-Ijebu, and Ilaporu, as an emerging agglomerated city, present a veritable location for the study. They have developed and merged to form an emerging medium-sized urban area. The recent decades of the 21st Century have been considered essential to this study, as they have been considered and proposed as decades with fast urbanization. Urban expansion is expected to persist in the coming decades, with projections indicating severe impacts on food production and natural areas (Seto, Guneralp & Hutyra, 2012; Ramankutty *et al.,* 2018). This study will cover three epochs in the first five decades of the century (2002, 2013, 2024) and predict 2046 on urban issues, especially international bodies. For instance, United Nations (2018) predicted that the urban population and area will tremendously increase by the end of the fifth decade of the 21st Century. Hence, the justification of this study. This scope is believed to provide insight large enough to make a reasonable conclusion about urban expansion and predict the future sustainable green cities in Nigeria.

2. METHODOLOGY

2.1 Study Area

Ijebu North LGA is one of the twenty LGAs (Abeokuta North, Abeokuta South, Ado Odo/Ota, Egbado North, Egbado South, Ewekoro, Ifo, Ijebu East, Ijebu North, Ijebu North-East, Ijebu Ode, Ikenne, Imeko-Afon, Ipokia, Obafemi-Owode, Odeda, Odogbolu, Ogun Waterside, Remo North, and Sagamu) in Ogun State, southwestern Nigeria (Independent National Electoral Commission- INEC, 2015). Ijebu North Local Government Area shared a boundary with Oyo State in the north; Odogbolu LGA, Ijebu Ode LG in the south; Iremo North LGA and Ikenne LGA in the west; and Ijebu North East and Ijebu East LGA in the east. Atikori, Japara/Ojowo, Omen, Osun, Oke Agbo, Oke Sopin, Oru/Awa/Ilaporu, Ago Iwoye I, Ago-Iwoye II, Ako-Onigbagbo/Gelete, and Mamu/Etiri are eleven wards in Ijebu North LGA (INEC, 2015). Ago-Iwoye-I, Ago-Iwoye-2, and Oru/Awa/Ilaporu are three political wards that form Ago-Iwoye and its environs are an agglomerated emerging urban area considered the study area for this research.

2.2 Source and Type of Data

The satellite data used for this study were Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 8 Operational Land Imager (OLI), and Landsat 9 OLI. Landsat 7 ETM+ of 2002, Landsat 8 OLI, and Landsat 9 OLI at Path 191 and Row 055 were sourced from the United States Geological Survey (USGS) through https://glovis.usgs.gov/app (Table 3.1). This makes three epochs for the study. The coordinates of ground control points for ground truthing were taken using a Global Positioning System (GPS) version of Global Navigation Satellite Systems (GNSS) at a 3-metre accuracy level. The shapefile of the study area was sourced from the archive of Geo-Referenced Infrastructure and Demographic Data for Development (GRID3) through http://grid3.gov.ng.

2.3 Data Processing and Analysis

Supervised classification was done in ERDAS IMAGINE. The satellite imageries for each of the three epochs (2002, 2013, 2024) were imported into ERDAS IMAGINE. All the bands in TIFF format were combined for each epoch. Colour composite was carried out. The appropriate training areas using a maximum likelihood algorithm were based on homogamous representative samples of the different surface cover types using Signature Editor to generate numerical signatures for each training class. Each pixel in the image was compared to these signatures and labeled appropriately. Classification Level-I, as recommended by Anderson (1976), was used to categorise the area into five classes as Built-up, Agriculture, Forest, Water, and Bare land. Ground truthing of each land cover was done using a global navigation satellite system. Each land cover was measured in hectares. A confusion matrix was calculated for accuracy assessment. The overall classification accuracy was 98.63%, 97.55%, and 98.75% for 2002, 2013, and 2024, respectively. The overall Kappa statistics were 0.97, 0.96, and 0.98, respectively, for 2002, 2013, and 2024.

