

Geospatial Mapping and Accuracy Assessment of Land Cover Classes in Anambra State, Nigeria Using Sentinel-2 Imagery: A 2023 Baseline Analysis

Ohanyiri, C. G.,^{1*} Enendu, C. S.,² Ngwu, E. O.,³ Okoli, F. I.,⁴ and Uguru, V. N.⁵

¹⁻⁶Department of Surveying and Geoinformatics, Faculty of Environmental Sciences, Nnamdi Azikiwe University, Awka, Nigeria.

Corresponding Author: *cgh.ohanyiri@stu.unizik.edu.ng

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ABSTRACT

Land cover mapping is necessary for environmental monitoring and planning, providing detailed information about the Earth's surface. This study addresses the need for updated land-cover data in Anambra State, Nigeria, where the scarcity of high-resolution spatial baselines may have hindered effective land management, urban planning, and environmental conservation. The project's primary aim is to conduct a detailed land-cover classification of Anambra State using Geographic Information System (GIS) techniques. The objectives of the study include: To identify and extract primary land-cover classes using 10-meter Sentinel-2 spectral bands, to quantify the spatial distribution and proportional area coverage of each land-cover class, and to evaluate classification accuracy using verified reference data collected from high-resolution auxiliary sources and field samples. The methodology utilizes the pre-classified 10-meter annual land cover product derived from Sentinel-2 observations by the Environmental Systems Research Institute (ESRI), which was clipped and analyzed in ArcGIS. The classified map was validated using a confusion matrix, comparing the classified data with ground truth data to assess accuracy. Metrics included an overall accuracy of 88% and a Kappa coefficient of 83%, with class-specific producers and user's accuracies ranging from 75% to 100%. The final land cover map was produced in ArcGIS, with the spatial distribution of seven land cover classes delineated, while accuracy metrics were rigorously derived from the five primary classes possessing sufficient spatial representation. It is recommended to periodically update this baseline 2023 land cover map using recent satellite imagery to maintain its relevance for spatial planning. Future iterations can incorporate higher-resolution datasets to refine class-specific accuracies.

Keywords: Geospatial mapping, Accuracy assessment, Anambra State, Remote sensing, ESRI land cover, Land-use/Land-cover.

1.0. Introduction

Land cover refers to the physical materials on the Earth's surface such as vegetation, water bodies, bare soil, and artificial structures, whereas land use denotes the socioeconomic purpose and human utilization of those surfaces, including urban development and agricultural production (Barnsley & Barr, 2000). High-resolution mapping of these surface dynamics is important for regional environmental monitoring, urban planning, and sustainable resource allocation. Historically, regional land-cover assessments in southeastern Nigeria have relied heavily on medium-resolution legacy sensors, such as the 30-meter Landsat satellite series, or localized historical surveys (Ezeomodo & Igbokwe, 2013; Udo et al., 2021; Ezeomodo et al., 2024).

While these foundational studies establish macro-scale historical trends, their coarse spatial resolution introduces mixed-pixel errors, frequently failing to resolve fine-scale landscape features such as narrow river channels, fragmented smallholder farms, and scattered rural-urban settlements. Furthermore, global land-cover models (e.g., Meiyappan & Jain, 2012) lack the local thematic granularity required for micro-level spatial planning.

To address these constraints, contemporary earth observation studies emphasize the superior capabilities of the European Space Agency's Sentinel-2 Multispectral Instrument (MSI) constellation. Operating with high revisit frequencies and 10-meter spatial resolution bands, Sentinel-2 data significantly enhances the detection of complex surface transformations, capturing structural variations and fine-scale canopy properties across diverse landscapes (Malenovský et al., 2012; Karra et al., 2021; Ayadiuno & Ndulue, 2024; Nkemdirim & Nkemdirim, 2025). Furthermore, handling these 10-meter pixels requires careful consideration of spatial scale and object boundaries to minimize mixed-pixel errors during regional mapping (Drăguț et al., 2010). Capitalizing on advanced classification frameworks on Sentinel-2 data allows researchers to capture fine-grained environmental interactions that older, medium-resolution datasets overlooked.

Consequently, a critical research gap exists for a rigorous, high-resolution, contemporary baseline map of the region. To bridge this gap, this study aims to produce and evaluate a high-resolution land-cover map of Anambra State, Nigeria, using Sentinel-2 MSI imagery. The specific objectives are: (i) to identify and extract primary land-cover classes using 10-meter Sentinel-2 spectral bands; (ii) to quantify the spatial distribution and proportional area coverage of each land-cover class; and (iii) to evaluate classification accuracy using verified reference data collected from high-resolution auxiliary sources and field samples. Establishing this validated 2023 baseline provides essential intelligence for regional planners and environmental scientists.

