GIS-Based Multi-Temporal Analysis of Urban Expansion Dynamics in the Federal Capital Territory (FCT), Nigeria Using Sentinel-2 Imagery and Google Earth Engine

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ABSTRACT

Rapid urbanisation has altered land use and land cover (LULC) in many emerging cities. This has posed issues for sustainable urban planning and environmental management. The study examined the dynamics of land use and land cover change and urban expansion of the Federal Capital Territory (FCT), Nigeria, using multi-temporal Sentinel-2 satellite images acquired for the years 2016, 2018, 2020, 2022 and 2025. Image processing and classification was done using Random Forest algorithm on Google Earth Engine (GEE) platform using spectral indices like Normalised Difference Vegetation Index (NDVI), Normalised Difference Built-up Index (NDBI), Modified Normalised Difference Water Index (MNDWI), Bare Soil Index (BSI) and Digital Elevation Model (DEM) as predictor variables. Five land cover classes were established (built-up, vegetation, agricultural land, bare land and water). The classification accuracy was tested using Overall Accuracy, Kappa Coefficient, Producer's Accuracy and User's Accuracy. The overall accuracy of the classification was 75.43%, and the Kappa coefficient was 0.693, showing a good agreement between the classified and reference data. The results revealed that vegetation was still the major land-cover class, but decreased from 4,543.49 km² in 2016 to 3,486.20 km² in 2025, whereas, agricultural land rose from 1,718.50 km² to 3,039.07 km² in the same period. The built-up land area increased from 780.67 km^2 in 2016 to 1269.04 km2 in 2022 and then decreased to 572.78 km^2 in 2025. However, the analysis of urban expansion found that there was about 228.48 km2 of new urban land, indicating that urban growth still existed despite classification uncertainty in the last year. The results also showed that the urban sprawl was mostly centred around the metropolitan core and the main transportation corridors and this led to changes in vegetation and agricultural land. The study concluded that the multi-temporal remote sensing approach with cloud-based geospatial analysis is a robust approach in monitoring urban expansion and land-use changes. It recommended institutionalisation of geospatial monitoring systems, better land use planning and protection of environmentally sensitive regions to assist sustainable urban development within the FCT.

Keywords: FCT, Google Earth Engine, Land use and land cover, Random Forest, Remote sensing, Sentinel-2, Urban expansion, Urban planning,

INTRODUCTION

There is remain a steady acceleration in global urban proliferation which has considerable effects on land and environmental interactions at both regional and local levels (Zheng et al., 2021). The related alterations in land use and cover present a significant obstacle to environmental sustainability and sustainable urban development (Wang et al., 2024). In this framework, environmental sustainability is characterised as the state that enables human civilisation to fulfil its present requirements without jeopardising the existing and future vitality of natural ecosystems (Allan et al., 2022). Sustainable urban development depends on the design of urban spaces that account for resource consumption (such as energy) and various forms of pollution (including waste, water, air, and soil), while also integrating social, economic, and cultural factors to establish a viable urban environment for both present and future populations. Enhancing environmental sustainability and sustainable urban development can be achieved through strategic land use planning (Alkali 2005; Abdrabo et al., 2021). Disorganised, unregulated, or absent land use planning can lead to chaotic development and significant degradation of both constructed and natural surroundings. In less developed nations, especially in Sub-Saharan Africa, fast urbanisation and the proliferation of informal settlements pose significant obstacles to sustainable land use planning initiatives (Bukoye et al., 2023). Land use planning, the method of designating land for various purposes to harmonise social, economic, and environmental goals, emphasises the spatial and geographical dimensions of socioeconomic and ecological elements to enhance spatial utilisation while reducing conflicts (Sultan et al., 2025).

The application of land use planning exhibits considerable variation; however, the overarching procedure encompasses preparation (establishing goals and objectives), data gathering and analysis, plan development, negotiation and decision-making, execution, and monitoring and revision (Enoguanbhor et al., 2022). Land use planning procedures can be executed at several levels, such as urban, regional, and national. At the regional level, land use planning endeavours to reconcile discrepancies between national objectives and local priorities by harmonising various functions such as new developments, conservation zones, intensive farming, and livestock management (Mehra and Swain, 2024). In less developed nations, such as Nigeria, land use planning initiatives are significantly hampered by a lack of accessible data. This is similarly true for Federal Capital Territory (FCT), which is among the rapidly expanding cities in Sub-Saharan Africa. The capacity of Geographic Information Systems (GIS) and remote sensing (RS) technologies to provide novel perspectives on land use planning and urban development remains largely unexplored (Enoguanbhor et al., 2022).

Prior studies in developing nations have effectively utilised GIS and RS methodologies to measure land use/cover alterations; however, the existing literature has not investigated the direct correlation of these techniques with land use planning (Ramadhan and Hidayati, 2022; Alimi et al., 2023). In FCT, Nigeria, there is a documented rise in urban land cover at the expense of unoccupied land. They contend that the geographical configuration of urban growth in FCT is predicated on the master plan and demonstrates sprawl towards adjacent satellite towns (Abdrabo et al., 2021). They proposed that the city's master plan requires urgent revision and that a thorough regional land use strategy should be developed to tackle the issues of urban sprawl, yet they failed to compare the intended land cover with the actual situation. In the analysis of urban development across three African metropolises (Bamako, Cairo, and Nairobi), it is evident that urban sprawl is on the rise, coinciding with a reduction in undeveloped area, suggesting that there is haphazard urban growth in swiftly expanding African cities (Durowoju et al., 2022; Nzabarinda et al., 2025). Comparable findings have been observed in urban areas beyond Africa. For instance, Issa et al. (2021), noted a rise in urban expansion and a decline in urban greenery across three cities in United Arab Emirates, indicating that vegetation had to be conserved through urban planning and design. Cropland reductions attributable to urban sprawl in China over the last forty years have been noted, although the absence of urban land use planning precluded an assessment of the extent of disorganised development (Abubakar et al., 2023).