The final output of the land cover in ERDAS IMAGINE was exported to ArcMap. The change detection for 2002-2013, 2013-2024, and 2002-2024 were thereafter carried out to determine the urban expansion. This process involves using a Change Detection Tool under an Imagery Panel in ArcMap. The change detection output was converted from raster into vector using

Raster to Polygon tool. In the attribute table, the GridCode represents each change of land cover. Dissolve Tool was used to group the similar land cover using GridCode as a dissolved field. Only classes that changed from other land covers to built-up were extracted to ascertain urban expansion. The urban expansion was categorized into different forms using the Landscape Expansion Index (LEI) plugin in ArcGIS. The LEI index is less than equal to 100, and greater than 50 is infilling expansion, when it is less than or equal to 50, and greater than zero is edge expansion, and when it is equal to zero is leapfrogging. Calculate Geometry Tool was used to determine the areas in hectares for each form of urban expansion in the study area. Data for the road network of the area was added to the urban expansion forms for a better explanation.

The prediction of urban expansion for 2046 was done using Cellular Automata simulation analysis in QGIS. The first stage was to add the plugin called MOLUSCE to QGIS. The classified raster imageries for 2002, 2013, and 2024 were imported into QGIS. MOLUSCE was opened and the two epochs of classified imagery (2002 and 2013) were added to MOLUSCE as Initial and Final, respectively. After that, a change map (2002-2013) was created, with a transition potential modelling using random as a mode, and an artificial neural network as a method. Simulated 2024 imagery was then created using Cellular Automata Simulation with the selection of 1 as a simulation iteration. The validation of the 2024 simulated map was done by inputting the 2024 classified imagery as a reference map, which revealed the overall validation of the prediction which was 0.99. The validation was preferable; the simulated map for 2035 was formed using stimulation iteration of 1. In order to predict the urban expansion for 2046, the classified imagery of 2024 was used as the initial, and stimulated imagery of 2035 was used as the final, with a stimulation iteration of 1. The 2046 landcover was formed, and the predicted urban expansion was extracted and classified into different forms.

3. RESULTS AND DISCUSSION

3.1 Urban Expansion for 2002-2013 and 2013-2024

Classifications reveal the extent of bare land, farmland, built-up, water, and vegetation for 2002, 2013, and 2024. The built-up for 2002 was not as large as that of 2013, and ditto for 2024 (Figure 1 and Figure 2). Since 2002, as a base year for this study, there has been persistent urban expansion in the study area, as Figure 1 shows that there were newly built-up areas as of 2013 which spread across the area. By 2024, the expansion of the built-up area has increased and covered more area, as presented in Figure 2. Based on the different forms of dominant urban expansion in the study area, Figure 3 presents three forms, namely, infilling, edge expanding, and leapfrogging urban expansion for 2013 and 2024. It has been revealed that the existing built-up area in 2002 had more edge expansion occurred in the area, with minimal infilling and leapfrogging urban expansion. Likewise, in 2024, the dominant urban expansion was edge expanding, with more leapfrogging than infilling urban expansion (Figure 3).

