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GIS-Based Multi-Temporal Land Use and Land Cover Classification for Urban Expansion Planning in the Federal Capital Territory (FCT), Nigeria

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ABSTRACT

Rapid urbanisation in the Federal Capital Territory (FCT) of Nigeria has led to increased demand on land resources; hence it is imperative to have reliable and up-to-date land use and land cover (LULC) information for planning and environmental management. This project established a cloud-based GIS procedure for mapping LULC in the FCT using the processed Sentinel-2 Level-2A imagery in Google Earth Engine. The Random Forest classifier was trained using stratified reference samples from the ESA WorldCover dataset. Six spectral bands of Sentinel-2 (B2, B3, B4, B8, B11 and B12), four spectral indices (NDVI, NDBI, MNDWI and BSI) and elevation from Shuttle Radar Topography Mission (SRTM) were used as the predictor variables. Classification performance was tested using an independent validation dataset and standard accuracy metrics, including the confusion matrix, Overall Accuracy, Kappa coefficient, Producer's Accuracy and User's Accuracy. The classification produced an Overall Accuracy of 75.43% and a Kappa coefficient of 0.6928 showing a strong agreement between the classified and the reference data. Vegetation was the dominant land-cover class (47.44%), followed by agriculture (41.33%), built-up land (7.80%), bare terrain (3.11%) and water bodies (0.34%). The spatial distribution of built-up areas indicated high urban concentration in the Abuja Municipal Area Council, while vegetation and agricultural land dominated the outer area councils. The suggested methodology demonstrates the usefulness of merging Sentinel-2 imagery, machine learning and cloud computing for rapid regional LULC mapping. The resulting dataset provides an important baseline for monitoring future urban expansion, analysing environmental change, and enabling evidence-based spatial planning and sustainable land management inside the FCT.

Keywords: GIS; Google Earth Engine; Land use/land cover; Random Forest; Remote sensing; Sentinel-2; Sustainable urban planning; Urban expansion; Federal Capital Territory; Nigeria

INTRODUCTION

Land use and land cover (LULC) denote separate but interconnected ideas, illustrating both anthropogenic utilisation and the inherent attributes of the terrain (Nedd *et al.* 2021; Akaolisa *et al.* 2023; Alegbeleye *et al.*, 2024). Land use specifically refers to the various ways individuals utilise land for purposes such as agriculture, leisure, conservation of habitats, and management of wildlife (Rajendran *et al.* 2020; Mephors *et al.* 2021; Nedd *et al.* 2021), whereas, land cover pertains to the visible characteristics of the Earth's surface, encompassing vegetation, bodies of water, exposed soil, urban development, and more (Koko *et al.*, 2022). The identification of land use and land cover alterations is becoming progressively essential owing to its influence on human requirements and ecological systems (Olayungbo, 2021), and it is imperative for comprehending landscape dynamics and realising sustainable management strategies (Akaolisa *et al.* 2023). In emerging nations or areas, economic and industrial advancement might intensify land use and land cover alterations, therefore resulting in climate change, erosion, landslides, deforestation, land degradation, and loss of biodiversity (Hasan *et al.* 2020; Zhang and Li 2022). Comprehending land use and land cover alterations in these areas is essential for resource management, evaluating environmental states, and formulating climate change mitigation strategies.

Nigeria exemplifies a growing nation in West Africa undergoing swift population expansion and alterations in land use and land cover. As per Adesola *et al.* (2024), Nigeria stands as the most populous nation in Africa, with a population of 218.5 million and encompassing a total area of 923,769 km². Throughout the years, Nigeria has had a swift rise in population growth due to its elevated birth rate, making it the seventh most populous nation globally. By the year 2050, it is anticipated that Nigeria would possess the third biggest population globally, exceeding that of the United States. In 2019, Nigeria's urban demographic rose to 51.2% from 29.7% in 1990 (Faisal Koko *et al.* 2021), indicating a geographical expansion of constructions in urban locales, especially within the Federal Capital Territory (FCT). The swift increase in population and urban migration has strained the FCT's restricted natural land cover, including forests, resulting in land fragmentation, deforestation, and climate change. The trend and magnitude of natural ecosystem degradation have been associated with both direct and indirect human endeavours, including agricultural development, urban expansion, deforestation, firewood harvesting, and infrastructure construction, among others (Oyediji and Adenika 2022; Fashae *et al.* 2022; Adeyemi *et al.* 2022).

Throughout the years, there have been notable advancements in remote sensing data (from coarse to high-resolution images and temporal frequency), classification techniques (from conventional to deep-learning classifiers), and platforms (from standalone software to cloud-based systems) utilised in land use and land cover studies. Furthermore, the examination of LULC classification accuracy has progressed through several assessment metrics and methodologies. A multitude of research endeavours have explored land use and land cover (LULC) dynamics as either principal or ancillary aims in Nigeria, employing diverse remote sensing methodologies, geographic information systems (GIS), and statistical modelling tools. These investigations have examined topics including deforestation (Aliyu *et al.* 2020; Fitz *et al.* 2022; Fabolude *et al.* 2023), urban sprawl (Adebayo *et al.* 2019; Samuel and Atobatele 2019), alterations in agricultural land use (Duke *et al.* 2022; Abubakar *et al.* 2023), and the deterioration of ecosystems. The escalating significance of LULC data in tackling environmental issues and its extensive utilisation in Nigeria demands a comprehensive examination of land cover alterations in the FCT due to heightened urban migration.

This study, therefore, suggests a reproducible cloud-based method for high-resolution land use and land cover (LULC) mapping in FCT, Nigeria by incorporating Sentinel-2 multispectral data, Google Earth Engine (GEE), spectral indices, Shuttle Radar Topography Mission (SRTM) elevation data and Random Forest machine-learning algorithm (Okoduwa and Amaechi, 2024). Most of the previous land cover mapping studies in Abuja and other cities in Nigeria have relied on Landsat imagery, desktop GIS environment, or conventional classification algorithms with low spatial resolution and restricted computing scalability (Enoguanbhor *et al.*, 2019; Enoguanbhor *et al.*, 2021; Alegbeleye *et al.*, 2024; Izuegbu *et al.*, 2025). The purpose of this effort is to build an updated and operational LULC map overcoming these restrictions by exploiting the cloud computing capacity of GEE and the improved geographical resolution of Sentinel-2 . The work also combines multiple spectral indices (NDVI, NDBI, MNDWI and BSI) with topographical information to enhance the class categorisation in a difficult urban scene. This study gives a transparent, scalable, programmed and totally repeatable approach and a land cover map to be used on other Nigerian cities and fast urbanising places. The gathered information can be utilised as a baseline for future change detection and environmental monitoring and sustainable urban planning.

As a result, the following objectives are derived from the aforementioned discussions;

1. To determine the major land use and land cover (LULC) classes in the FCT
2. To assess the accuracy of Random Forest algorithm classification of land use and land cover in the
3. To investigate the spatial distribution and extent of the identified land use and land cover classes across the FCT
4. To provide the implications of the observed land use and land cover patterns for urban expansion planning and sustainable development in the FCT.