In Sub-Saharan Africa, there has been no prior research evaluating land cover alterations to examine the discrepancies between urban growth patterns and land use strategies. This research aims to bridge the gap by measuring the discrepancies between suggested land uses and actual developments, thereby promoting more sustainable urban planning and development in the FCT city-region. This study contributes to the urban growth studies in the FCT by extending single-date land-cover mapping to a multi-temporal assessment of urban expansion dynamics utilising a consistent Google Earth Engine-based machine-learning methodology (Etuk et al., 2023; Gilbert and Shi, 2023). Unlike previous studies that either describe land-cover conditions at a specific point in time or use imagery with a lower resolution, this study quantifies the magnitude, direction, spatial pattern, and land-cover transitions associated with urban expansion over multiple years based on Sentinel-2 imagery (Issa et al., 2021; Dahy et al., 2022). The paper combines change detection, transition matrix analysis, urban growth hotspots detection, annual growth-rate estimation and temporal trend analysis in a unified cloud-computing environment. The study provides evidence that can directly inform strategic land-use planning, infrastructure development and environmental management by identifying where urban growth is occurring, which land-cover classes are being transformed and the implications for sustainable urban development (Abdrabo et al., 2021). It also offers a transferable analytical framework for tracking urban expansion in quickly emerging cities in Nigeria and other developing nations. Consequently, specific objectives are;

1. To classify land use and land cover for selected years using Sentinel-2 imagery and Google Earth Engine.

2. To quantify changes in land use and land cover over the study period.
3. To determine the spatial dynamics of urban expansion in the FCT.
4. To provide the implications of urban expansion for sustainable urban planning and environmental conservation.

LITERATURE REVIEW

Land use/Land Cover Change and Urbanization

Numerous diverse sources provide information regarding current land use and land cover, as well as the alterations taking place. The majority of planning bodies utilise comprehensive data produced from field surveys that encompass counting and observation (Feizizadeh et al., 2023). The analysis of extensive aerial images has been extensively utilised for many purposes, while satellite imaging provides an additional means of obtaining precise data on land usage and land cover, as well as identifying changes that transpire (Ouma et al., 2022). Land utilisation influences land coverage, and alterations in land coverage may or may not result in urban development. Land can be succinctly described as a fundamental input and production factor that remains unconsumed, yet is essential for any production to occur; it is characterised as a resource devoid of production costs, and while its application may transition from less to more lucrative uses, its availability cannot be augmented (Chughtai et al., 2021). Land, by virtue of its accessibility and role as a production element, necessitates utilisation to derive significance; thus, land use is characterised as the human application of land, encompassing the administration and alteration of the natural environment into constructed settings like fields, pastures, and settlements (Fentaw and Abegaz, 2024). It has also been characterised as the actions and resources that individuals engage in within a specific land cover type to generate, alter, or sustain it. Characterising land use in this manner creates a direct connection between human activities in the environment and land cover, with instances of land use encompassing urban development, agriculture, forestry, recreation, and mining (Patil and Panhalkar, 2023). In contrast, land cover pertains to the visible biophysical layer of the Earth's surface, broadly encompassing flora and anthropogenic structures, indicating that regions characterised by bare rock, soil, or aquatic bodies are classified as land rather than land cover. Nevertheless, in practical applications, science typically refers to these elements as "land cover," which is applicable in the context of this study.

Historically, deforestation was a prominent consequence of land use on land cover, particularly in temperate areas; however, contemporary substantial impacts of land use encompass soil erosion, soil degradation, salinisation, desertification, and urban expansion, which is the primary emphasis of this study (Oyediji and Adenika, 2022). Essentially, land use and cover can be modified by two primary forces: natural factors such as weather, climatic variations, and ecosystem dynamics, and anthropogenic influences, which predominantly refer to human impact. A modification in land use results in a transformation of land cover, thus the phrase land use/land cover change; this can primarily be identified by field surveys and remote sensing imaging analysis, with urbanisation being a significant outcome of this change. The degradation of peripheral land surrounding urban areas in various parts of the globe due to urbanisation has garnered international focus. Scholars including Oyediji and Adenika (2022) and Paudel et al. (2024), conducted comprehensive investigations to highlight the circumstances by examining the social and ecological ramifications linked to urbanisation. Urbanisation, characterised by alterations in land use and land cover, stands as a prominent demographic trend of our era; in 1900, urban populations numbered 150 million, escalating to 2.9 billion by 2000, a remarkable 19-fold increase, and projections indicate that by 2020, over half of the global population will reside in urban areas, marking humanity's emergence as an urban species. A brief examination of the circumstances in Nigeria reveals that almost 50% of the populace resides in metropolitan areas, with at least 24 cities boasting populations above 100,000 (Gilbert and Shi, 2023).

The entire notion of urbanisation has attained a significant benchmark lately: Although it appears that most of the Sub-Saharan populace continues to reside in rural regions, the average yearly urban growth rate of 4.58% from 1980 to 1993 has been more accelerated in these areas than anywhere else globally, which is a matter of considerable concern (Akpu et al., 2017). Worldwide, the projected yearly urban population growth rate of 1.78% is almost double that of the global population, and if this pattern persists, 5 billion individuals out of an overall world population of 8.1 billion will inhabit cities by 2030 (Yu, 2022). The significant rise in population density has necessitated urban expansion in both scale and characteristics, resulting in a complete transformation of morphology; agricultural areas are repurposed for industrial development, open spaces are constructed upon, forests are reduced to meet housing demands, and certain types of vegetation, such as grasslands and parks, may face extinction (Fabolude et al., 2023). It is unsurprising that large metropolitan regions serve as battlegrounds for economic development, societal issues, and environmental concerns. Urban areas contend with numerous ecological challenges, including elevated temperatures manifested as heat islands, air contamination, traffic congestion, excessive ambient noise, vacant properties, and neglected land, all of which detract from the living standards of residents and foster a pessimistic perception of city life (Zhang and Li, 2022).

METHODOLOGY

Study Area - FCT

This research centers on FCT, a rapidly expanding metropolis in Sub-Saharan Africa. The research region, illustrated in Figure 1, is situated within the Nigerian FCT and includes the cities alongside all communities. The overall expanse of the research zone is roughly 1994 km^2 (Audu and Sule, 2024). It encompasses the principal sections of two local government jurisdictions within the FCT, namely FCT Municipal and Bwari Local Government Areas (Bello et al., 2026). It stretches into the Gwagwalada and Kuje Local Government Areas of the FCT in the southern section of the urban area.

In 1976, FCT was designated as Nigeria's new capital city because of overcrowding, limited area for urban growth, deviations from the master plan, and traffic congestion in the previous capital, Lagos. In contrast, FCT offered ample area for urban expansion, a centrally located position ensuring nearly equal accessibility for various ethnic groups throughout Nigeria, and a territory devoid of ethnic bias. The FCT was created from four states (Gumel et al., 2020). The governmental headquarters was formally moved to FCT in 1991, and the area has subsequently experienced significant urban expansion. The populace of FCT was 1.406 million in 2006. Utilising the 2006 demographic data, we project the population of FCT to reach 3,770,376 million by 2017. This demographic surge and the resultant expansion have exerted strain on the adjacent natural resources, resulting in the diminishment of alternative land uses in the area. In 1979, the FCT master plan was developed to include regional and urban land utilisation strategies. The regional land use plan encompasses the FCT, whilst the urban land use plan pertains just to the city of FCT and is segmented into four sections.