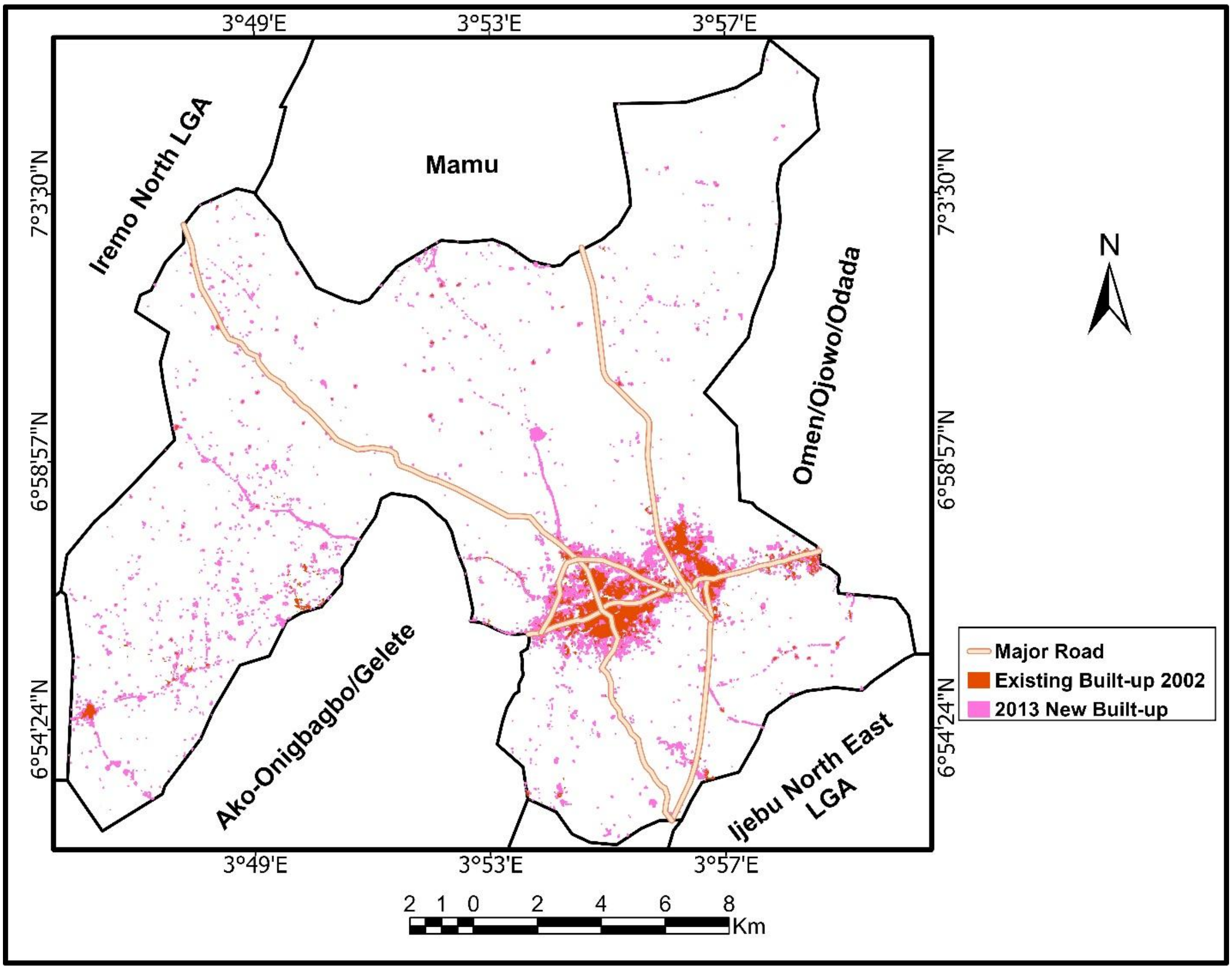

Figure 1: Urban Expansion for 2013

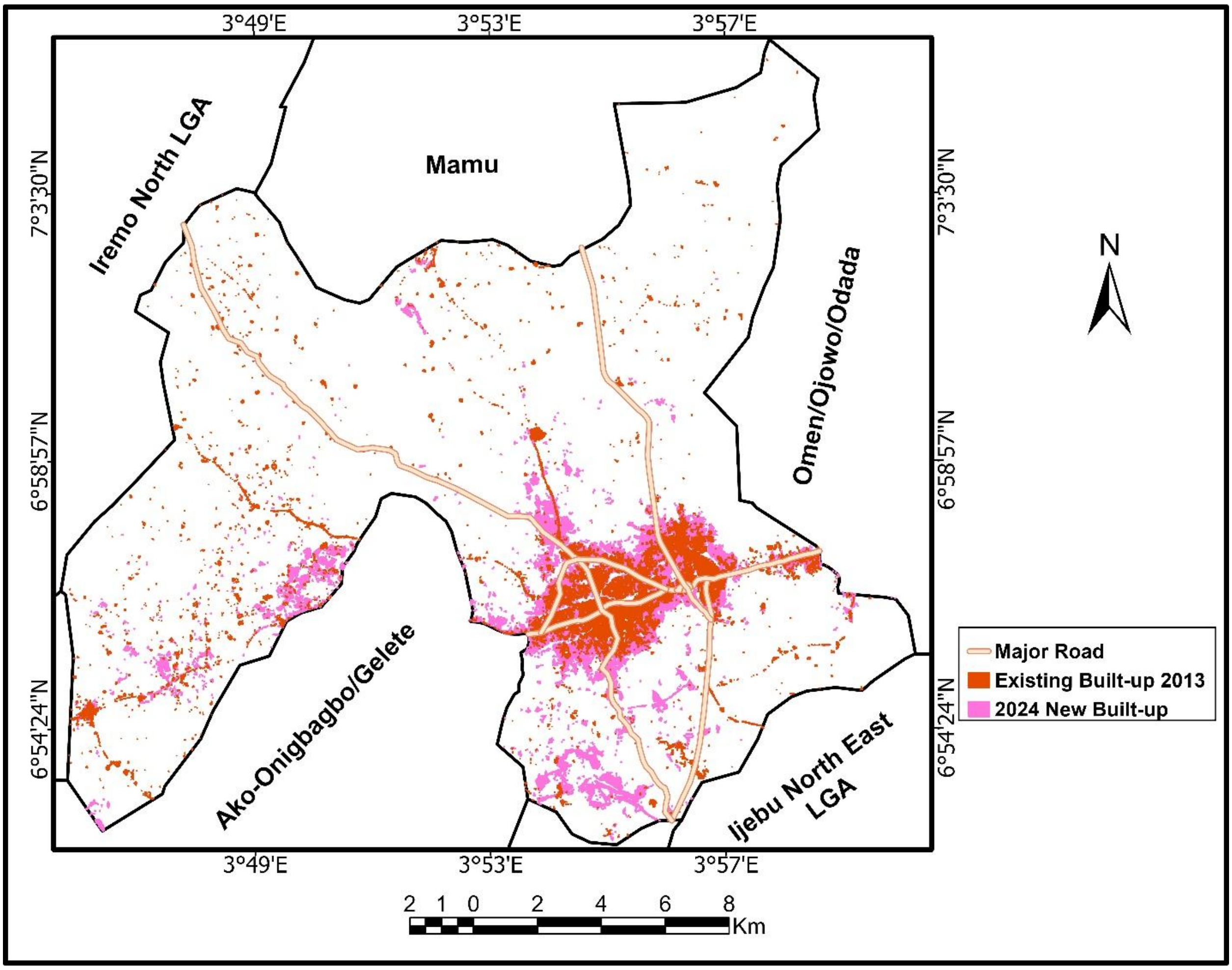

Figure 2: Urban Expansion for 2024

Precisely, Figure 3 shows that edge-expanding urban expansion was 479.88 hectares in 2002-2013, which was far below that of 2013-2024; leapfrogging urban expansion of 198.63 hectares, which was far above that of 2013-2024; and infilling urban expansion of 1.54 hectares, which was a bit above that of 2013-2024. From 2013 to 2024, edge-expanding urban expansion covered 1,488.61 hectares of land, leapfrogging urban expansion covered 62.22 hectares of land, while infilling occurred in 1.22 hectares (Figure 3). In a nutshell, it is obvious that edge expanding urban expansion was the dominant form of urban expansion in 2002-2013 and 2013-2024. In comparison, 2013-2024 experienced more edge-expanding urban expansion than 2002-2013; while it experienced less infilling and leapfrogging urban expansion than 2002-2013. This indicates that in 2002-2013 builders tended to leave the core old area to an area far apart, which signifies a break in the communal way of life, where people move away from their traditional compounds. The desire for wider land at a cheaper rate, which may not be readily available at the core, may be one of the reasons why the infilling urban expansion was minimal for the two-time intervals. Urban expansion typically follows three primary modes: infilling, edge expansion, and leapfrogging.

