Analyzing Land Cover Changes (2013-2024) Using Remote Sensing: A Case Study of Lagos City, Nigeria

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Abstract
This study examines land cover changes in Lagos State, Nigeria, utilizing remote sensing techniques to understand the dynamics and implications of land cover changes emanating from rapid urbanization processes. In the use of Landsat satellite images spanning 2013 to 2024, a supervised classification technique was utilized in categorizing land cover into five classes namely: bare soil, vegetation, canopy, water, and built-up areas. The analysis revealed that there was significant upshot in built-up and bare soil areas, accompanied by a decline in canopy and vegetation, highlighting the environmental and socio-economic urbanization pressure. Notable findings include the identification of land cover transitions which are dominant, such as the conversion of vegetation and canopy to built-up areas, as well as evidence of land cover change intensifications near water bodies. This study highlights the potential of remote sensing for tracking land cover changes and offers insights for sustainable urban planning and environmental conservation. These findings contribute to the understanding of urban growth and land cover change patterns in cities which are developing rapidly and emphasize the importance of the integration of geospatial tools into environmental planning and policy frameworks.

Keywords: Cellular Automata Markov Chain (CA-MC), Classification, Land Use Land Cover (LULC), Prediction, Supervised Classification, Support Vector Machine (SVM)

1. Introduction

Urbanization can be defined as the increase in population of urban areas and the adaptation of communities to physical, industrial, and economic growth [1]. According to projections from the United Nations, the population of developing countries would expand by about 2.4% yearly between 2002 and 2030, taking 29 years to double. In more developed nations, 68% of inhabitants are projected to reside in cities by 2030 [2]. Moreover, between 2011 and 2050, the population of the world is anticipated to surpass 9 billion, with the urban population estimated to increase drastically. The upshot will be that nearly all the population increase of 64% will occur in developing-country cities as urban areas worldwide are estimated to take in the anticipated population expansion over the next 40 years while also absorbing part of the rural population. Urban development encompasses physical, social, and economic changes in urban areas, driven by population growth, economic expansion, and technological progress which includes activities such as urban planning and design, construction, and the maintenance of infrastructures. Urban developments are meant to help create sustainable and livable environments meeting urban population needs in a manner at which the environment is protected and preserved [3].

Land cover change is a global occurrence internationally recognized as a central aspect of policy debates, especially in meeting climate targets. This is driven by rapid urbanization and population boom with about 17% of the earth's surface being estimated to have experienced land cover changes at least once over the last seven decades with the total land cover change extent at 43 million km². The global loss of forested areas is about 800,000 km² with the global south region being the most affected region [4] and [5]. Africa on the other hand is indicated to be the hotspot of a worldwide climate change impact based on report by the Intergovernmental Panel on Climate Change (IPCC), with land cover change highlighted as one of the largest drivers of biodiversity loss leading to land degradation, especially in densely populated cities.

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Unmonitored rapid developments can be hazardous, but remote sensing offers valuable insights into development rates, aiding policymakers, urban planners, and regulatory agencies in making well informed decisions. By gathering, analysing, and presenting results, remote sensing helps to manage urban development and prevent chaotic growth.

Utilizing five of the most advanced global climate models (GCMs) for simulation over a six-year period, Land cover changes in West Africa from 1950 to 19990 were accessed. Consistent degradation in terms of the surface's bio-geophysical response was prioritized over a consistent change in land classification [6]. This demonstrated the effects that were common throughout the July, August, and September peak-monsoon months. Similarly, the study by [7] evaluated West Africa from 1990 to 2010 applying Markov modeling to estimate land cover changes for 2020, 2030, and 2040 revealing a loss of 73% of forested lands. 4% of forest areas and 7% of agricultural lands were modeled to be converted to built-up. [8] investigated changes in land cover in Accra, Ghana between 1958 and 2010 which showed that the built-up areas experienced more positive change, increasing from 65.1 km² in 1985 to 145.5 km² in 2010 due to the population boom, urban-based development strategies, and the dominance of real estate developers. Multi-temporal remote sensing data was used in the analysis of land cover change scenarios in Lagos state, Nigeria by [9]. Land cover changes between 1990 and 2020 were assessed at an interval of 10 years where the analysis showed a decrease in the vegetation cover from 51.9% in 1990 to 41.1% in 2020. Built-up areas grew rapidly from 496 km² in 1990 to about 1256 km² in 2020.