The four stages of development encompassed multiple districts (Japan International Cooperation Agency, 2025). Phase 1 encompassed the center district (designated for the governmental seat and the center Business District), along with four additional residential areas (Progress in Planning, 2026). Separate urban land use plans were developed for the satellite settlements.

Nonetheless, our field investigations revealed that the urban land use strategies for the satellite communities remain mostly unexecuted in numerous regions. These regions are presently defined by unregulated housing developments (Audu and Sule, 2024). The objectives of the FCT land use plans encompassed the allocation of zones for urban development, the conservation of the natural environment, enhanced accessibility throughout all regions, and the coordination of land use, among others. The oversight of urban sprawl and the revision of land use strategies are impeded by swift urbanisation, particularly due to the proliferation of informal settlements in peri-urban or satellite areas of the city-region (Enoguanbhor et al., 2021).

In FCT, the utilisation of urban land has broadened from a limited number of development zones to establish various urban extensions (Enoguanbhor et al., 2022). The flora in the FCT city-region, an essential aspect of land cover, resembles that found in other areas of the FCT. The flora is classified within the West African ecoregion known as the Guinean Forest-Savannah mosaic (Gumel, 2020). The FCT city-region, situated in the northern section of FCT, is mostly characterised by savannah vegetation, featuring deciduous trees interspersed with grasslands.

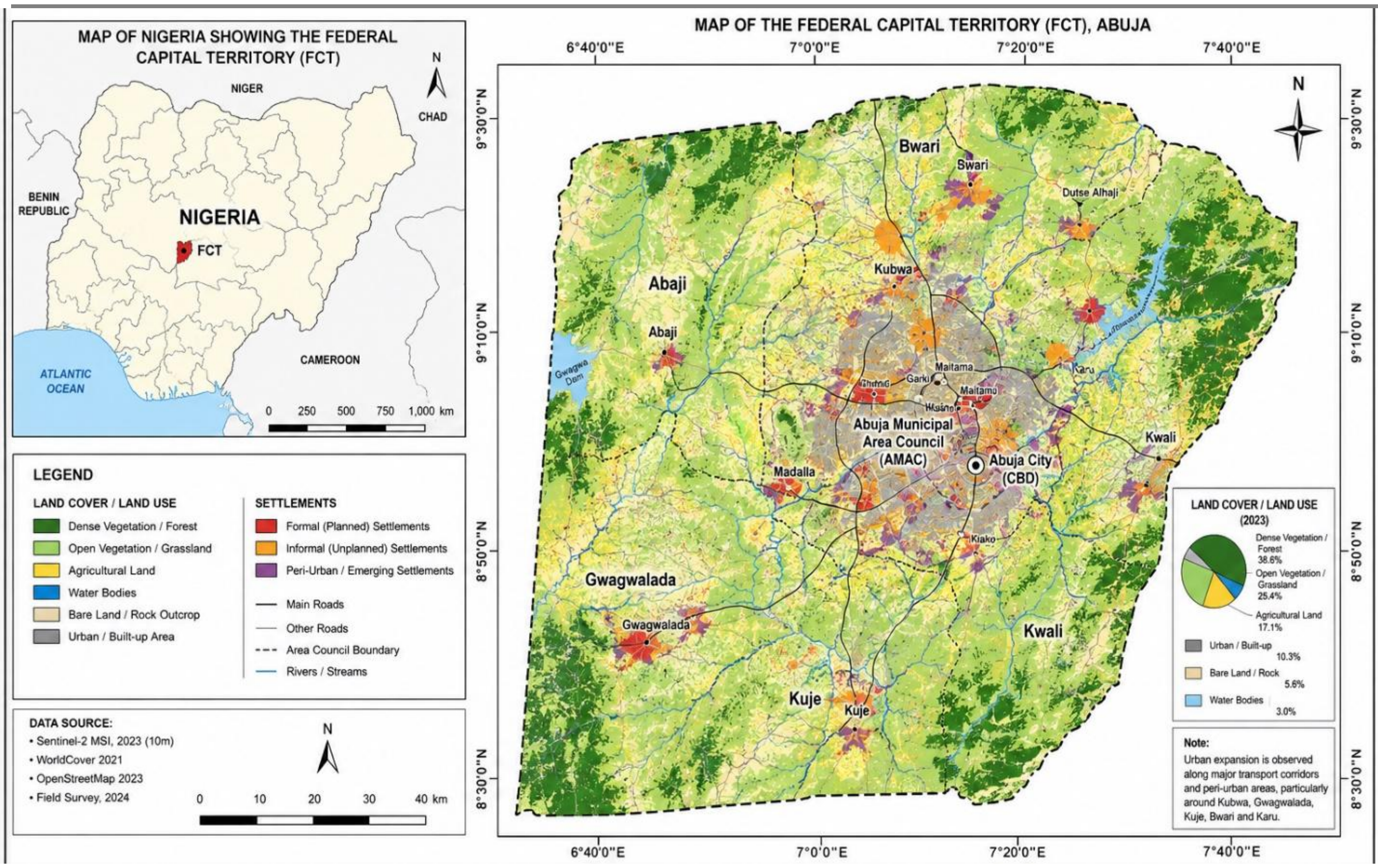

Figure 1: Location of the Study Area: FCT, Nigeria

Source: Sentinel-2 MSI (2023)

Research Design

This study employed a quantitative geospatial research design, integrating remote sensing and Geographic Information Systems (GIS) techniques to analyse temporal land use and land cover changes and urban expansion using multi-temporal satellite imagery (Patil and Panhalkar, 2023).