MATERIALS AND METHODS

Study Area - FCT, Nigeria

Figure 1: Geographical position of FCT, Nigeria, administrative boundaries of study area and Major Area Councils. The study was conducted in the FCT, Nigeria. The FCT is situated at the centre of Nigeria's North-

Central geopolitical zone (Alegbeleye *et al.*, 2024). The FCT is situated approximately between latitudes 8°25° and 9°25° N and longitudes 6°45° and 7°45° E, and has an estimated landmass of about 7,315 km². It is bounded by Kaduna State in the north, Nasarawa State in the east and south, and Niger State in the west (Abubakar, 2014). The territory is made up of six Area Councils, namely; Abaji, Abuja Municipal Area Council (AMAC), Bwari, Gwagwalada, Kuje and Kwali. These Area Councils include the administrative capital of Nigeria and its fast-growing metropolitan area. The climate of the FCT is tropical wet and dry (Aw) with distinct wet and dry seasons. The wet season generally spans from April to October and the dry season from November to March. typical yearly rainfall varies from 1,100 to 1,600 mm and typical temperatures vary from 22°C to 32°C depending on the season and elevation. The climatic conditions permit varied vegetation groupings, predominantly Guinea savanna, interspersed with agricultural area, riparian vegetation and developing urban populations (Mahmoud *et al.*, 2016).

In the previous three decades, FCT has been one of the fastest growing metropolitan areas in Nigeria (Idoko *et al.*, 2010). The migration of people from rural to urban regions, population growth, infrastructure development and the incessant expansion of residential, commercial and transit systems have had a profound impact on the environment (Alegbeleye *et al.*, 2024). The country’s political and administrative capital, Abuja, has continued to tighten the squeeze on the surrounding agricultural land, natural vegetation, wetlands and other environmentally sensitive ecosystems. Therefore, understanding the spatial distribution and dynamics of land use and land cover is of crucial importance for more sustainable urban planning, environmental protection and evidence-based land management (Okoduwa and Amaechi, 2024). The FCT has a physical terrain of rolling plains, isolated inselbergs, river valleys and low mountain ranges. The drainage patterns, the distribution of the flora and the adaptation of the land for diverse human activities are affected by the elevation (70m to more than 760m) (Pérez-Cutillas *et al.*, 2023). Important rivers such as the Usuma, Gurara and Wupa rivers drain the area and provide essential ecosystem services and part of the territory’s water resources (Okoduwa and Amaechi, 2024). Among others, the elevation data from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) were used as predictor variable to estimate the topographic heterogeneity in the picture categorisation (Nasiri *et al.*, 2022).

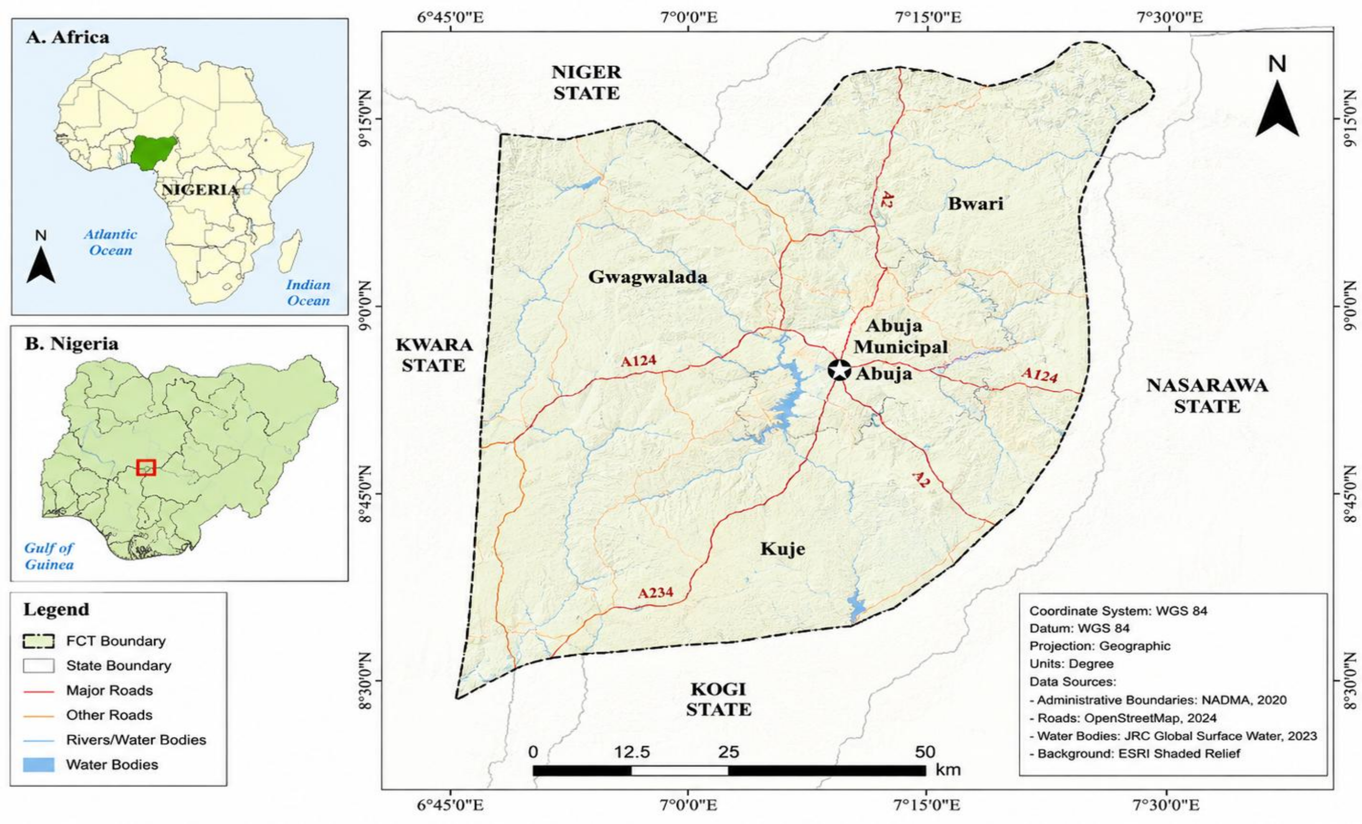

Figure 1: The geographical location of the FCT within Nigeria

Source: Google Earth Engine (2026)

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FCT was chosen for this study because it is one of the fastest growing planned capital cities in Africa and because the shift in land use is one of the biggest hindrances to sustainable development (FMITI, 2015). The mixed character with urban infrastructure, rural areas, natural vegetation, bare surfaces and water bodies within a relatively short administrative border makes it a great place to test cloud based geospatial technologies (Enoguanbhor *et al.*, 2022). Additionally, the availability of high-resolution Sentinel-2 imagery and reference datasets globally through the Google Earth Engine platform makes the FCT an attractive study site for developing scalable and reproducible land use and land cover categorisation algorithms (Pham-Duc *et al.*, 2023). Recently, cloud-based remote sensing systems and machine learning techniques have been shown to map regional land-cover efficiently, reproducibly and scalably (Pérez-Cutillas *et al.*, 2023 Pham-Duc *et al.*, 2023).

Research Design

The current study employed a quantitative geospatial research methodology. Application of Satellite Remote Sensing, Geographic Information System (GIS), Cloud Computing and Machine Learning Technologies for Land Use and Land Cover (LULC) Classification in FCT Nigeria This is to provide a realistic and reproducible LULC dataset for future studies on land cover changes, urban planning and environmental monitoring (Cheng *et al.*, 2021). The technical framework was developed in five successive steps, namely data collection, picture pre-processing, feature engineering, supervised image classification, and accuracy assessment (Figure 2). The entire workflow was implemented on the Google Earth Engine (GEE) cloud computing platform, which allows the efficient large-scale geospatial analysis by providing access to large archives of Earth observation data and overcoming the computational limitations of conventional desktop GIS software (Zanag *et al.*, 2022). The fast photo processing, repeatability and collaborative research of GEE's cloud-based approach is of increasing significance for regional and national land-cover mapping (Amani *et al.*, 2023). For this situation, supervised categorisation was adopted, since the land-cover classes of interest were known a priori at the beginning of the inquiry. In unsupervised classification, pixels are grouped into classes according to the similarity of their spectra. The model is trained in a supervised classification to learn the mapping between predictor variables and the land-cover classes as indicated by representative training samples (Nasiri *et al.*, 2022). This strategy can also improve thematic accuracy in some cases, especially in diverse metropolitan regions with several land-cover classes with comparable spectral signatures (Pérez-Cutillas *et al.*, 2023), under the assumption of credible and available reference data. The analysis was carried out for five primary land cover types of the principal landscape features of FCT viz. Built-up areas, Vegetation, Agricultural land, Bare land and Water bodies.