Urbanization in Lagos City has been rapid owing to it being the country's capital city for decades making it the commercial and economic hub of the country. The rapid economic and industrial growth can be attributed to population increase and extensive physical, commercial, industrial, and environmental developments. Located in the southwestern region of Nigeria, Lagos City stands as the most populated African city, with a projected 15 million inhabitants, according to a recent world population review [10]. Remote sensing, an advanced technique for assessing changes within a given region, is leveraged using satellite images to identify and monitor changes in Lagos State between 2013 and 2024. The aim of this study is to determine where changes have occurred as well as the rate of change.

2. Data and Methodology

2.1 Study Area

With a coastline that extends for nearly 180 km along the Atlantic Ocean, Lagos city is situated in the south-west region of Nigeria between longitudes 2°99'E and 3°99'E and latitudes 6°22' N and 6°42' N (Figure 1).

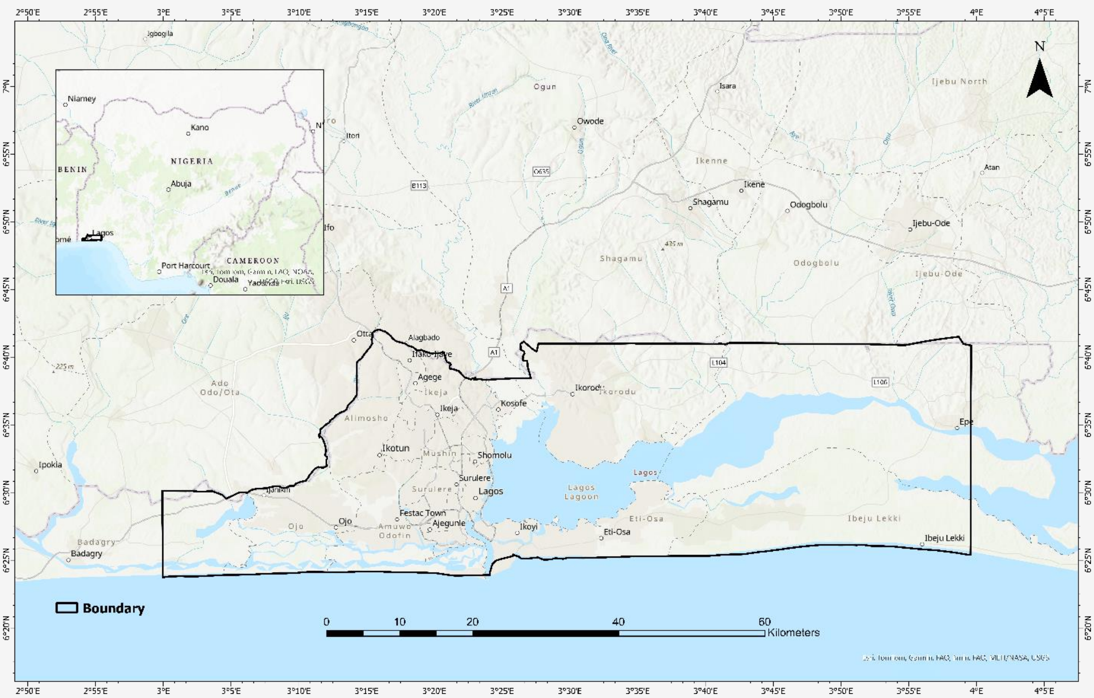

Figure 1: Map of Lagos Nigeria and the selected area of interest (AOI) delimited by black line

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The city is bounded to the west by the Republic of Benin, to the north by Ogun State, Nigeria, and to the west by the Benin Republic. The political boundaries of Lagos State cover an area of 3,700 km² with waterbodies occupying about 725 km² [11]. It is characterized by a marshy environment, mangrove swamps, low-lying coastal regions, islands, and a lengthy coastline, particularly the southern section.