2.0 Methodology

Anambra State is situated in the southeastern region of Nigeria, as shown in Figure 1, bordered by Delta State to the west, Imo State to the south, Enugu State to the east, and Kogi State to the north. It lies between latitudes $5^{\circ}40'N$ and $6^{\circ}46'N$ and longitudes $6^{\circ}35'E$ and $7^{\circ}21'E$. The state's capital and largest city is Awka, located approximately at $6.21^{\circ}N$ latitude and $7.07^{\circ}E$ longitude. Anambra State covers an area of approximately 4,844 square kilometers with a raster-derived analysis extent of 4,807.92 square kilometers and is characterized by diverse landscapes, including plains, hills, and river valleys. The state is traversed by several rivers, including the Niger River, which forms its western boundary, and the Anambra River, which flows through the central part of the state (Ayadiuno et al., 2022).

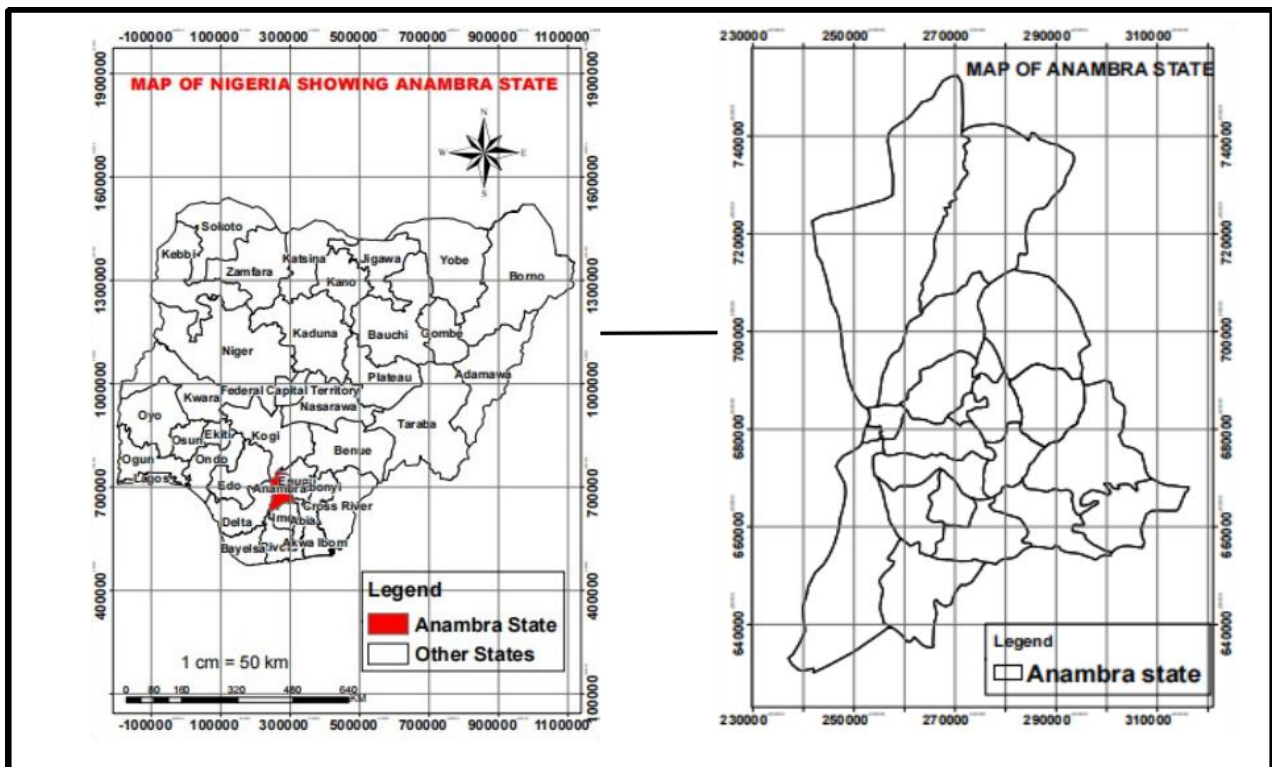


Figure 1: Map of the study area

- i) **Population and urbanization:** Anambra State has a diverse and dynamic population. As of recent estimates, the population is approximately 5.8 million people. The state's demographic profile reflects a youthful population with a significant proportion under the age of 30. The population density is relatively high compared to other regions in Nigeria, driven by both natural growth and rural-to-urban migration. This high density and rapid pace of urbanization heavily drive land-use changes, spatial expansions, and continuous pressure on regional environments.
- ii) **Topography, geology, and soil:** Anambra State features a predominantly rolling terrain with a mix of lowland and upland areas, characterized by gently undulating hills and valleys, particularly in the northern and central regions, and is crossed by the Niger and Anambra rivers. The geological composition includes sedimentary rock formations, with the region primarily part of the Anambra Basin, which contains rich deposits of limestone and other mineral resources supporting agricultural activities and water resources. The soil is mainly loamy and well-suited for crop cultivation, though soil erosion and degradation occur in some areas due to deforestation and intensive farming.