The selected classes are indicative of the main types of land cover changes related with urban expansion in the study area. These classifications are consistent with internationally accepted land cover categorisation systems, such as the ESA WorldCover product (Cheng *et al.* 2021). In the experiment, multiple types of predictor variables were used in addition to the spectrum reflectance values so as to obtain the highest discrimination capability of the classifier. The predictor dataset includes six spectral bands of Sentinel 2, four spectral indices and one topographic variable of Shuttle Radar Topography Mission (SRTM) (Zanag *et al.*, 2022). The addition of spectral, environmental and topographic information has been shown to boost class separability and reduce spectral confusion between, in particular, built-up land, bare soil and agricultural land. The pictures were identified using the non-parametric ensemble learning method Random Forest (RF). RF generates many decision tree models and merges their forecasts by majority voting (Abubakar *et al.*, 2023). Random Forest has good classification accuracy, captures complicated non-linear correlations, is somewhat robust to noise and multicollinearity, and works well with a large number of predictor variables (Fabolude *et al.*, 2023) thus it is highly employed in remote sensing applications. Its prediction accuracy is good for different landscapes and the parameters are very easy to tune.

The training data was generated using stratified random sampling of the ESA WorldCover 2021 land-cover product. Stratified sampling increases the representativeness of model training for each land-cover class, thus reducing sample bias and improving classification stability. In the study area, reference samples were collected, of which roughly 1500 samples were separated into training and validation datasets for independent model evaluation (Fitz *et al.*, 2022). The remote sensing methods standardly used were applied to assess the obtained categorisation findings. Confusion matrix was computed based on the independent validation data set; Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA) and Kappa coefficient were calculated (Nedd *et al.*, 2021). The extra measurements help to provide a holistic assessment of the categorisation accuracy taking omission and commission defects into consideration. Total accuracy is the sum of the correctly identified samples. Producer's accuracy is the probability that a sample from the reference is properly classified. The accuracy of the user (Olayungbo, 2021) is the dependability of the classified map to the map users.

The detected pixels were then transformed into area data of square kilometres and percentage of overall research area to assess the extent of each land cover class (Cheng *et al.*, 2021). The results give a quantitative assessment of the actual composition of landcover in the FCT and can provide a basis for future studies on urban growth and landscape change. Thus, the study design seeks to provide a robust, unambiguous and reproducible basis for regional LULC mapping (Zanaga *et al.* 2022). The technique also presents a scalable approach that might be applied in other rapidly urbanising countries with comparable land management and environmental issues using open satellite photos, cloud computing, machine learning and freely available reference data internationally.

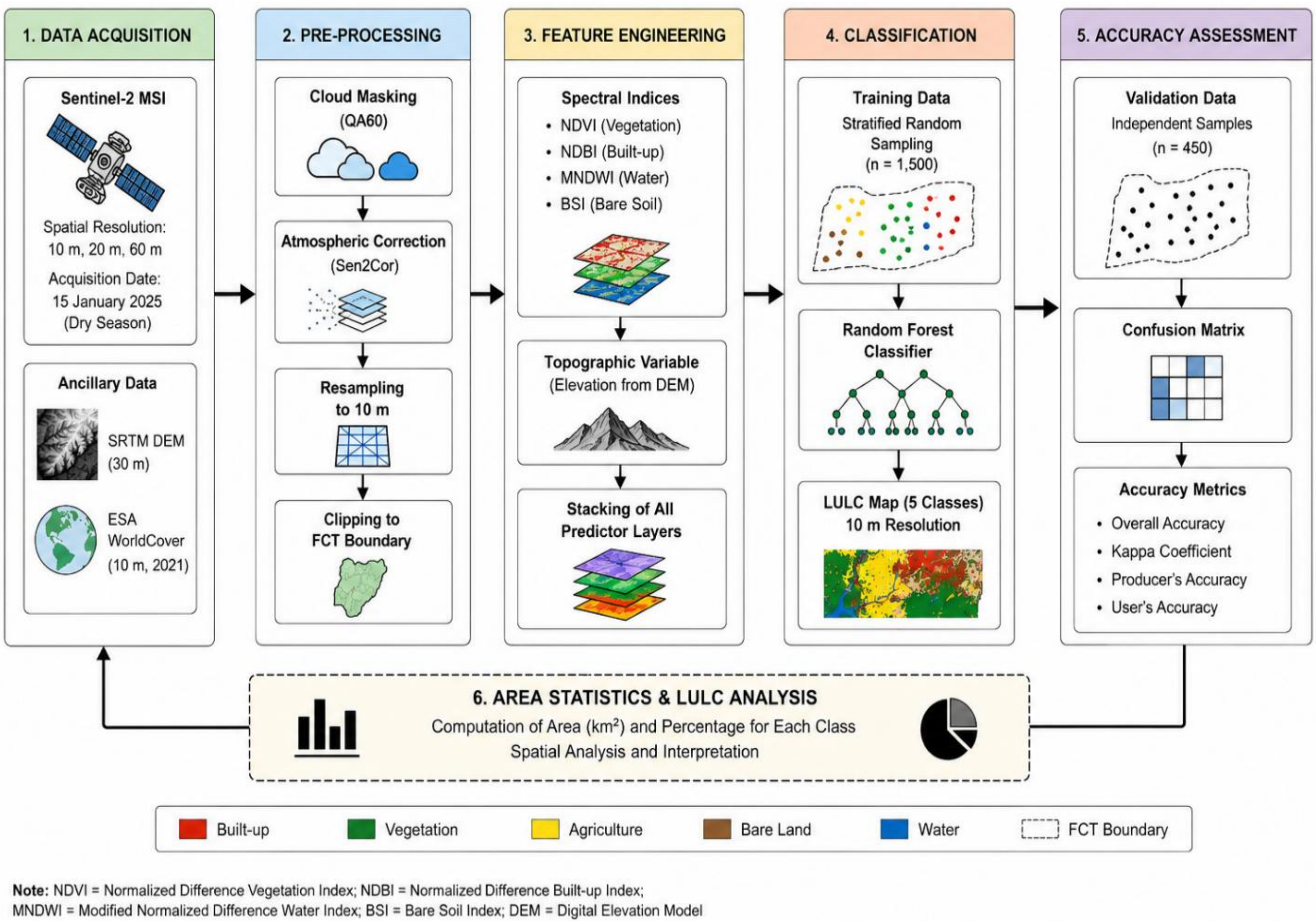

Figure 2: Final LULC Map

Source: Google Earth Engine (2026)

Methodological Procedure

Satellite Data

Sentinel-2 Level-2A surface reflectance imagery (COPERNICUS/S2_SR_HARMONIZED) for 2025 was obtained from Google Earth Engine. Images with cloud cover greater than 20% were filtered out and remaining scenes were composited using the median reduction . For classification, only six Sentinel-2 bands were retained, which have been found to be relevant for LULC discrimination. These are Band 2 (Blue, 490 nm, 10 m), Band 3 (Green, 560 nm, 10 m), Band 4 (Red, 665 nm, 10 m), Band 8 (Near Infrared, 842 nm, 10 m), Band 11 (Shortwave Infrared 1, 1610 nm, 20 m) and Band 12 (Shortwave Infrared 2, 2190 nm, 20 m) (Enoguanbhor *et al.,* 2022). These bands give complementary information on vegetation health, soil moisture, urban materials, surface water and exposed land, and therefore they are particularly useful for supervised categorisation in heterogeneous urban landscapes.