2.2 Multi-Temporal Satellite Data

Land cover change investigation utilizing Landsat satellite images is a well-established technique due to its high spatial resolution and consistent data collection [12][13][14] and [15]. In this study, Landsat 8 satellite images acquired from the USGS's Earth Explorer site (https://earthexplorer.usgs.gov) were utilized to examine the changes in land cover within Lagos city between 2013 and 2024. However, only satellite images from the years 2013, 2019, and 2024 were selected for the study adherence to the applicable standards for cloud cover which is recommended to be below 20% (specific acquisition days: 18th December 2013, 1st January 2019, and 30th November 2024). The rainy season, spanning from April to October, limited the availability of cloud-free images. The Satellite images obtained from the USGS's Earth Explorer have been pre-processed by the USGS, which includes systematic radiometric and geometric corrections to ensure positional and radiometric accuracy. Additionally, these images were processed to account for the impact of atmospheric effects, although no specific atmospheric correction to derive surface reflectance was applied in this study. Given the coastal location of Lagos and the potential for aerosols, we acknowledge the presence of such atmospheric conditions in the analysis, but TOA reflectance was deemed sufficient for the objectives of this study.

2.3 Land Cover Classification

Maximum likelihood technique is a popular supervised classification used in remote sensing. This was used in the previous studies by [16][17][18] and [19] in various image classifications. Using spectral information from training samples, the algorithm calculates the likelihood that each pixel belongs to a class of land cover. Its implementation in the ArcGIS Pro software (https://www.esri.com) was utilized where training samples were determined based on visual assessment of satellite images, actual data, and Google Earth data in combination with previously established personal knowledge of the study area. The land cover types were categorized into five groups: Built-up, Bare soil, Canopy, Vegetation, and Water as illustrated in table 1.

The data analysis employed a supervised maximum likelihood classification technique, using 70% of the training samples and 30% of the validation samples drawn from the reference data. The findings of the maximum likelihood classification were compared to reference data obtained from Google Earth images to gauge its correctness. Accuracy was evaluated using the confusion matrix approach, and the validation data was selected at random from the reference data. A confusion matrix assessment was utilized to determine the accuracy of the categorized maps. Alongside the Kappa values, the overall accuracy (*OA*) of each classified map was determined by dividing the total number of entries in the confusion matrix by the sum of the diagonal entries.

2.4 Change Detection and Post-Classification Comparison

The Post-Classification Comparison (PCC) approach proved effective in identifying changes within the study area as it employs classifications in building thematic maps from satellite images. It provides accurate information on the land cover change matrix and measures the extent and rate of land cover change due to its ability to minimize atmospheric and environmental variations among independently classified images [20]. Post-classification methods are popular in change detection applications, and they compare the classification maps from independent classification [18].

Table 1: Description of Land Cover classes

Class	Description
Built-up	Commercial, industrial, and residential areas, including villages, towns, and districts.
Bare soil	Undeveloped lands, exposed soil, landfill sites, and construction sites.
Canopy	Forested areas and lands occupied by dense trees.
Vegetation	Farmlands, grazing lands, and mild vegetation cover.
Water	Rivers, lagoons, open water, lakes, and ponds.