Analytical Sequence

Data sources and acquisition include the use of Sentinel-2 Level-2A imagery, ESA WorldCover dataset (training/reference data), Shuttle Radar Topography Mission (SRTM) DEM, administrative boundary of the FCT. The image Pre-processing include image filtering, cloud masking, image compositing, clipping to the FCT boundary, band selection, image harmonization, spatial consistency checks. The Feature Extraction include Spectral bands, Blue, Green, Red, NIR, SWIR1, SWIR2, Spectral indices, NDVI, NDBI, MNDWI, BSI, Terrain variable and Digital Elevation Model (DEM). The training sample development indicates ESA WorldCover as reference data, sample generation, class balancing, five LULC classes, built-up, vegetation, agriculture, bare land and water. The Image Classification aspect indicates the employment of Random Forest algorithm while classification was implemented in GEE. 500 decision trees were used. Predictor variables included spectral bands, indices and DEM. Random Forest was selected due to its high classification accuracy, handles nonlinear relationships, resistant to overfitting and suitable for high-dimensional remote sensing data. The classification accuracy assessment includes validation samples, confusion matrix, accuracy measures such as overall accuracy, producer's accuracy, user's accuracy and Kappa Coefficient.

Consequently, classified maps from 2016, 2018, 2020, 2022 and 2025 were compared. Area statistics were computed for each LULC class. Temporal changes were analysed while LULC dynamics were evaluated using temporal trend analysis, percentage composition and area change. Urban expansion was quantified via Extraction of built-up class, Comparison of built-up areas between years and Urban growth statistics. Variables computed through Built-up area, Net change,

Percentage change, Average annual growth, and Urban expansion area while urban expansion maps were produced to visualise spatial growth. Equally, data analysis and presentation were done using descriptive statistics, area calculations, trend analysis, maps, tables, graphs while the presentations were made using LULC maps, line charts, bar charts and urban expansion maps. Furthermore, the Software and Computational Platform include GEE, QGIS, Microsoft Excel and Python.

Table 1: Applied Software with Purpose

Software	Purpose
Google Earth Engine	Image processing and classification
QGIS	Cartographic presentation and map preparation
Microsoft Excel	Statistical summaries and charts
Python	Figure generation and additional analysis

Source: Author's Computation

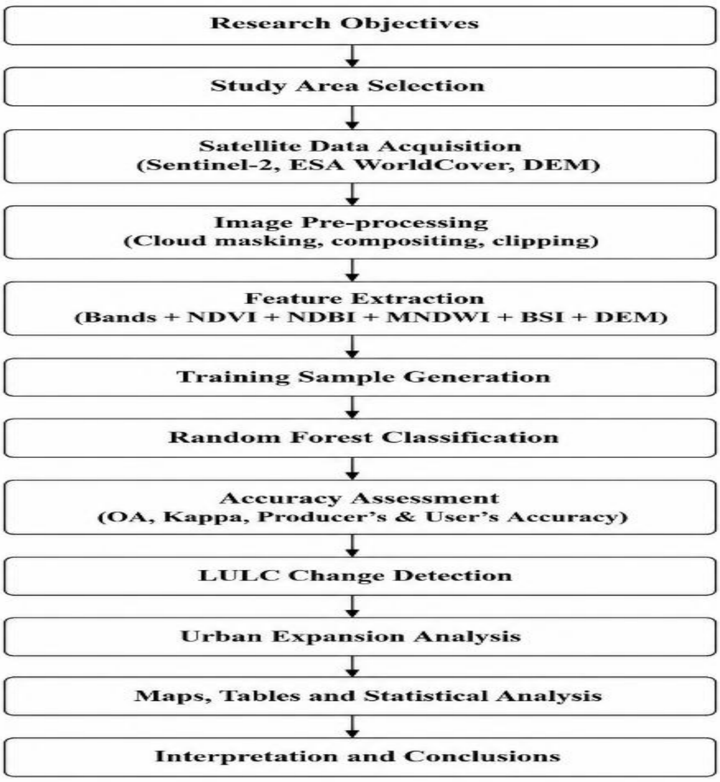

Figure 2: Graphical Illustraion of Analytical Sequence

Source: Author's Construct (2026)

RESULT AND DISCUSSION

Classification Accuracy Assessment

Table 2 shows the accuracy assessment of detailed classification. The supervised Random Forest classification accuracy was tested using Overall Accuracy, Kappa Coefficient, Producer's Accuracy and User's Accuracy. The classification resulted in Overall Accuracy of 75.43% and a Kappa Coefficient of 0.693, showing a good agreement between the categorised images and the reference data. The results show that the Random Forest classifier worked well in classifying the five land-cover types. Water and agricultural land had the best producer's accuracies. Water had the best user's accuracy (95.29%) showing a high level of categorisation dependability for this class. The comparatively lower user's accuracy found for the built-up class implies some degree of confusion with surrounding land-cover categories, which is frequent in varied metropolitan areas. The overall categorisation accuracy is regarded sufficient for the analysis of temporal land-use change and urban sprawl in the research area.

Table 2: Classification Accuracy Assessment

Accuracy Metric	Value
Overall Accuracy	75.43%
Kappa Coefficient	0.693
Producer's Accuracy - Built-up	72.63%
Producer's Accuracy - Vegetation	68.82%
Producer's Accuracy - Agriculture	86.25%
Producer's Accuracy - Bare land	65.05%
Producer's Accuracy - Water	87.10%
User's Accuracy - Built-up	63.89%
User's Accuracy - Vegetation	85.33%
User's Accuracy - Agriculture	71.13%
User's Accuracy - Bare land	67.68%
User's Accuracy - Water	95.29%

Source: Google Earth Engine (2026)

Spatial Distribution of Land Use/Land Cover

Figure 3 shows the spatial distribution of land use and land cover in the FCT for 2016, 2018, 2020, 2022 and 2025. Built-up, vegetation, agricultural, bare land, and water bodies were identified as five major land-cover classes. The classification maps show that vegetation was the dominating land cover class across the study period and occupied large areas of the study region, especially in the outlying districts. The agricultural land was predominantly located around suburban and rural settlements. The built-up areas were focused in the FCT Municipal Area Council and gradually extended to the surrounding districts. The bare land area was comparatively tiny while the water bodies were small in proportion to the research region. A visual comparison of the classed maps indicates apparent variations in the spatial extent of the land cover classes with time, especially the outward development of urban centers and the associated changes in vegetation and agricultural land.