Feature Engineering

Feature engineering is the process of selecting and transforming variables to enhance the prediction ability of standard models for machine learning. Instead of using the original Sentinel-2 spectral bands, this study used other environmental variables that define the status of vegetation, urban development, exposure of soil, presence of water and terrain (Ibitoye *et al.,* 2022). Thus, the final predictor stack contained eleven variables namely Blue (B2), Green (B3), Red (B4), Near Infrared (B8), Shortwave Infrared 1 (B11), Shortwave InfraInfrared 2 (B12), Normalised Difference Vegetation Index (NDVI), Normalised Difference Built-up Index (NDBI), Modified Normalised Difference Water Index (MNDWI), Bare Soil Index (BSI) and Shuttle Radar Topography Mission (SRTM) Elevation . This combination of variables is because they complement each other's information content. While the original spectral bands are proxies for surface reflectance, derived indices are effective in identifying certain land cover aspects such as vegetation activity, urban surfaces, exposed soils and water bodies (Ogunjobi *et al.,* 2018). Elevation provides more environmental information to discriminate spectrally similar classes in different terrain conditions. This multidimensional feature space allows the Random Forest algorithm to describe sophisticated non-linear relationships between predictor factors and enhance classification performance compared to techniques that only utilise spectral reflectance (Thanh and Kappas, 2018).

Training Data and Classification

Table 1 shows training reclassification referenced from ESA WorldCover 2021 dataset. Stratified random sampling was performed and around 1500 training samples were acquired. We trained a Random Forest classifier on Google Earth Engine with 500 trees. The ESA WorldCover 2021 dataset (Ismail *et al.,* 2023) was the major reference dataset utilised to construct the training and validation samples. ESA WorldCover is a 10 m resolution global land cover map product produced by fusing Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 optical data using advanced machine learning techniques (Duke *et al.,* 2022). The dataset is a good reference for supervised classification as it provides globally consistent land-cover classes and is validated in varying climatic situations with great care. To fit the aims of this study, the classes of the first version of the WorldCover were aggregated into five thematic classes. Image pre-processing: Cloud and cirrus contamination was masked with QA60 cloud masking. Images were clipped to the FCT boundary and resampled, when appropriate, to a standard 10m spatial resolution.

Table 1: Training Reclassification

Original ESA WorldCover Class	Reclassified Category
Tree Cover, Shrubland, Grassland	Vegetation
Cropland	Agriculture
Built-up	Built-up
Bare/Sparse Vegetation	Bare Land
Permanent Water Bodies	Water

Source: Author’s Computation (2026)

The reclassified dataset was subsequently used to generate stratified random samples for Random Forest model training and independent validation.

Accuracy Assessment

Classification performance validated on independent validation dataset. Calculation of the confusion matrix, Overall Accuracy, Kappa coefficient, Producer's Accuracy and User's Accuracy was done. Accuracy of land use and land cover (LULC) classification depends not only on the application of the classification approach but also on the robustness of validation procedure (Zheng *et al.,* 2021). The accuracy assessment is a non-biased measure of the uncertainty of the classification process and the degree to which the categorised image resembles the true ground conditions. Accuracy assessment is an essential component of supervised classification in remote sensing studies, as it enables quantification of classification errors and the determination of the usefulness of the resulting map for scientific and practical applications (Venter *et al.*, 2022). The classification accuracy was determined using an independent validation data set that was not utilised for training the model. The training and validation data sets are separated so as to limit the chance of over-fitting the model and this gives an impartial estimation of the classification performance. The evaluation was made by confusion matrix which is the commonly known technique in remote sensing. The OA, PA, UA, and Kappa coefficient were calculated based on the matrix (Zheng *et al.,* 2021).

Area Estimation

Following classification, the spatial extent of each land-cover class was estimated using the pixel area function available within Google Earth Engine. The area occupied by each class was computed in square kilometres and subsequently converted into percentages of the total study area.

Methodological Strengths and Limitations

The cloud-based design provided a number of advantages to the inquiry. First, it significantly lowered the calculation time by enabling large-scale picture processing on Google's distributed servers (Thanh and Kappas, 2018). Second, it removed the requirement for high-performance computing gear, enabling investigators and institutions with modest processing power to do advanced geospatial analysis. Thirdly, the entire analytical technique was written, rendering it fully reproducible and transparent. The study used Sentinel-2 Level-2A Surface Reflectance imagery that delivers acceptable quality multispectral observations at spatial resolutions of 10-20m and with a revisit duration of around five days (Okeke *et al.,* 2022). A major advantage for the operational monitoring of land cover is the free and internationally consistent imagery, which removes many of the budgetary constraints associated with commercial satellite datasets (Eludoyin & Adewale, 2020). Another strength is that it contains numerous complimentary predictor elements, not only the original spectral bands. The classification consisted of six spectral bands from Sentinel-2, i.e., Normalised Difference Vegetation Index (NDVI), Normalised Difference Built-up Index (NDBI), Modified Normalised Difference Water Index (MNDWI), Bare Soil Index (BSI) and Shuttle Radar Topography Mission (SRTM) elevation (Zheng *et al.*, 2021). The class separability was increased substantially by incorporating spectral, environmental and topographic information into the multidimensional feature space. Another key strength of the methodology is the application of the Random Forest algorithm (Ismail *et al.,* 2024). The Random Forest has several characteristics which makes it very suitable for remote sensing applications including high predictive accuracy, resistance to overfitting, capability to model complex non-linear relationships, robustness to noisy datasets and effective handling of correlated predictor variables (Ismail *et al.,* 2024).

The constraints are the use of poor spatial resolution of Sentinel-2 Imagery. The 10 m spatial resolution is a considerable improvement over previous medium resolution satellites but still has some pixels with mixed land-cover categories in highly urbanised metropolitan areas (Okeke *et al.*, 2022). The mixed pixel effect is particularly noticeable in peri-urban areas where buildings, roads, vegetation, construction sites and bare soil are in close proximity to each other. Therefore some spectral confusion between built-up land and naked soil has to be accepted. Another drawback is the inherent spectral similarity of some land cover classes. The confusion matrix revealed that the highest misclassifications were between built up regions and barren terrain, and vegetation and agricultural land (Durowoju *et al.,* 2022). Most of the problems are related to the similarities in the surface reflectance, and not to the absence of the Random Forest approach. The training and validation samples were derived from the ESA WorldCover data set. This product has been extensively examined and is a convenient and reproducible reference source, but is not without classification problems.

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The errors in the reference data set could be propagated to the supervised classification model. Another challenge is the lack of rigorous field verification (Venter *et al.,* 2022). The statistical accuracy of the categorisation was reasonable using independent validation samples, but direct field observations would increase confidence in the correspondence between mapped land-cover classifications and the ground truth (Ibitoye *et al.,* 2022). A full field survey for the whole FCT would entail huge financial resources, logistical planning and time. Such validation would be difficult under the circumstances of the present study. The research presented here describes the land-cover situation for one reference year (2025). Therefore, the study assesses the spatial distribution of land cover at a certain point in time, not the temporal change of land cover. This baseline is useful for planning purposes but further research should extend the methodology in multi-temporal datasets.