- iii) **Economy, trade, and industry:** Agriculture serves as the backbone of the economy, with major crops like cassava, yams, maize, and oil palm cultivated by the majority of the population. Trade and commerce thrive with significant market activities centered in Onitsha and Nnewi, while the growing industrial sector focuses on manufacturing, automotive parts, machinery, and electronics. Additionally, tourism features natural and cultural attractions such as the Ogbunike Caves and Agulu Lake.
- iv) **Climate:** Anambra State experiences a tropical climate with distinct wet and dry seasons. The wet season typically spans from April to October, characterized by heavy rainfall and high humidity. The dry season lasts from November to March, with lower humidity and less rainfall. Temperatures generally range from 25°C to 32°C (77°F to 90°F), with slight variations between the seasons.
- v) **Culture, education, and heritage:** The population predominantly speaks Igbo alongside widespread English use, and practices Christianity alongside traditional beliefs. Traditional heritage is marked by celebrations like the Ofala and New Yam festivals, as well as local arts and crafts including beadwork, carvings, and pottery. The state also maintains a well-established educational system featuring primary, secondary, and higher institutions like Nnamdi Azikiwe University in Awka and Chukwuemeka Odumegwu Ojukwu University in Uli.
- vi) **Infrastructure and governance:** The state features an interconnected road network highlighted by the Onitsha-Enugu Expressway and a railway line, alongside a healthcare sector composed of government hospitals, private clinics, and specialized medical centers. Administratively, the state operates under a democratic governance system divided into 21 local government areas.

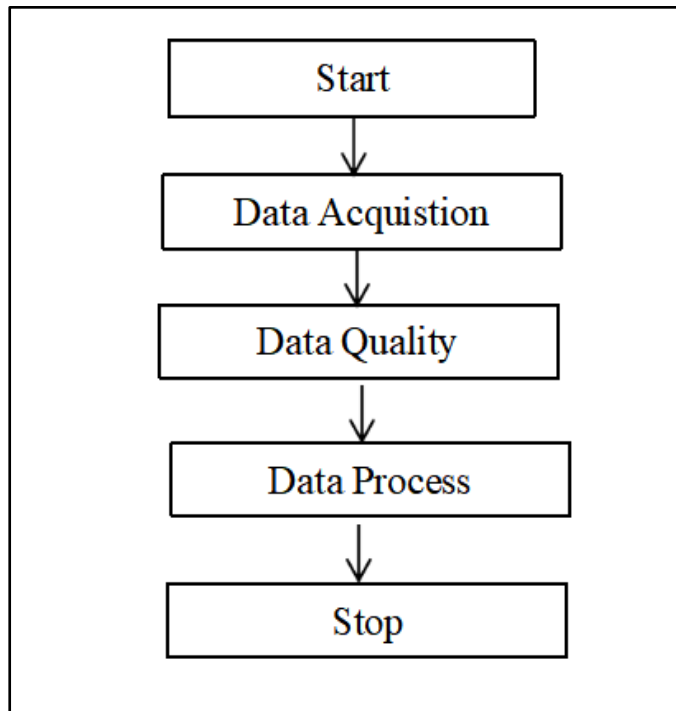


Figure 2: Methodology flowchart

2.2 Data acquisition

The 2023 Esri 10-Meter Land Use/Land Cover raster dataset, generated via AI classification of Sentinel-2 observations, was downloaded from the Esri Living Atlas (<https://livingatlas.arcgis.com/landcover/>) covering the study area and providing a 10-meter spatial resolution. Because this dataset is utilized as a pre-classified thematic raster product rather than raw multispectral imagery, acquisition parameters such as individual tile IDs, satellite platform specs, and cloud cover thresholds are governed by Esri's standardized annual global processing baseline. The administrative shapefile of Nigeria was obtained from the Humanitarian Data Exchange (<https://data.humdata.org>). This constitutes a secondary data acquisition framework.