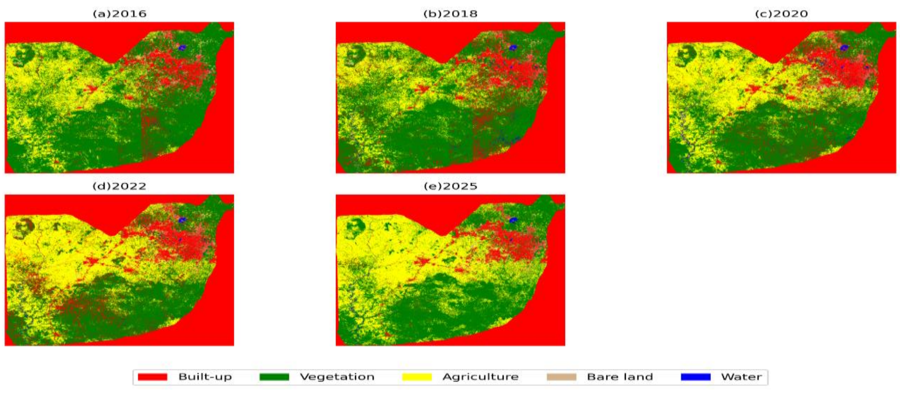

Figure 3: Classified Land Use/Land Cover Maps (2016–2025)

Source: Google Earth Engine (2026)

Temporal Changes in Land Use/Land Cover

Table 3 displays temporal changes of the area occupied by each land use/land cover (LULC) class from 2016 to 2025. Figures 4 – 6 shows the trends and proportional distributions of the identified land cover classes during the study period. Results showed that the spatial extent of five land cover groups had significantly changed over the research period. Vegetation remained the most dominant land cover type but fell from 2016 to 2022 and only barely recovered in 2025. Agricultural land continued to expand from 2020 onwards and by the end of the research period it was the second largest land-cover class. Relatively few differences were seen in the classes of bare land and water bodies compared to other classes. The urbanised land increased from 780.67 km2 in 2016 to 1269.04 km2 in 2022 which indicates a strong urbanisation throughout this period. However, the classified built-up area declined to 572.78 km2 in 2025. Thus, this dip should be viewed with caution due to the well-documented tendency of continued urban expansion within the FCT which can be caused by classification uncertainty or spectral confusion and not a real decrease in the extent of urban development. The temporal variance of the different land cover classes shows how dynamic land use change in the FCT has been during the research period.

Table 3: Land Use/Land Cover Area Statistics (2016–2025)

Year	Built-up	Vegetation	Agriculture	Bare land	Water
2016	780.67	4543.49	1718.5	290.18	18.53
2018	1043.13	4557.11	1500.83	205.96	44.34
2020	1071.05	3656.53	2350.23	225.35	48.19
2022	1269.04	3103.24	2693.04	254.56	31.49
2025	572.78	3486.2	3039.07	228.31	24.99

Source: Google Earth Engine (2026)

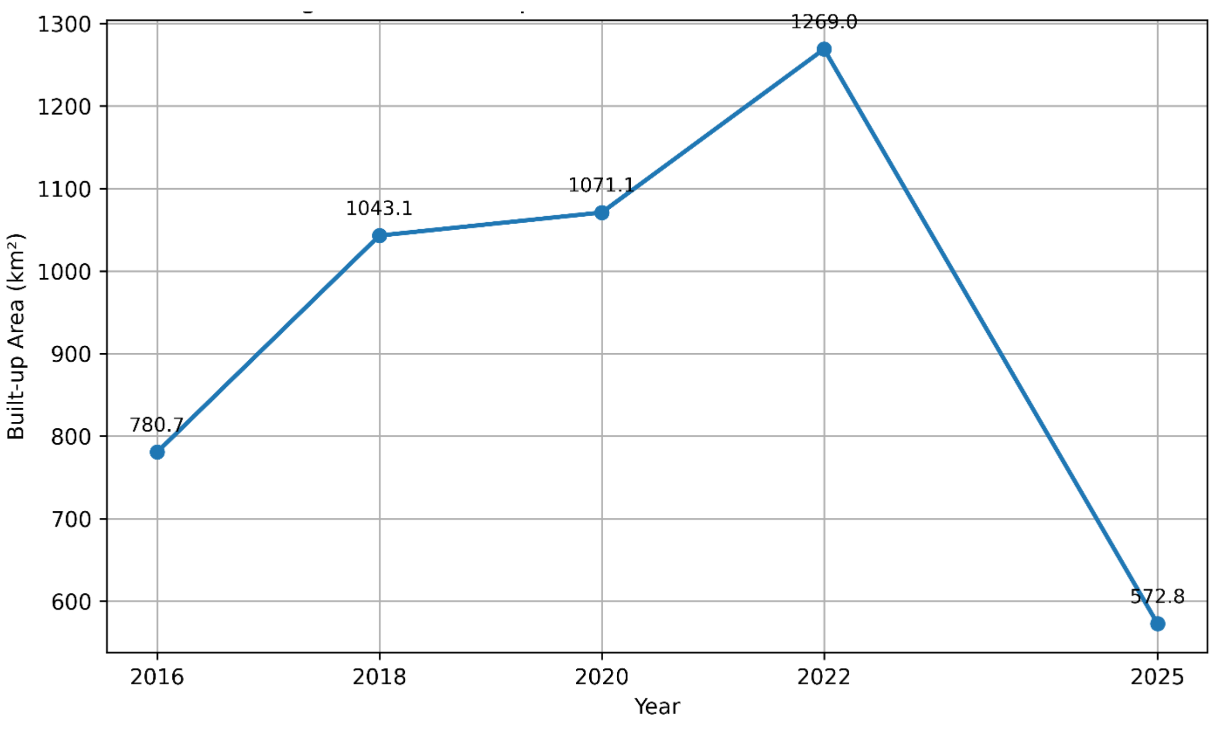

Figure 4: Temporal trend of built-up land in the FCT, Nigeria, from 2016 to 2025

Source: Google Earth Engine (2026)