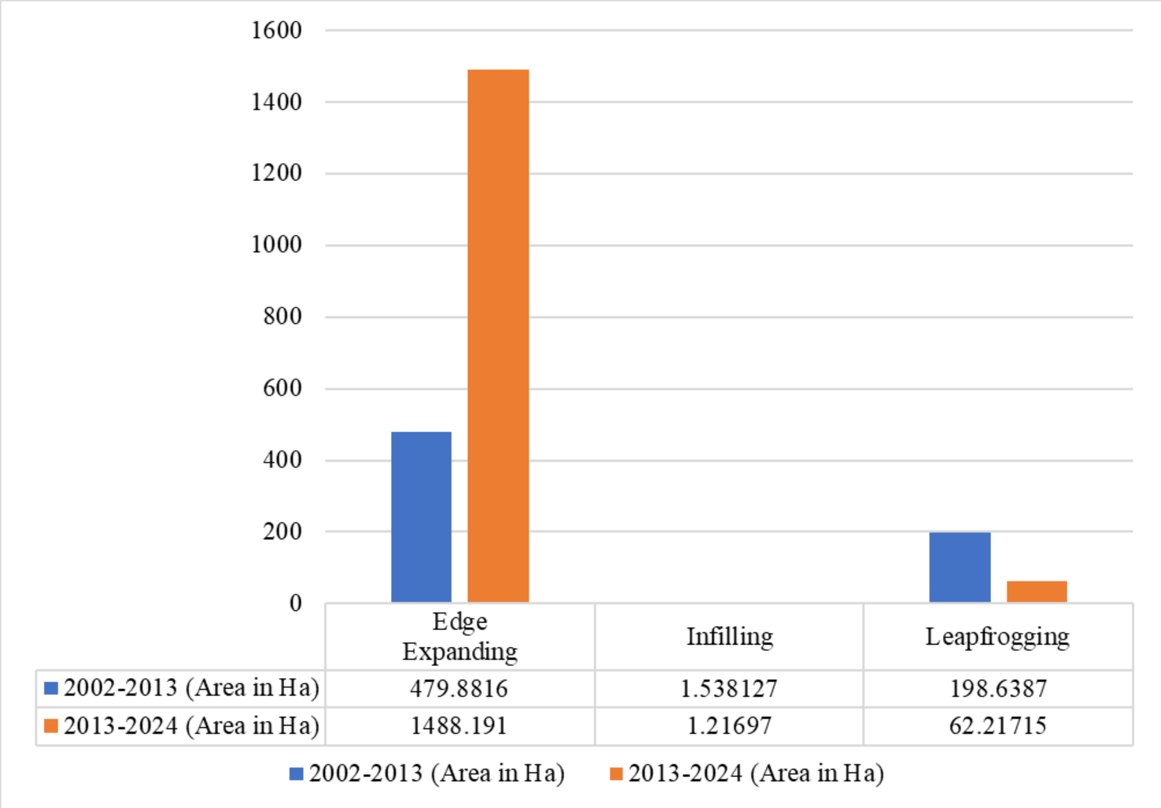

Figure 3: Categories of Urban Expansion from 2002-2024

3.2 Predicted Level of Urban Expansion for 2046 in the Study Area

Figure 4 shows that by 2046, 2252.4 hectares of the 2024 built-up area will remain built-up. Though it lost some areas to other land covers such bare land (71 hectares), farmland (61.4 hectares), vegetation (21 hectares), and waterbody (58 hectares); the expansion that will occur by 2046 will offset the urban loss. The built-up area will gain 323 hectares from bare land, 1,107 hectares from farmland, 757 hectares from vegetation, and 305 hectares from water (Figure 4). This indicates that 1,864 hectares of green land will be lost due to predicted urban expansion. Based on this, by 2046, the urban built-up area will expand by 2,492 hectares (Figure 4). Out of the predicted 2,492 urban expansions that will occur in the area in 2046, the majority will be edge expanding and leapfrogging as shown in Figure 5. The leapfrogging will occur mostly towards the west and north of the area. The edge expansion occurs in the south and the mainland of the area (Figure 5). To be precise, Figure 6 reveals that 1,570.1 hectares will be edge-expanding urban expansion, 920.7 hectares will be leapfrogging, and 1.2 hectares will be infilling urban expansion.