RESULT

The Random Forest classifier provided a solid five-class LULC map which included built-up terrain, vegetation, agricultural, bare ground and water. The overall Accuracy was 75.43% with Kappa coefficient equal to 0.6928 which indicates a good agreement. Water (87.10%) and Agriculture (86.25%) had the highest Producer's Accuracy while Bare Land (65.05%) had the lowest. User's Accuracy ranged from 63.89% for built-up areas to 95.29% for water. The area statistics showed that vegetation occupied 3486.20 km2 (47.44%), agriculture 3039.07 km2 (41.33%), built up land 572.78 km2 (7.80%), bare land 228.31 km2 (3.11%) and water 24.99 km2 (0.34%). The findings show that the natural vegetation and agricultural landscape are still prominent in spite of the rapid urbanisation in Abuja Municipal Area Council. The results are then shown in table 2 – 7 and figure 3 – 5

Sentinel-2 Image Acquisition Characteristics

The characteristics of Sentinel-2 image acquisition are presented in Table 2. Consequently, the selected 2025 median composite, with a spatial resolution of 10 m, a cloud threshold of less than 20%, and QA60 cloud masking, provides superior, cloud-free imagery for accurate land use/land cover (LULC) categorisation (Chenge *et al.,* 2021). Employing standardised Sentinel-2 data alongside the WGS 84 coordinate framework enhances data uniformity and spatial precision within the research region.

Table 2: Sentinel-2 Image Acquisition Characteristics

Parameter	Specification
Satellite	Sentinel-2 MSI (Level-2A, Surface Reflectance)
Dataset	COPERNICUS/S2_SR_HARMONIZED
Acquisition period	1 January–31 December 2025 (median composite)
Spatial resolution	10 m (selected bands); 20 m resampled where applicable
Spectral bands used	B2, B3, B4, B8, B11, B12
Cloud threshold	< 20% CLOUDY_PIXEL_PERCENTAGE
Cloud masking	QA60 cloud and cirrus mask
Projection	WGS 84
Platform	Google Earth Engine

Source: Google Earth Engine (2026)

Random Forest Classification

The predictor variables utilised in the Random Forest model are the spectral bands, spectral indices and topographic factors presented in Table 3. The use of raw spectral bands coupled with derived indices like NDVI, NDBI, MNDWI and BSI improves the classifier's performance to discriminate vegetation, built-up areas, water bodies and bare land. The incorporation of DEM provides topographic information that enhances classification accuracy in terrain-affected regions.

Table 3: Predictor Variables Used in the Random Forest Classification

Variable	Description	Purpose
B2	Blue	Spectral information
B3	Green	Spectral information
B4	Red	Spectral information
B8	Near Infrared	Vegetation discrimination
B11	SWIR1	Built-up/bare land
B12	SWIR2	Surface material discrimination
NDVI	Normalized Difference Vegetation Index	Vegetation
NDBI	Normalized Difference Built-up Index	Built-up
MNDWI	Modified Normalized Difference Water Index	Water
BSI	Bare Soil Index	Bare land
DEM	SRTM Elevation	Topographic information

Source: Google Earth Engine (2026)

Random Forest Classification Parameters

The design of the Random Forest classifier used in the experiment is shown in Table 4. The robust and reliable classification system is built on 500 decision tree models, 1,500 stratified training samples, an independent validation dataset and ESA WorldCover 2021 as reference data (Zanaga *et al*., 2022). The fixed random seed guarantees the consistency of the results and the implementation in Google Earth Engine permits the efficient processing of large geographical information.

Table 4: Random Forest Classification Parameters

Parameter	Value
Classifier	Random Forest (smileRandomForest)
Number of trees	500
Training samples	1,500 stratified samples
Validation samples	Independent test subset
Reference dataset	ESA WorldCover 2021
Spatial resolution	10 m
Random seed	123
Software	Google Earth Engine

Source: Google Earth Engine (2026)

Confusion Matrix

Table 5 shows the confusion matrix and classification performance of Random Forest classifier on separate validation dataset. The model achieved OA of 75.43% and Kappa coefficient of 0.6928 indicating excellent agreement between the categorised map and reference data. The results indicated that the classification framework was robust in classifying the five land cover types in the FCT. The values in the confusion matrix are dominated by the main diagonal and most of the validation samples are correctly identified (Rajendran *et al.*, 2020). Water showed the most consistency in classification with 81 samples classified correctly, followed by agricultural (69), vegetation (64), built-up areas (69) and barren terrain (67). The largest errors were seen between built up areas and bare ground and between vegetation and agricultural land, indicating the spectral similarity of peri-urban areas. The precision measurements for the classes also reflect the performance of the classifier (Duke *et al.*, 2022). Producer's Accuracy was 65.05% for bare land and 87.10% for water. The User's Accuracy was 63.89% for built-up and 95.29% for water. The classification accuracy obtained is satisfactory for the mapping of land use and land cover at regional scale using medium resolution Sentinel-2 data, and provides a viable basis for the investigation of spatial distribution and composition of the land-cover classes inside the FCT.

Table 5: Confusion Matrix

Reference \ Classified	Built-up	Vegetation	Agriculture	Bare Land	Water
Built-up	69	2	4	20	0
Vegetation	7	64	21	1	0
Agriculture	1	8	69	2	0
Bare Land	29	1	2	67	4
Water	2	0	1	9	81

Source: Google Earth Engine (2026)

Accuracy Assessment

The accuracy assessment of the used categorisation is illustrated in Table 6. Water class had the greatest Producer's Accuracy (87.10%) followed by Agriculture (86.25%) showing low omission mistakes for both classes. Moderate omission was seen for Built-up (72.63%) which was probably due to confusion with bare terrain and minimally vegetated surfaces (Fabolude *et al.*, 2023). Vegetation (68.82%) was misclassified as agricultural land due to the similarity of spectral responses. The lowest Producer's Accuracy was obtained for Bare Land (65.05%) which means that it was the most challenging class to discriminate (Okeke *et al.*, 2022). The overall accuracy (75.43%) and Kappa coefficient of 0.6928 indicate a substantial agreement and satisfactory classification performance of Sentinel-2 based LULC mapping in the FCT.

Table 6: Accuracy Assessment

Metric	Value
Overall Accuracy	75.43%
Kappa Coefficient	0.6928
User Accuracy - Built-up	63.89%
User Accuracy - Vegetation	85.33%
User Accuracy - Agriculture	71.13%
User Accuracy - Bare Land	67.68%
User Accuracy - Water	95.29%

Source: Goggle Earth Engine (2026)

Classified Land Use and Land Cover (LULC) Classes

The quantitative distribution of the specified land use and land cover (LULC) groups in the FCT is presented in Table7 and Figure 4. Area statistics were calculated using the Random Forest classified output and the pixel area tool in Google Earth Engine. These data provide a quantitative evaluation of the presence and spatial scale of each land-cover type in the research region, and complements the spatial patterns presented in the classified map (Figure 3). The study found that the FCT landscape is largely covered by flora and agricultural land, although the lower parts of the territory are formed of built-up areas, barren ground and water bodies (Okoduwa and Amaechi, 2024). The distribution below is an illustration of the projected development pattern of Abuja, which will lead to substantial urbanisation within defined districts, leaving large portions of the country under natural vegetation and agricultural.

Vegetation is the most dominant land cover class covering about 3,486.20 km 2 or 47.44 % of the examined area. The next is agricultural land with 3,039.07 km2 (41.33%) which shows the continued significance of farming activities in the FCT. Built-up areas are 572.78 km2 (7.80%) which is a reflection of the concentration of urban expansion around Abuja Municipal Area Council and the nearby satellite settlements. The study region has an overall land cover of 228.31 km2 consisting of 3.11% bare land and 0.34% water bodies (Okeke *et al.*, 2022). Vegetation and agricultural land cover more than 88 . 77 % of the FCT showing the domination of ecological and agricultural landscapes in the area in spite of the ongoing urbanisation . The findings serve as a benchmark for tracking future land cover changes, analysing urban development trends and evidence-based land use planning and environmental management (Oyediji & Adenika, 2022).