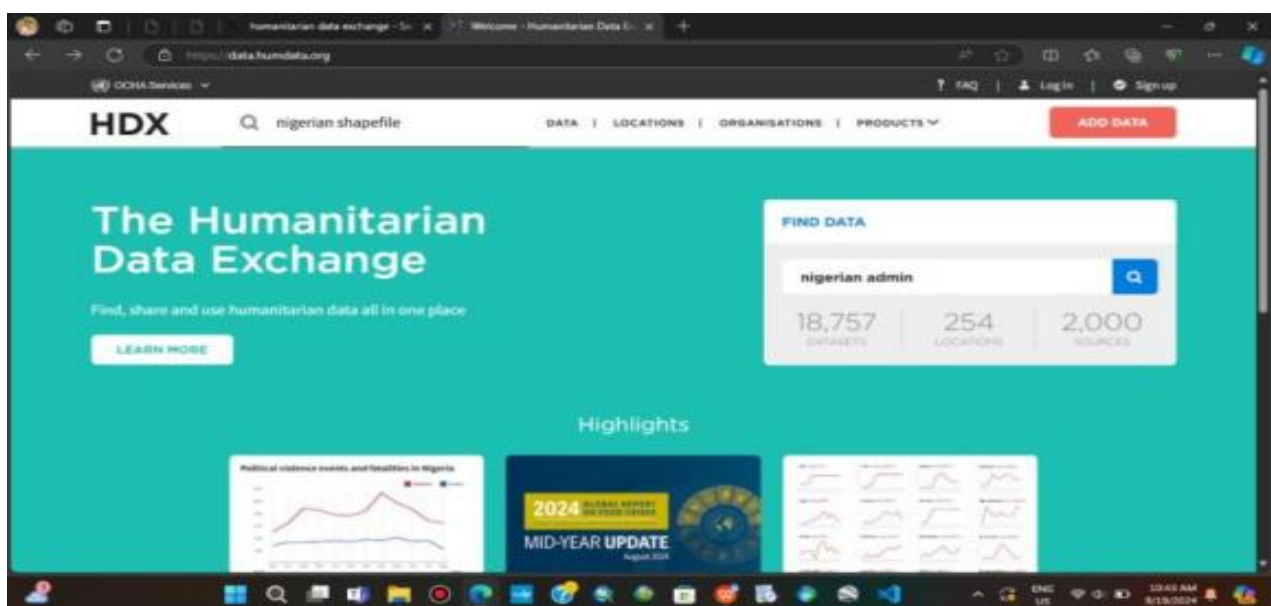


Figure 3: Showing the download of the Nigeria administrative shapefile from the Humanitarian Data Exchange website