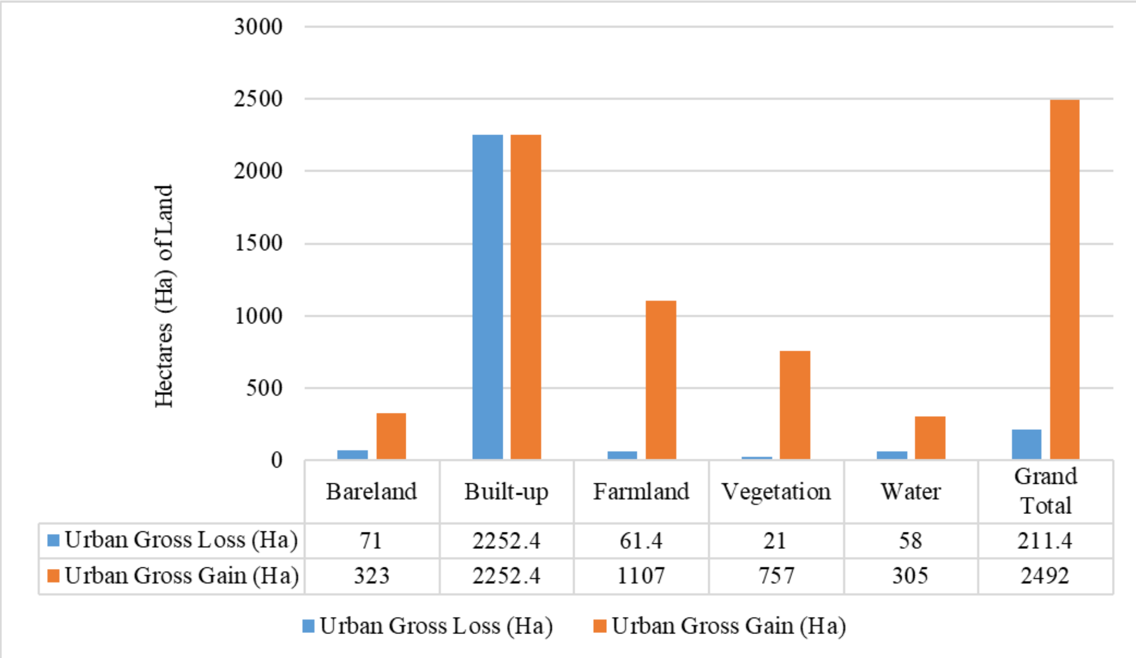

Figure 4: Urban Gross Loss and Gain by 2046

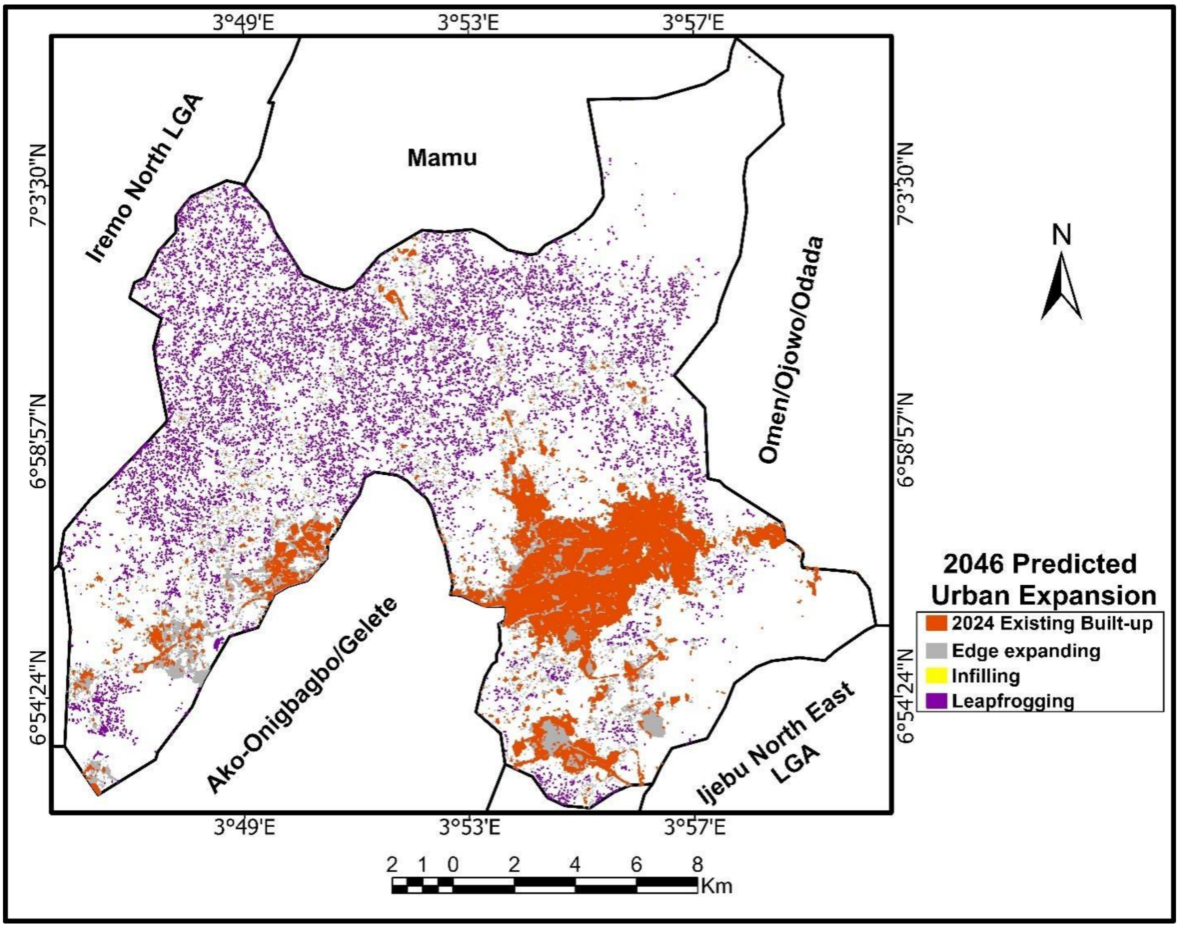

Figure 5: Predicted Urban Expansion for 2046

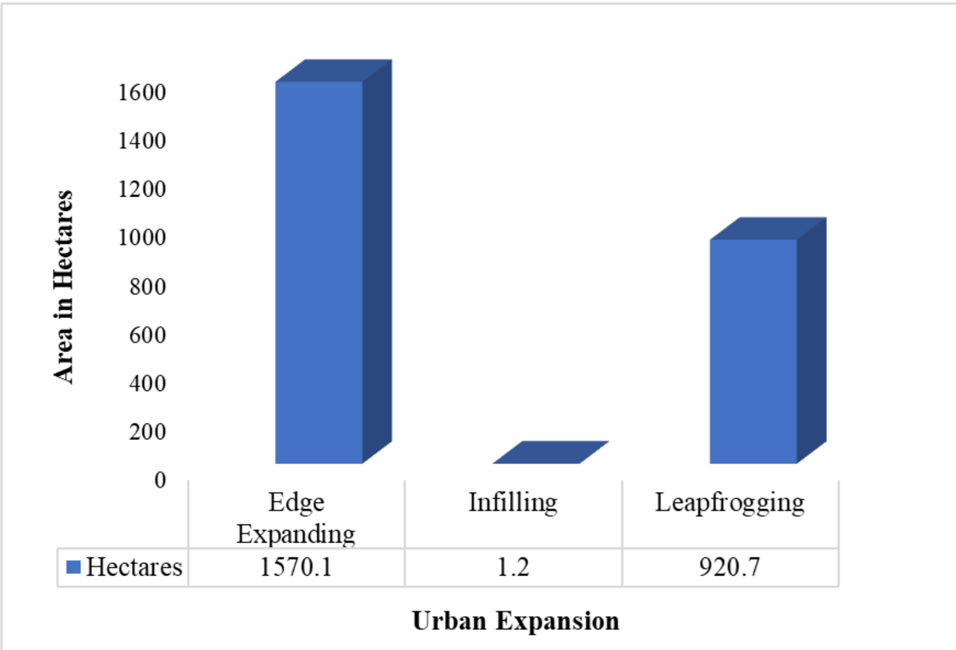

Figure 6: Hectares of Different Forms of Predicted Urban Expansion for 2046

4.6 Discussion of Results

It is evident from this study that there is persistent urban expansion, with the dominant form being edge expansion, covering the larger parts of the area. This edge expansion can be associated with what is called an edge city in the Urban Realm Model. However, this does not imply the absence of other forms, as two additional forms of urban expansion- infilling and leapfrogging are also present in Ogun State of Nigeria. This indicates the presence of three forms of urban expansion in the area. Gong *et al.* (2018) identified these three forms of urban expansion, in which infilling occurs within already developed areas, edge expansion is prevalent in urban fringe zones, and leapfrogging disperses over areas distant from existing urban zones. In the study area, the dominance of edge expansion over the others might be due to the lack of expansive land within the core center, which has propelled builders to the edge of the city, where the distance to the center in terms of cost and time is minimal compared to those in leapfrogging areas. The latter may be driven by the desire to access larger expanses of land at a cheaper rate than the price of land at the core and immediate fringe of the area.

A decrease in infilling expansion might be due to the reduction in communal living, where family members prefer to stay within their family compound rather than in other locations. The movement out of the family compound is also identified in the Urban Realm Model, where the first wave involved the expansion of residential areas beyond traditional city boundaries. The