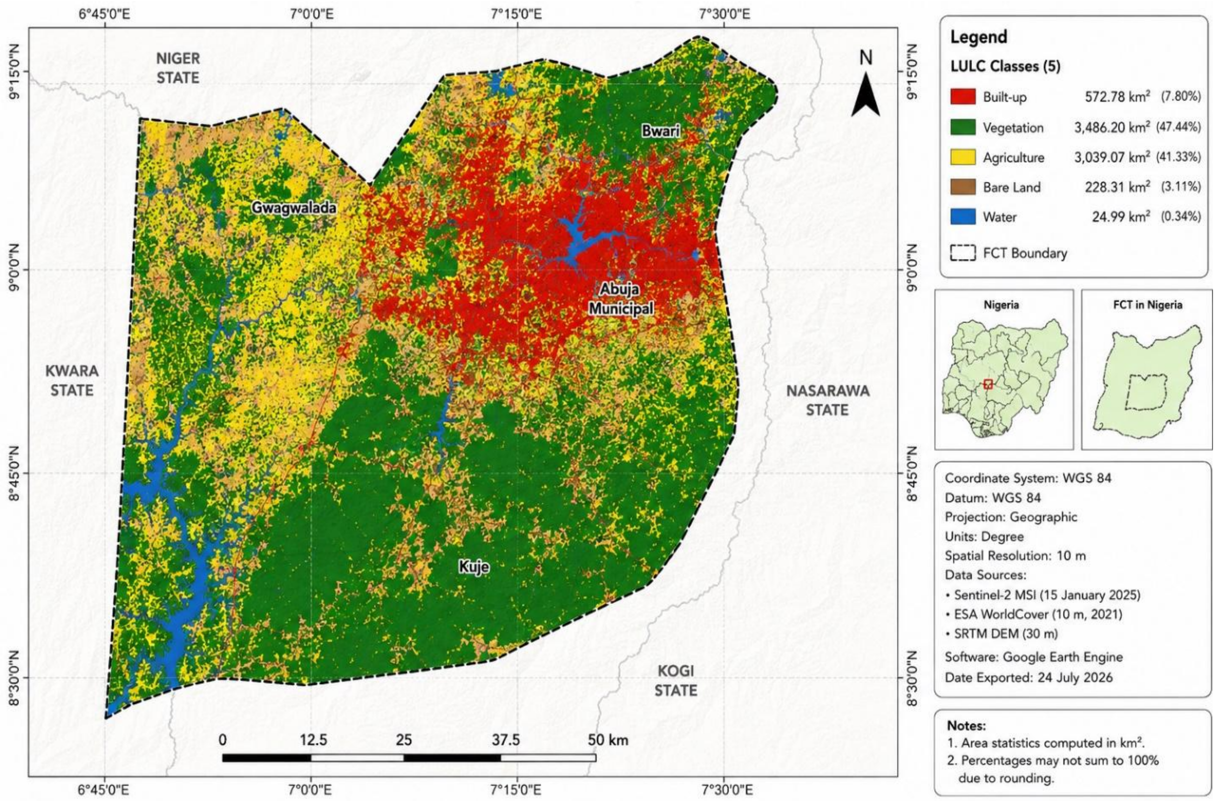


Figure 3: Land use/Land cover Map of the FCT, Nigeria

Source: Google Earth Engine (2026)

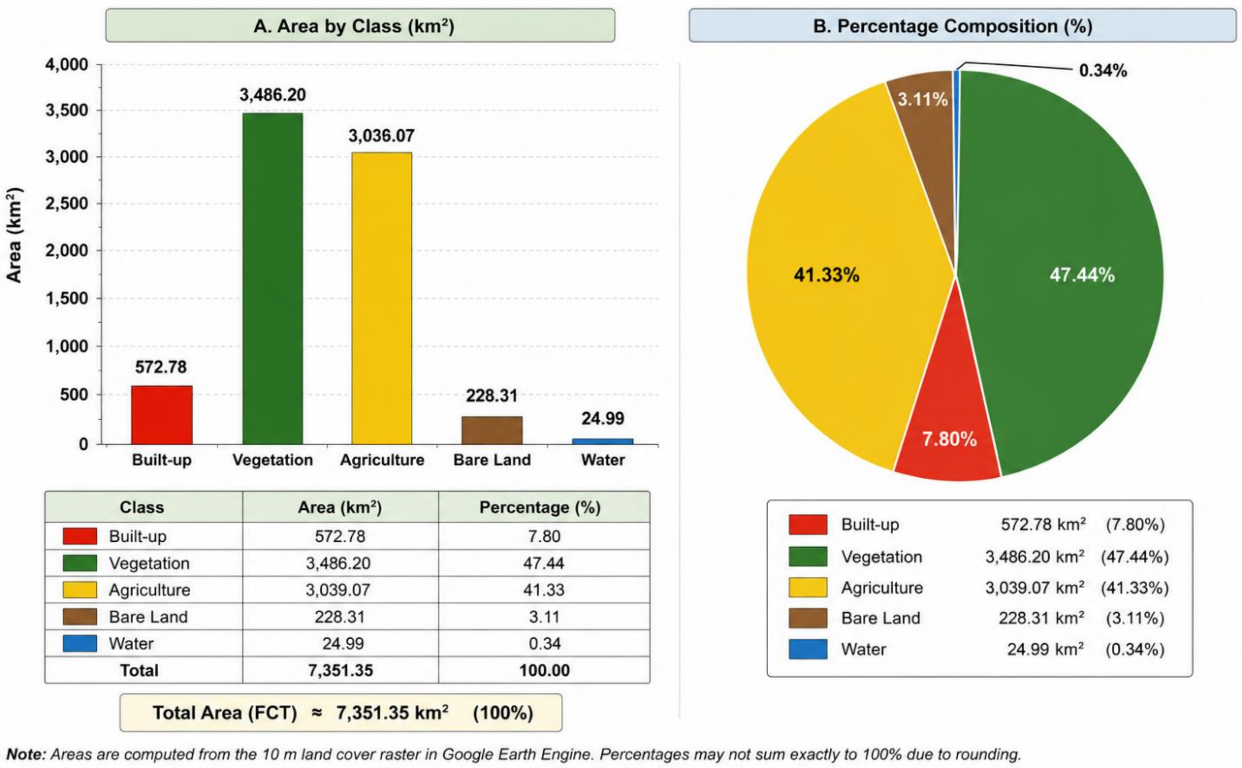


Figure 4: Land-Cover Composition of the FCT (January, 2025)