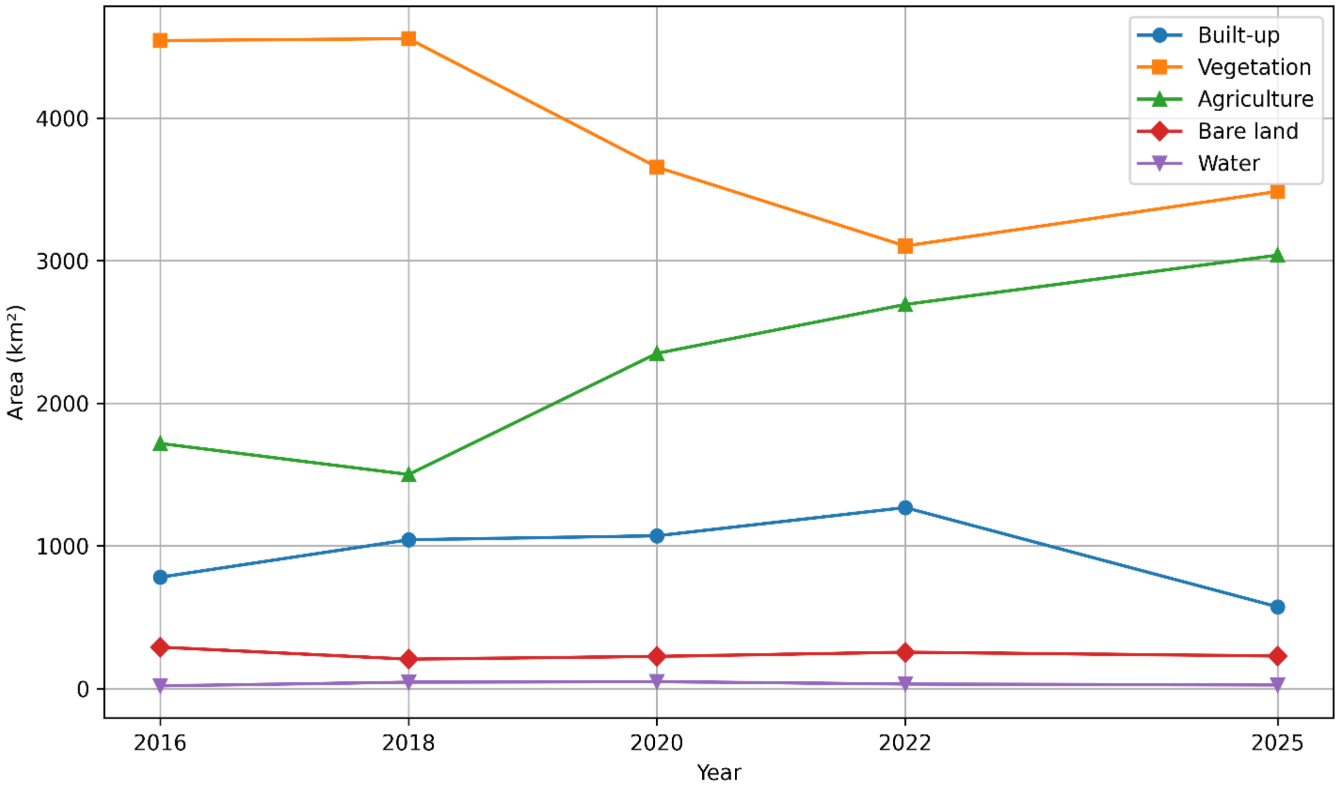

Figure 5: Temporal dynamics of the five-land use/land cover classes in the FCT, Nigeria, between 2016 and 2025.

Source: Google Earth Engine (2026)

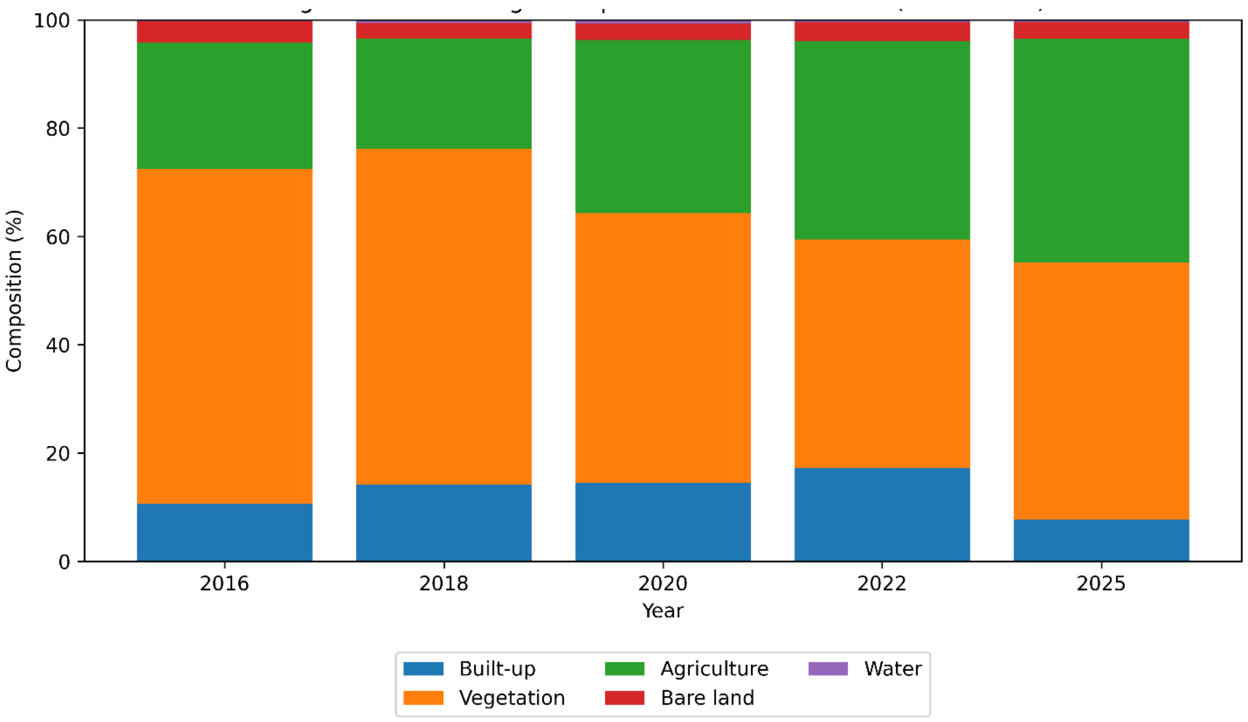

Figure 6: Percentage Composition of LULC Classes (2016 – 2025)

Source: Google Earth Engine (2026)

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Urban Expansion Dynamics

Table 4 depicts the urban growth statistics. The study was carried out to examine the growth of the FCT by evaluating the change in the number of built-up areas from 2016 to 2025. The results show the amount, time trend and spatial structure of urban expansion in the research area.

Table 4: Urban Growth Statistics (2016–2025)

Indicator	Value
Built-up Area (2016) (km²)	780.67
Built-up Area (2025) (km²)	572.78
Net Change (km²)	-207.89
Percentage Change (%)	-26.63
Average Annual Growth (%)	-2.96
Urban Expansion Area (km²)	228.48

Source: Google Earth Engine (2026)

Figure 7 shows the spatial distribution of the urban expansion in the FCT within the time of investigation. The picture also shows that the built-up environment has grown to the existing metropolitan core and to adjacent districts, an outward growth of the built-up environment. Much of the land conversion was concentrated in large transit corridors and rapidly expanding suburban neighbourhoods, reflecting the influence of infrastructure development and population growth.