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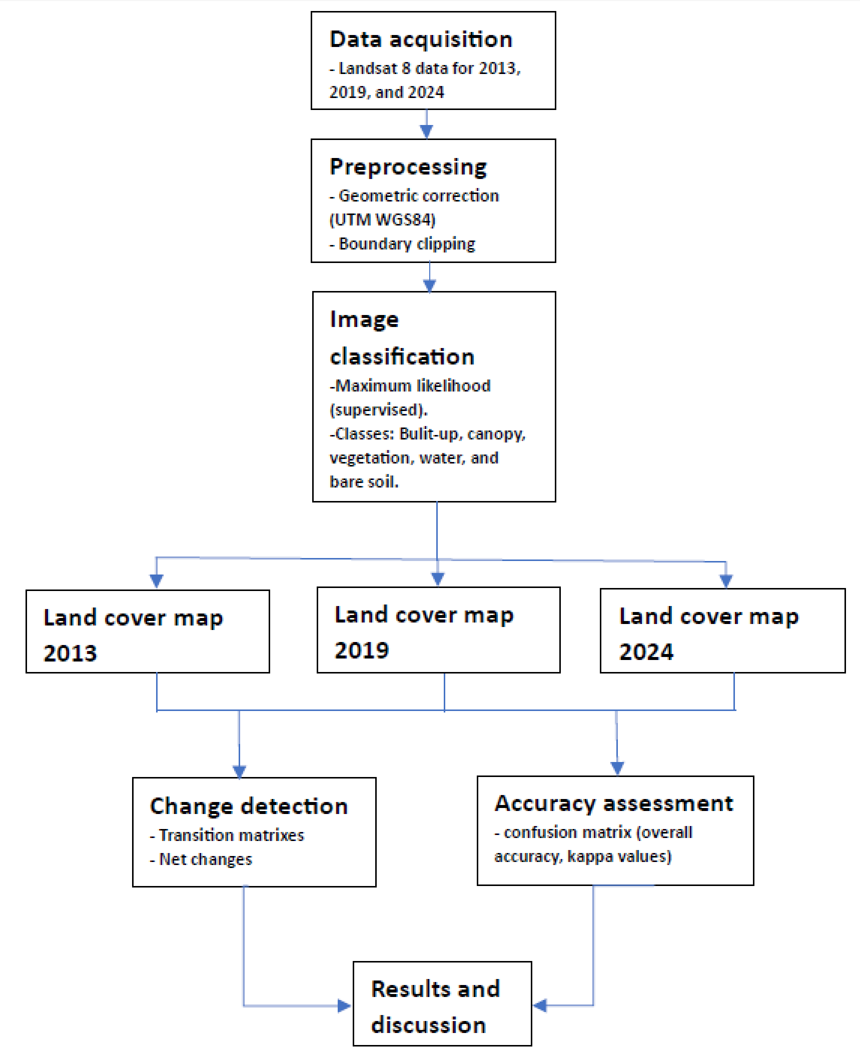

Figure 2: Workflow of the land cover change analysis utilized in this study

Using the change detection analysis tool on ArcGIS Pro, Post-Classification Comparison (PCC) was used to assess changes in land cover and measure the rate of urban expansion. In this study, the Post-Classification Comparison (PCC) method was implemented using the change detection analysis tool in ArcGIS Pro to assess changes in land cover and measure the rate of urban expansion. The analysis examined land cover transitions across the time intervals of 2013 to 2019, 2019 to 2024, and 2013 to 2024. By comparing pixels from different land cover maps, this technique identified transitions between classes over each interval, offering insights into the patterns and progression of land cover changes. The steps outlined in this study are summarised in Figure 2.

3. Results and Discussion

3.1 Results of Classification

Using satellite images acquired between 2013 and 2024, supervised classification using the maximum-likelihood method generated thematic land cover maps (Figure 3). To effectively assess the land cover changes over time, the classification and change detection analysis were conducted in year pairs/phases, highlighting areas of significant changes (Figure 4). Based on ground truth and ArcGIS visual interpretations, 100 random points were utilized in this study to evaluate the accuracy of each classification map for 2013, 2019, and 2024. For each of the observed years, the revised assessment results indicate overall accuracies of 90.5%, 88.5%, and 89.0%, respectively, with corresponding Kappa values of 0.88, 0.86, and 0.87 (table 2).