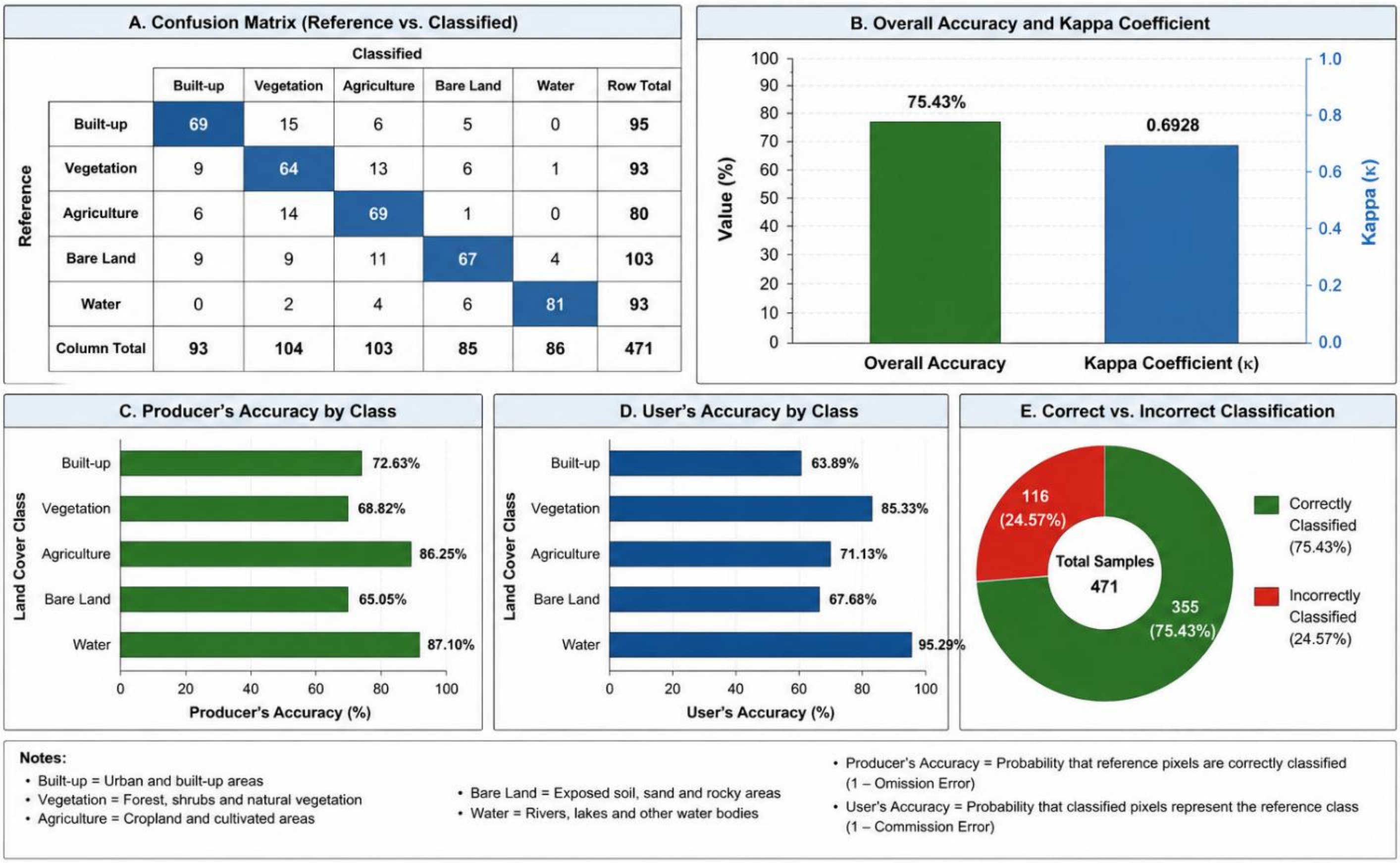
Source: Google Earth Engine (2026)

Table 7: Land Cover Distribution

Land-cover class	Area (km²)	Percentage (%)
Built-up	572.78	7.79
Vegetation	3486.20	47.42
Agriculture	3039.07	41.34
Bare Land	228.31	3.11
Water	24.99	0.34
Total	**7351.36**	**100.00**

Source: Goggle Earth Engine (2026)

- Vegetation constitutes the primary land-cover category, encompassing 3,486.20 km² (47.44%).
- Agricultural territory encompasses 3,039.07 km² (41.33%), underscoring its persistent significance.
- Developed land comprises 572.78 km² (7.80%), predominantly situated in the vicinity of Abuja city.
- Uncultivated terrain (3.11%) and aquatic environments (0.34%) are comparatively minor segments of the landscape.



	Built-up	Vegetation	Agriculture	Bare Land	Water	Row Total
Built-up	69	15	6	5	0	95
Vegetation	9	64	13	6	1	93
Agriculture	6	14	69	1	0	80
Bare Land	9	9	11	67	4	103
Water	0	2	4	6	81	93
Column Total	93	104	103	85	86	471

Figure 5: Accuracy Summary of Land Use/Land Cover Classification of FCT, Nigeria

Source: Google Earth Engine (2026)

DISCUSSION

The spatial distribution of the classified land use and land cover (LULC) classes in the FCT is shown in Figure 3. The classification indicates a heterogeneous landscape with five major land-cover types i.e. built-up, vegetation, agricultural land, barren land and aquatic bodies. These classifications presented different spatial patterns due to the influence of urban growth, agricultural activities, natural vegetation and hydrological factors on the landscape structure of the FCT. Therefore, the classified map shows that the FCT is still mostly covered with vegetation and agricultural area with built-up development mostly centred around the Abuja metropolis and its bordering satellite settlements. This physical arrangement is a reflection of the original planning philosophy of the FCT which was to protect large areas of natural space and agricultural land, and to concentrate intensive urban development within designated growth corridors.

Distribution of Built-up Areas

Urbanisation development was primarily focused in the Abuja Municipal Area Council (AMAC) which is the administrative and commercial nerve centre of the FCT. The Central Business District, Garki, Wuse, Maitama, Asokoro, Jabi, Utako, Gwarinpa, Lugbe, Kubwa and other fast rising districts saw high density urban growth. Outside the built-up areas of the city centre, development extended out from the main transit routes that linked Abuja to nearby communities. Huge urban expansion has occurred in Bwari, Lugbe, Gwagwalada, Kuje and Kwali where residential estates, commercial developments, educational institutions and public infrastructure have developed considerably over the previous years (Mahmoud *et al.*, 2016). The geographical plan is mostly a radial urban expansion pattern with sprawl from the city core along important highways. This is a pointer to the continually increasing population growth, the growing need for housing and the continuous expansion of infrastructure in FCT (Izuegbu *et al.*, 2025). Even with this expansion, built-up land still constitutes a very small share of the total land area, which indicates that substantial parts of the territory are covered with natural or agricultural land.

Distribution of Vegetation

Vegetation is the most dominant natural land cover category in the total study region and is widespread in the FCT. The major vegetation cover still exists in the north, west and south-west of the area as the forest, woodland, shrubland and natural grassland (Fabolude *et al.*, 2023). Large forested areas near Bwari, Kwali, Kuje and sections of Abaji are less affected by urban growth than the metropolitan core. Support for the larger vegetation is provided by the hills and protected regions, streams and undeveloped government reserve land. Vegetation coverage across a large region has a very essential role in ecological stability, such as increasing biodiversity, regulating local climate, reducing soil erosion, and increasing carbon sequestration (Okeke *et al.*, 2022). Vegetated areas also provide as an ecological buffer to the environmental impacts of expanding urbanisation.

Distribution of Agricultural Land

Agricultural land is another prominent element of the FCT landscape, mostly in the peri-urban and rural districts surrounding Abuja city. Agriculture still remains one of the important economic activity in Kwali, Abaji, Kuje, Gwagwalada and parts of Bwari where large agricultural fields can be seen (Olayungbo, 2021). They are mostly agricultural areas with rural people and fields lying dormant. The spatial distribution is typified by concentration of agricultural activities outside the substantially urbanised core. Pockets of cultivated land in peri-urban communities are undergoing rapid urbanisation. The sites are highly vulnerable to land conversion with urban expansion (Durowoju *et al.*, 2022). The dynamic changes in land use in the FCT is seen in the existence of agricultural with increasing residential constructions.