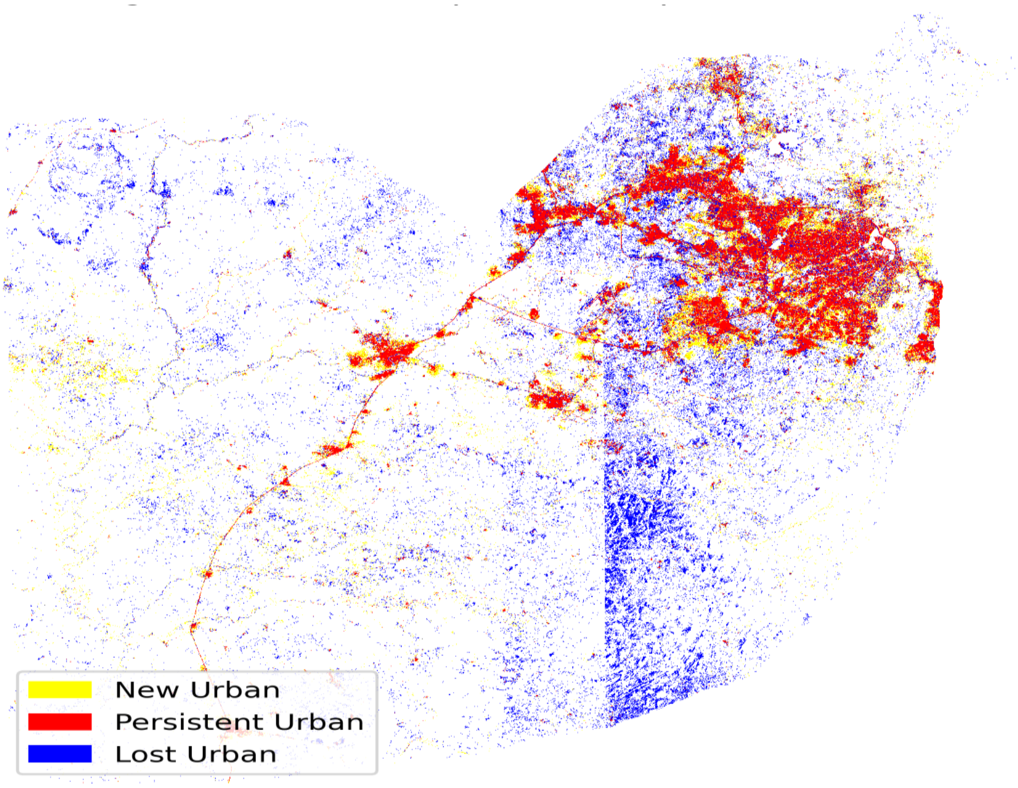

Figure 7: Urban Expansion Map of the FCT (2016–2025)

Source: Google Earth Engine (2026)

Urban growth map reveals that urban expansion begins in many parts of the study territory, however, the overall built-up region is predicted to shrink between 2022-2025. This apparent disparity is due to the reclassification of some pixels labelled as built-up area to other land-cover classifications in the picture classification. Therefore, the projected reduction in built-up area should be viewed with caution, and interpreted as a potential limitation of the classification approach, rather than as irrefutable evidence of urban contraction. The temporal study shows that the main expansion of the city took place between 2016 and 2022 with a great expansion of the built-up area. This increase in urban space has resulted in a shift of vegetation and agricultural land, which shows the pressure of urban sprawl on the natural and semi-natural environment of the city. The results show that urbanisation has resulted in significant changes in the geographical organisation of the FCT during the period of the study. The pattern of outwards urban expansion observed emphasises the requirement of integrated land use planning, supply of infrastructure and sustainable environmental management for future urban development without detrimental impact on natural ecosystems.

DISCUSSION

Land Use and Land Cover Changes in the FCT

Results showed that there was significant LULC change in the FCT between 2016 and 2025 which is indicative of the changing nature of the urban landscape. Vegetation was the dominant land-cover class during the period of research (Table 4.2). Its coverage shrank from 4,543.49 km^2 in 2016 to 3,103.24 km^2 in 2022 and then slightly rose to 3,486.20 km^2 in 2025. By contrast, the agricultural land area increased dramatically from 1,718.50 km^2 in 2016 to 3,039.07 km 2 in 2025, the largest net increase of all land-cover groupings. The built-up land increased from 780.67 km2 in 2016 to 1,269.04 km^2 in 2022 then declined to 572.78 km^2 in 2025. The last fall is not coherent with the known urban expansion history of FCT and should be handled with caution. To summarise, the temporal analysis indicates major landscape changes. The results indicate that the FCT has continued to evolve because of growing urbanisation, infrastructural expansion and rising human activities (Issa et al., 2021). The observed patterns are consistent with the well-established pattern of land transformation in rapidly urbanising areas where natural landscapes are increasingly modified to satisfy the needs of growing residential, commercial and institutional buildings (Abubakar et al, 2023). Hence, the continual surveillance of land-use patterns is essential for sustainable land management and planning for development (Chen et al., 2025).

Magnitude and Spatial Pattern of Urban Expansion in the FCT

The study discovered that the urban expansion of the FCT was mainly directed towards the existing metropolitan centre and gradually into the peripheral suburban areas. The new urban settlements were placed along the main transport linkages and the metropolitan border indicating outward spatial development (figure 4.2). The temporal trend of figure 4.3 also showed that built-up land increased from 780.67 km^2 in 2016 to 1043.13 km2 in 2018, 1071.05km^2 in 2020 and greatest in 2022 of 1269.04 km^2. The analysis of urban growth showed 228.48 km^2 developed urban land. Hence, the built-up area in 2025 was limited to 572.78 km2 even with the urban sprawl during the research period. Therefore, the estimated net change of -207.89 km^2, percentage change of -26.63% and average yearly growth rate of -2.96% need to be interpreted with caution, as they are likely to reflect classification ambiguity instead of true urban decay (Abdrabo et al., 2021). The spatial evidence suggested that urban sprawl was still taking place in the FCT as a consequence of population increase and infrastructural development in general (Paudel et al., 2024). The results show to the importance of strategic urban planning, improved infrastructure provision and appropriate land use planning for sustainable development of the urban fabric (Abubakar et al., 2025).