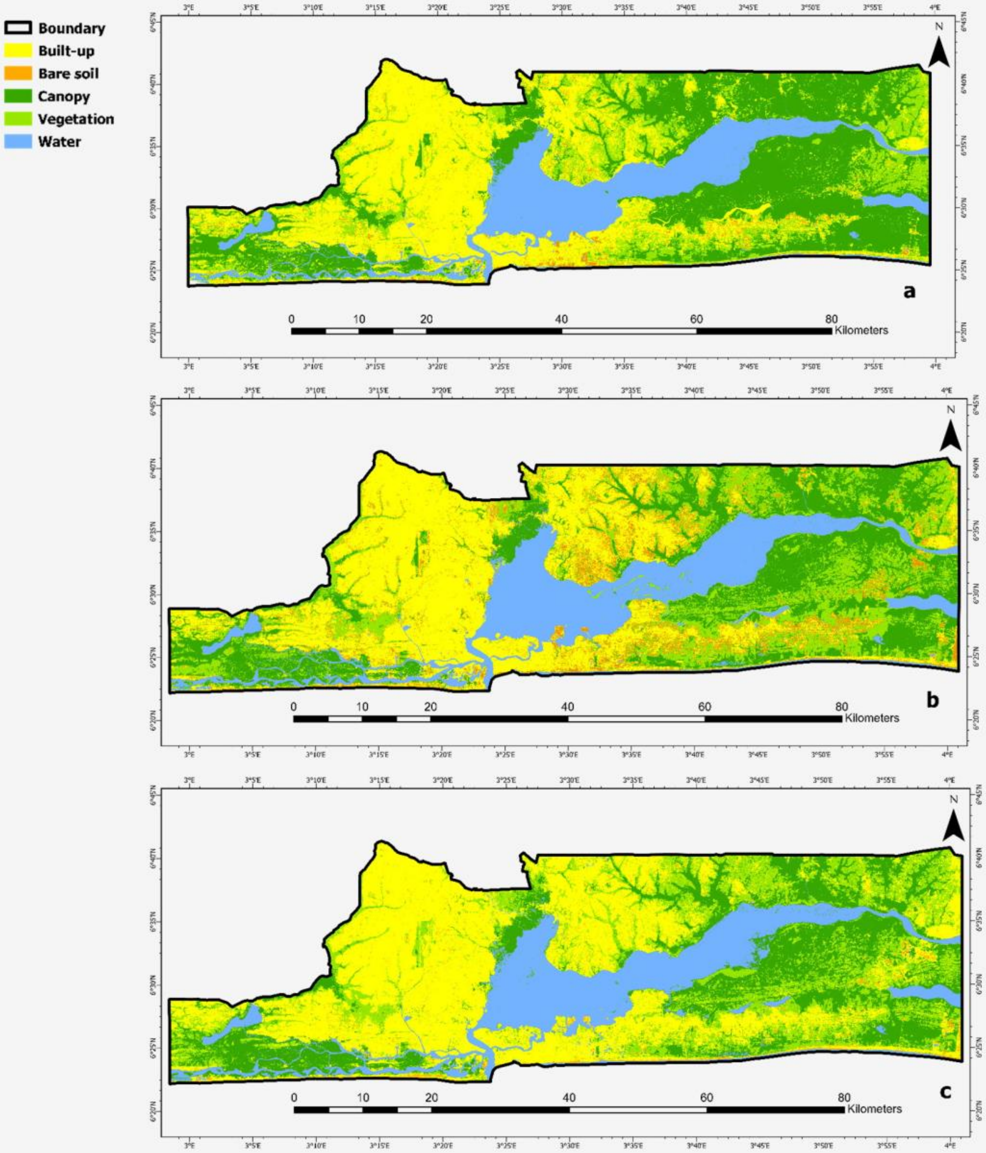

Figure 3: LULC supervised classification of Lagos, Nigeria (a) 2013, (b) 2019 and (c) 2024