decline in leapfrogging could be the result of persistent insecurity, such as robbery, kidnapping, assassination, and other crimes prevalent in the state and other parts of Nigeria. It has been found that urban expansion exerts considerable pressure on fragmented tenure and traditional systems, especially with edge expansion at the urban fringe. However, Usman *et al.* (2017) and Asibey *et al.* (2024) identified other factors influencing different forms of urban expansion, claiming that urban expansion varies due to factors such as the natural environment, demographics, economy, transport systems, proximity preferences, and governance. These three forms of urban expansion significantly influence the pace and spatial orientation of urbanization patterns, which is discussed in the next subsection.

In this study, it has been predicted that the expansion will continue with more edge urban expansion. By 2046, farmlands will contribute more to urban expansion than other categories of land cover. By then, the area will also experience greater leapfrogging urban expansion compared to 2013 and 2024, affecting farmlands, bare land, water bodies, and vegetation. One consequence of rapid urban expansion is the loss of open space, with deforestation and the conversion of adjacent farmlands being serious problems due to population pressure and the need for food crops (Chen *et al.,* 2020; Tilahun, Gashu & Shiferaw, 2022). This expansion often encroaches on valuable farmland and forests around cities, reshaping urban morphology and environmental conditions (Zhang *et al.,* 2020). This calls for effective urban land planning and management to ensure that urban expansion is sustainable without affecting farmlands that serve as sources of agricultural products for urban residents, disrupting or encroaching on water bodies, leading to deforestation, and exposing the area as bare land. This is similar to the findings of Maconachie (2016), and Malaquias (2024), who observed that in Nigeria, Africa's most populous nation, urban issues have escalated to critical levels, demanding urgent action.

CONCLUSION

This study inferred that there is a persistent urban expansion in the study area. The major urban expansion in the area was edge expansion, but in the recent period, more leapfrogging with less infilling expansion, which might be a result of the non-availability of a large vacant expanse of large at the core of the study area. Due to the increase in urban populations and limitations in land size, achieving equitable and sustainable urban development becomes a significant challenge. Urban expansion varies due to factors like the natural environment, demographics, economy, transport systems, consumer proximity preferences, and governance (Usman, Sanusi & Musa, 2017; Asibey, Osei, Doe & Agyei, 2024). The predicted urban expansion for 2046 reveals that some hectares of farmlands and vegetation will be encroached by built-up areas, and this calls for effective urban land planning and management that will make the urban expansion sustainable without causing harm to farmlands as a source of agricultural products to urban residents, and vegetation as a source of valuable trees, thereby building sustainable green cities.

RECOMMENDATIONS

This study recommends that urban planning units of the three tiers (federal, state and local) of government in the area should ensure compliance to the ethics of effective urban development. Each individual should also comply with the planning laws that ensure the conservation of forests and fertile agricultural land, while directing urban development toward unfertile or less fertile areas. This requires an effective zoning approach to urban planning and management in the area.

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