Land-Cover Classes Contributing to Urban Expansion

The results of the temporal LULC analysis showed the dominant land-cover classes that were impacted by urban growth in the time of the study which are vegetation and agricultural land. As indicated in Table 4.2 and Figure 4.4, vegetation declined by around 1,440.25 km^2 from 2016 to 2022 and significantly increased in 2025. The agricultural land grew steadily from 1,718.50 km^2 to 3,039.07 km^2. Meanwhile, the built-up land increased dramatically until 2022, indicating that urban expansion was accompanied by large-scale land conversion. Although, this work has not resulted in a pixel-level transition matrix, the temporal trends are evident in demonstrating that urban growth has occurred predominantly through conversion of vegetated and cultivated land (Malarvizhi et al., 2016; Fabolude et al., 2023). Figure 4.5 further shows the changes of proportional composition of the five land-cover classes, illustrating the increasing dominance of agriculture and the decreasing proportion of vegetation over time. The results show an increasing competition of land resources with urban growth radiating from the city centre to peri-urban areas (Dahy et al., 2022). This conversion of land might potentially lead to loss of ecosystem services and increased habitat fragmentation, which may further stress agricultural output (Akpu et al., 2017). Hence, land use planning should be aimed at the protection of environmentally sensitive areas and that future urban growth should be allowed to develop in such a way as to limit the loss of productive agricultural land and natural vegetation (Gupta et al., 2024).

Implications of Urban Expansion for Sustainable Urban Planning and Environmental Management

The results of this study show that land use changes and urban growth have a great impact on sustainable urban and environmental planning in the FCT. Figure 4.2 depicts the steady spread of built-up regions, and Table 4.2 demonstrates the large changes which result from the increasing pressure on the natural landscapes and on the existing infrastructure. There was a large conversion of vegetation to built-up area with an increase of about 488.36 km^2 between 2016 and 2022 highlighting the environmental effects of rapid urbanisation. The built-up land has less in the 2025 figures. As for the urban growth map, the new developed urban areas are 228.48 km^2 indicating that urban development is still continuing on with some classification flaws (Manohar et al., 2021). The results show the need for proper land use zoning, infrastructural design and urban green spaces preservation for improving environmental sustainability (Ouma et al., 2022). It further demonstrates the promise of Sentinel-2 photos for monitoring urban development and land use change over time using GEE. The application of these geospatial technologies to the planning operation of government agencies can help to make better choices on land distribution, protection of the environment and infrastructure construction (Akpu et al., 2017). With the implementation of evidence-based urban planning procedures over time, the FCT will be better prepared to respond to future growth without compromising the quality of environment and sustainable urban development.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study that examined the dynamics of land use and land cover change and urban expansion in FCT, Nigeria was examined using multi-temporal Sentinel-2 satellite imageries on GEE platform. The study mapped and analysed the changes in five primary land cover types including built-up areas, vegetation, agricultural land, bare land and water bodies from 2016 to 2025. The results showed that over the research period, the spatial pattern of land use and land cover underwent significant changes.

Vegetation was still the dominant land cover type, although its total coverage fell dramatically with a little comeback in 2025. In contrast, there was huge increase of agricultural land, thereby increasing the pressure on peri-urban surroundings. The rapid increase in built-up areas between 2016 and 2022 was also evident, showing accelerated urbanisation within the FCT. The decrease of the categorised built-up area in the urban growth study in 2025 is attributable to the newly established urban areas, including the decline can be caused by the classification uncertainty and not by the decline in urban development.

The study also revealed that urban expansion was centred around the existing metropolitan area and along the important transportation corridors, suggesting outward spatial growth driven by population growth, infrastructure development and increasing land demands.

The temporal study also showed that vegetation and agricultural land were the main land-cover classes affected by urban growth, which indicates the increase of transformation of natural and productive landscapes to urban purposes. Finally, the study validates the reliability and effectiveness of remote sensing and cloud-based geospatial technologies in monitoring land use change and urbanisation. The findings provide useful insights for promoting sustainable urban design, environmental management and land administration in the FCT. Therefore, the study contributes to the knowledge of urban growth processes and provides a spatial context for informed planning and policy-making.

Policy Recommendations

The following recommendations are made on the basis of this study's conclusion.

1. There is a need for thorough land use planning to direct the urban development in the FCT towards compact urban growth and to minimise the unnecessary conversion of vegetation and agricultural land. Land-use plans should be periodically reviewed and enforced by government planning organisations to encourage orderly physical development.

2. The Federal Capital Development Authority (FCDA), Federal Capital Territory Administration (FCTA) and relevant environmental agencies should institutionalise the use of Remote Sensing, Geographic Information Systems (GIS) and cloud computing platforms like the GEE for routine monitoring of land-use change and urban expansion. Regular monitoring will in time identify uncontrolled development and support evidence-based planning decisions."

3. The continuing loss of vegetation emphasises the need to strengthen policies for environmental conservation. Existing green areas, forest reserves, riparian corridors and other environmentally sensitive landscapes must be accorded greater legal protection to preserve their biodiversity, reduce environmental degradation and foster urban resilience.

4. Urban expansion is increasingly taking place along suburban areas and transit corridors. Planning authorities should design growth management strategies to limit peri-urban development through suitable zoning restrictions, provision of infrastructure and development control measures.

Practical Implications of the Study

The results of this study have significant practical implications for future research, policy formulation, environmental management and urban planning. Firstly, the produced LULC maps and urban expansion analysis offer up-to-date spatial information to planners to identify quickly emerging areas, assess land-use trends, and prepare sustainable physical development plans for the FCT. Second, the study provides spatial evidence on vegetation loss and changing land use patterns for environmental managers to aid the development of conservation programmes, ecosystem restoration initiatives and environmental impact assessments. Third, the results give objective geographic data for policy makers to assess land-use policies, reinforce development control mechanisms and improve the management of urban growth. The results can also help in adopting sustainable urban development strategies that are consistent with national development goals and the Sustainable Development Goals (SDGs), particularly SDG 11 (Sustainable Cities and Communities) and SDG 15 (Life on Land). Fourth, recognising the geographical pattern of urban expansion helps government agencies to prioritise infrastructure investment in fast-growing regions, thereby boosting transportation planning, public service delivery and housing construction. Fifth, the successful utilisation of Sentinel-2 imagery with GEE exemplifies the feasibility of cloud-based geospatial technology for large-scale land-use monitoring. The approach established in this study offers a cost-effective and replicable framework that may be utilised by government agencies, planning organisations and researchers for continuous urban monitoring . Thus, this study adds to the increasing body of literature on urban expansion and land-use change in Nigeria, offering recent empirical findings from the FCT. The methodological framework can also be used to other fast urbanising areas for comparative research and a better understanding of urban growth patterns.

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