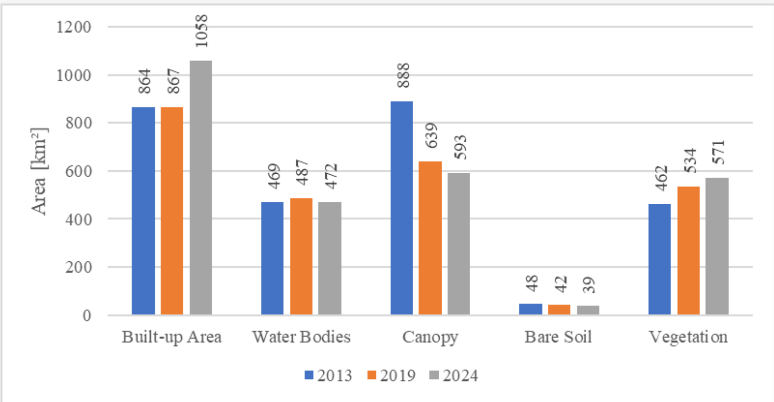

Figure 4: Land cover area distribution across 2013, 2019, and 2024

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Table 2: Accuracy assessment results for the land cover classification (2013–2024)

Year	Class	Bare soil	Built-up	Vegetation	Canopy	Water	Total	User's Accuracy (%)	Producer's Accuracy (%)	Overall Accuracy (%)	Kappa
2013	Bare soil	28	2	2	2	0	34	82.35	87.50	90.50	0.88
	Built-up	2	37	2	1	0	42	88.10	86.05		
	Vegetation	1	2	31	2	0	35	88.57	88.57		
	Canopy	1	2	3	30	0	36	83.33	85.71		
	Water	0	0	0	0	53	53	100.00	100.00		
2019	Bare soil	30	3	1	1	0	35	85.71	88.24	88.50	0.86
	Built-up	3	36	2	2		43	83.72	85.71		
	Vegetation	1	2	31	1	0	35	88.57	86.11		
	Canopy	2	2	2	28	0	34	82.35	84.85		
	Water	0	0	0	0	53	53	100.00	100.00		
2024	Bare soil	31	2	1	1	0	35	88.57	86.11	89.00	0.87
	Built-up	2	39	1	2		43	90.70	88.64		
	Vegetation	2	2	33	2	0	38	86.84	86.84		
	Canopy	2	2	2	28	0	34	82.35	84.85		
	Water	0	0	0	0	50	50	100.00	100.00		

Table 3: Coverage of land cover classes in 2013 and 2024

LU/LC Classes	Area (km²)			Percentage changes (%)
	2013	2024	Net changes	
Built-up	864	1058	194	22.45
Water	469	472	3	0.64
Canopy	888	593	-295	-33.22
Bare soil	48	39	-9	-18.75
Vegetation	462	571	109	23.59

These accuracy assessment results show a high degree of agreement between the classification maps and the reference imagery, with the overall accuracy and kappa statistics exceeding 85% and 0.80 respectively, indicating a reliable image classification. The main classification errors observed emanated from the confusion in the classification of built-up areas as bare soil. This is attributed to the brownish coloration of roofing sheets due to continuous exposure and reaction to oxygen and water spectrally resembling bare soil in satellite imagery. To resolve this, a post-classification correction technique was implemented involving visual examination to identify areas with a high likelihood of misclassification (densely developed areas) and targeted corrections were made by reclassifying pixels based on supplementary information, such as proximity to other built-up areas and manual reassessment of spectral properties where possible. Furthermore, a custom mask was created to isolate the known built-up areas, limiting the propagation of errors in the final map.

3.2 Change Detection

The LULC changes between 2013 and 2024 are presented in Table 3. The results show that Lagos witnessed pronounced land cover transformations, predominantly driven by the constant expanding urban infrastructure (Figure 5). The most significant transitions observed involved the conversion of vegetation and canopy to built-up areas. Specifically, 188.63 km² of vegetation and 48.82 km² of canopy were lost to built-up areas over the observed 11-year period. This trend underscores the continuous encroachment on natural landscapes, likely driven by population growth, increase in housing demands, and commercial expansion. Changes in bare soil classes were also marked by urban influence. Approximately 39.09 km² of bare soil transitioned into built-up areas across the entire period (2013 – 2024). Further observations revealed that this conversion surged between 2019 and 2024, accounting for 140.40 km² of the total transformations, compared to 26.88 km² during the 2013 - 2019 period. This steep increase in recent years reflects intensification of land developments.