Distribution of Bare Land

In study area, bare ground occupies relatively less area and is found in dispersed patches. These places are often linked to building sites, bare soil, quarrying, newly cleared land, road construction projects and naturally sparsely vegetated surfaces (Abubakar *et al.*, 2023). High densities of bare land were seen around fast developing metropolitan districts where plant clearance and soil exposure is a result of current infrastructure development. Additional bare land patches are present within agricultural landscapes during harvest or seasonal field preparation (Mephors *et al.*, 2021). The scattered spatial distribution of bare land is the reflection of the continual processes of land transformation accompanying urban growth and infrastructural development throughout the region

Distribution of Water Bodies

The least land cover class in the FCT is water bodies. Generally, they are limited to large rivers, lakes, reservoirs and marshes. The water bodies in the area are Jabi Lake, the Lower Usuma Dam, and a number of smaller rivers and seasonal streams criss-crossing the landscape. These water bodies are commonly located in drainage networks and low lying locations where surface runoff is collected (Okeke *et al.*, 2022). However, these water resources are a small component of the total land area but are important for residential water supply, irrigation, flood management, biodiversity conservation and recreational applications (Olayungbo, 2021). The great accuracy in classifying water class is due to the successful segregation of these characteristics from the other surrounding landcover classes.

The classified map clearly shows a spatial gradient from a highly urbanised metropolitan core to mainly vegetative and rural areas in the outer Area Councils. The urbanisation is mostly concentrated in the core administrative districts and along the main transport arteries, while the outer parts of the territory are covered by vegetation and agricultural fields (Zhang & Li, 2022). Most of the barren ground was found in the transitional zones of vigorous development. The water bodies are spatially limited and are generally linked with natural drainage system. The spatial organization is an instance of how FCT is evolving from a planned administrative capital to a fast-developing metropolitan city (Koko *et al.*, 2022). The obtained land cover distribution provides essential baseline information for monitoring urban growth, environmental change and sustainable land management methods in the future.

CONCLUSION AND RECOMMENDATIONS

Conclusion

The aim of this project was to establish a reliable and reproducible framework for land use and land cover (LULC) mapping in the FCT, Nigeria, utilising the Sentinel-2 multispectral picture, Google Earth Engine (GEE) and the Random Forest (RF) machine-learning algorithm. The research was conducted within the framework of rising urbanisation and increasing demand on natural resources, and aimed to provide up-to-date spatial information to help sustainable urban planning, environmental management and evidence-based policy making. We successfully developed and implemented a cloud-based geospatial workflow integrating Sentinel-2 Surface Reflectance imagery, cloud masking, annual median compositing, spectral indices (NDVI, NDBI, MNDWI, and BSI), Shuttle Radar Topography Mission (SRTM) elevation data, ESA WorldCover reference data, and Random Forest classification. The huge satellite datasets were efficiently processed using Google Earth Engine to ensure the transparency, repeatability and scalability of the methodology.

The classification resulted in five major land cover types viz. built up areas, vegetation, agricultural land, bare ground and aquatic bodies. The generated land cover map had an Overall Accuracy of 75.43% and a Kappa coefficient of 0.6928, showing a considerable agreement between the classified map and the reference data. The results show the combined use of Sentinel-2 images and Random Forest classification in a cloud-computing environment is a scientifically robust methodology for regional land-cover mapping in heterogeneous urban environments. Spatial research showed that the dominating land-cover categories in the FCT were still vegetation (47.44%) and agricultural land (41.33%) which together accounted for about 88.77% of the total land area. The built-up development is barely 7.80%, but its distribution clearly shows a continual outwards growth from the Abuja metropolitan core to the neighbouring peri-urban settlements. This trend demonstrates the effects of population increase, transport infrastructure and socio-economic development on land-use change in the territory.

Results further suggest the spectral signature classification of water bodies was quite accurate. But, the medium resolution satellite data has more misunderstanding between built-up regions and bare landscape due to spectral similarities and mixed-pixel effects. The results are in accordance with usual challenges of urban remote sensing studies and do not influence the robustness of the general classification system that can be implemented. The work offers a realistic and reproducible methodology that may be used for ongoing surveillance of the environment and urban planning along with the updated land-cover map. It demonstrates complicated geospatial analysis can be cheaply undertaken utilising powerful cloud computing, machine learning and free satellite data without requiring expensive software or specialist computer equipment. This is a major contribution to the increasing use of cloud based remote sensing technology in Nigeria and other poor countries.

The research additionally highlights the need to maintain the enormous areas of vegetation and agricultural landscapes that still cover much of the FCT. These ecosystems provide important environmental services such as biodiversity conservation, carbon sequestration, watershed protection, climate regulation, and food production. Hence, future management of urban sprawl has to be carried out to protect the ecological sustainability of the area together with economic development. The study demonstrated that the combination of Sentinel-2 data, Google Earth Engine and Random Forest classification offers an efficient, accessible and scalable framework for mapping land use and land cover. The land-cover information developed from this study provides an essential baseline for future environmental monitoring, urban growth assessment and sustainable land management in the FCT and offers a transferable methodology for application in other rapidly urbanising locations.

Recommendations

Based on the results of this investigation, the following recommendations are suggested.

1. The Federal Capital Development Authority (FCDA) and other planning bodies should establish regular satellite-based land-cover monitoring utilising Google Earth Engine and Sentinel-2 imagery. Routine monitoring would help planners to discover new trends of urban expansion, identify illegal developments and evaluate conformity with the Abuja Master Plan.Urban expansion should be regulated by means of integrated land-use planning policies that support compact development, mixed land-use zoning and optimal utilisation of existing urban spaces with minimum uncontrolled urban sprawl into environmentally sensitive areas.

2. Government institutions are recommended to integrate cloud-based geospatial technologies into their everyday land administration, environmental evaluation and execution of urban policies. The growing availability of free satellite imagery and cloud computing platforms gives an opportunity to improve evidence-based decision making and reduce reliance on expensive traditional mapping methods.

3. In carrying out their environmental protection responsibilities, government agencies ought to give priority to the conservation of significant vegetation corridors, forest reserves, wetlands and watershed areas recognised through the land cover classification. These natural habitats have important ecological roles that support climate regulation, biodiversity protection, flood mitigation and carbon sequestration. Therefore their conservation must be integrated into future plans of environmental management.

4. The spatial distribution of built-up development documented in this study should guide infrastructure investment in the future. Rapidly growing metropolitan areas should be given priority in waste management infrastructure electrical distribution, transportation infrastructure, educational institutions, water supply, drainage systems, healthcare facilities. By planning infrastructure proactively we can deliver services better and cheaper for future development.

5. Given the vast expanse of agricultural land in the FCT, planning authorities should institute measures to safeguard productive agriculture against haphazard urban expansion. Agricultural zoning restrictions, urban expansion borders and integrated urban-rural planning techniques should be reinforced to assure long-term food security while allowing future urban development.

Contributions of the Study

Although, remote sensing has been progressively employed in urban studies in Nigeria, the adoption of cloud-based geospatial systems has been limited. Previous studies have relied mostly on Landsat images, desktop GIS software, manual picture preprocessing, and traditional supervised classification methods. Conversely, this study shows the operational viability of combining freely available high-resolution Sentinel-2 images with cloud computing and machine-learning algorithms for regional land-cover mapping. The study thus contributes to the modernisation of geospatial research in Nigeria by demonstrating the potential of cloud-based analytical systems to greatly increase processing efficiency, reproducibility and accessibility. This workflow provides a useful framework that can be implemented by universities, government agencies, environmental organisations, and city planners across the country.

Similarly, besides the local relevance, the study adds to the international literature of machine learning based land-cover classification. The integration of Sentinel-2 data, Random Forest classification, Google Earth Engine, spectral indices, topographic factors and automated validation highlights the continued usefulness of cloud-based machine-learning workflows for mapping heterogeneous urban landscapes. These results contribute to an increasing international body of evidence that cloud computing platforms have the potential to significantly enhance the scalability and practical usability of remote sensing research. The analytical approach is not limited to the FCT, but can be applied to other rapidly urbanising areas in Africa, Asia and Latin America.

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