The water class, although generally more stable, experienced some notable transitions. From 2013 to 2024, around 1.97 km² of water bodies were converted to bare soil and 12.55 km² to canopy, while 7.74 km² transformed into vegetation. These shifts which are modest in scale compared to the changes observed in other classes, may suggest land reclamation activities. Despite these, 440.13 km² of water remained unchanged, indicating a relatively consistent water coverage throughout the period. Canopy areas, beyond their transition to built-up, also contributed significantly to vegetation increase, with over 315.17 km² changes from canopy to vegetation, suggesting either degradation of forested zones (lumbering activities and clearance for farmland preparations) or transformation into lower biomass vegetative cover. However, some reversals were observed, with 31.91 hectares of bare soil and 19.07 km² of built-up reverting to canopy, though these values remain relatively minimal when compared to the net losses. Vegetation dynamics were more diverse. While nearly 58.25 km² of vegetation were observed to have been converted to canopy, a significantly higher amount (208.28 km²) remained stable. Reversals on smaller scales were also observed, with 14.93 km² of vegetation being converted into water. Interestingly, 39.84 km² of built-up areas were converted back to vegetation, indicating some land restoration efforts, afforestation efforts, or land-use changes. These reversals though commendable, were far outweighed by vegetation losses to urbanization. Built-up areas remained largely stable, with 766.76 km² showing no change across the 11 years. However, some built-up land reverted to other classes, with 15.10 km² transitioning into bare soil and 19.07 km² into canopy. These changes, although relatively small in proportion, can be attributed to urban renewal, redevelopment, or environmental restoration efforts. In summary, the land cover change analysis from 2013 to 2024 reveals a trend which indicates a rapid transition geared toward urbanization, most notably through the conversion of vegetation, canopy, and bare soil to built-up areas. While minimal reversals and stabilizations were observed in some classes, they are insufficient to counterbalance the rapid pace of urban development. Overall, the analysis of the change detection across these periods underscores the highlights of Lagos city's unrelenting urbanization, which has impacted the land cover. The rapid expansion of built-up areas, at the expense of other classes of land cover (Figure 6) most especially the vegetation and canopy classes reflect the pressure mounted by urbanization.

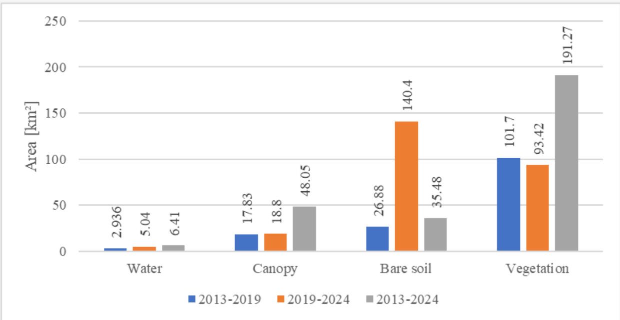

Figure 5: Land cover transitions to built-up areas from 2013 to 2024

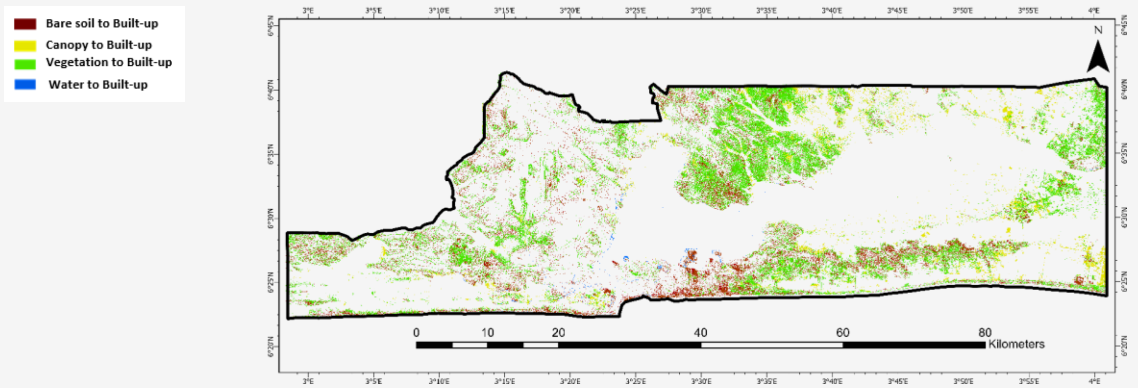

Figure 6: Significant areas converted to built-up land from other land cover classes over each Phase of the study period (2013 to 2024)

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4. Conclusion

The rate of urbanization observed in Lagos between 2013 and 2024 highlighted significant changes that have occurred within land cover classes. This was achieved by the utilization of remotely sensed Landsat 8 multispectral images. Within the observed 11-year period, it is evident that there was a substantial shift towards urban development as built-up areas recorded an increase of over 194 km², representing a 22.45% increase. The canopy class witnessed the most substantial reduction, decreasing by 295 km² (-33.22%) which indicates an extensive level of deforestation, decline in forest cover and transformation of natural vegetation. On the other hand, vegetation increased by 109 km², suggesting the afforestation or conservation efforts. Meanwhile, bare soil areas declined by 9km², most likely due to construction, infrastructure and land development activities. These figures reveal the distribution of land resources in a dynamic pattern, which are largely residential, commercial and infrastructural development driven.

The analysis of land cover transitions reveals further insights into the dynamics of urban growth in Lagos. Between 2013 and 2019, major land cover conversions to built-up areas occurred mainly from vegetation (101.70 km²), followed by bare soil (26.88 km²), canopy (17.83km²) and water bodies (2.94 km²). This trend intensified between 2019 and 2024 with 140.40 km² of bare soil, 93.42 km² of vegetation, 18.80 km² of canopy and 5.04km² of water converted into built-up areas. Overall, a total of 191.27 km² of vegetation, 48.05 km² of canopy and 35.48 km² of bare soil, and 6.41 km² of water transitioned into built-up areas between 2013 and 2024. This cumulative transformation underscores the rate at which natural areas are being rapidly converted to accommodate urban expansion with the vegetation and canopy classes alone contributing over 239 km² towards the built-up class.

These patterns not only illustrate the extent of urban sprawl but also highlights the intensity of land cover changes, particularly in recent years. The sharp increase in the conversion of bare soil to built-up between 2019 and 2024 (140 km²) suggest a period of heightened construction activities. Water bodies remained relatively stable over the observed years, with a slight net increase of 3 km² despite 6.41 km² of water bodies being converted to built-up areas due to land reclamation practices and an increase in coastal structures by fishing communities. This relative stability may be attributed to natural constraints and regulatory practices especially considering the frequent flooding challenges. Additionally, water bodies often act as natural barriers to developments, which may explain their minimal fluctuations.

Lagos experienced a net increase of 194 km² in built-up areas, a 295 km² decrease in canopy, and a 109 km² increase in vegetation between 2013 and 2024. The consistency in built-up expansion, along with the decline in forested areas, underscores the urgency in the need for sustainable urban planning. Without immediate and proactive intervention, the continued loss of forests could result in adverse consequences such as the loss of biodiversity, environmental degradation, and an increase vulnerability to the impacts of climate change. Although there have been land cover reversal efforts such as revisiting urban renewal processes, the overall decline in natural land cover (dense canopy and vegetation) and the upshot in built-up areas suggests that such efforts struggle to keep pace with the rate of urban expansion, thereby indicating an imbalance in land management practices.

Overall, this study highlights the necessity for urban planning strategies in Lagos which aligns with environmental sustainability and protection. Policy makers must design and enforce frameworks and policies which will balance urban growth and environmental preservation. This may involve strengthening land use policies, implementing conservation initiatives, implementing urban greening initiatives, and ensuring compliance to environmental regulations to foster a liveable and a more resilient city for the future.

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