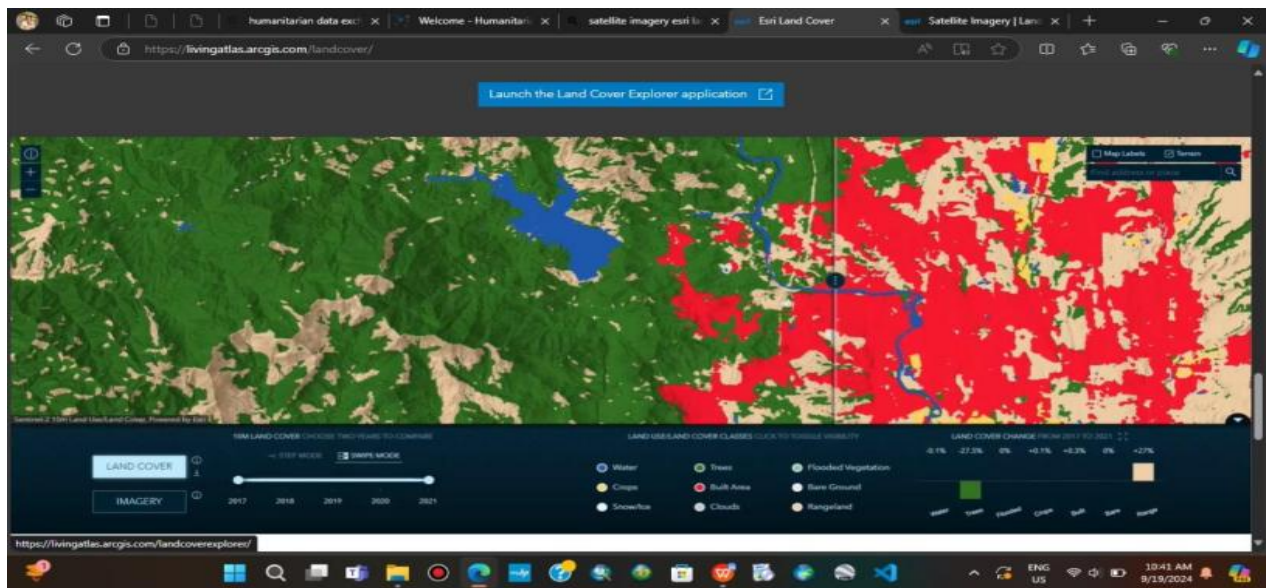


Figure 4: Showing the downloaded Esri 10-Meter Land Use/Land Cover dataset from the ArcGIS Living Atlas.

2.3 Data preparation and processing

The following items were used during the project work:

- i) Downloaded Esri 10-Meter Land Use/Land Cover raster dataset
- ii) ArcGIS 10.8 software
- iii) ArcGIS Earth as reference data
- iv) Anambra State administrative shapefile.

The downloaded raster dataset is a single-band categorical thematic map where individual pixel values correspond to land-cover class codes (e.g., water, vegetation, built-up areas). The pre-classified land-cover data were acquired in 8-bit single-band GeoTIFF (.tif) format, configured with an LZW compression scheme and a thematic source type containing a colormap for discrete class display.

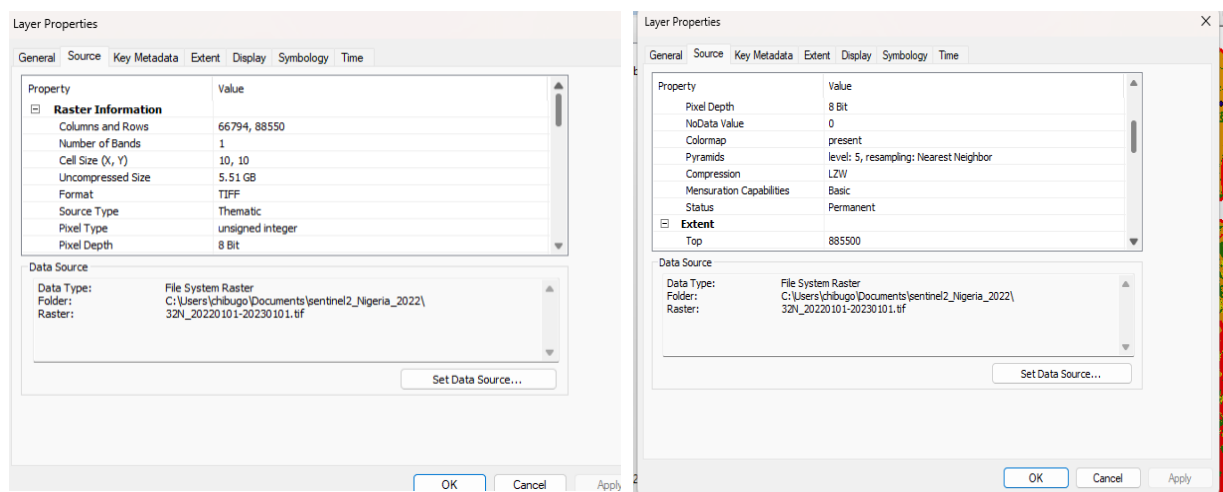


Figure 5: Raster properties and spatial reference metadata of the Sentinel-2 dataset

The downloaded raster dataset is a single-band categorical thematic map where individual pixel values correspond to land-cover class codes (e.g., water, vegetation, built-up areas). The pre-classified land-cover data were acquired in 8-bit single-band GeoTIFF (.tif) format, configured with an LZW compression

scheme and a thematic source type containing a colormap for discrete class display. Managing these fine spatial resolutions requires accounting for pixel scale configurations and boundary constraints to ensure that geoprocessing steps preserve structural integrity (Drăguț et al., 2010).

For the spatial reference information of the image; the XY coordinate system is WGS_1984_UTM_Zone_32N, the linear unit is Meter (1.000000), the angular unit is Degree (0.0174532925199433), the False_Easting is 500000, False_Northing is 0, Central_Meridian is 9 and the Scale_Factor is 0.9996.

i) Image mosaicing: A mosaic is a combination or merge of two or more images. In ArcGIS, you could create a single raster dataset from multiple raster datasets by mosaicking them together. Alternatively, it is done by creating a mosaic dataset and creating a virtual mosaic from a collection of raster datasets. The boundary of Anambra State could not be seen in one tile, requiring raster mosaicking to generate a seamless dataset prior to analysis.

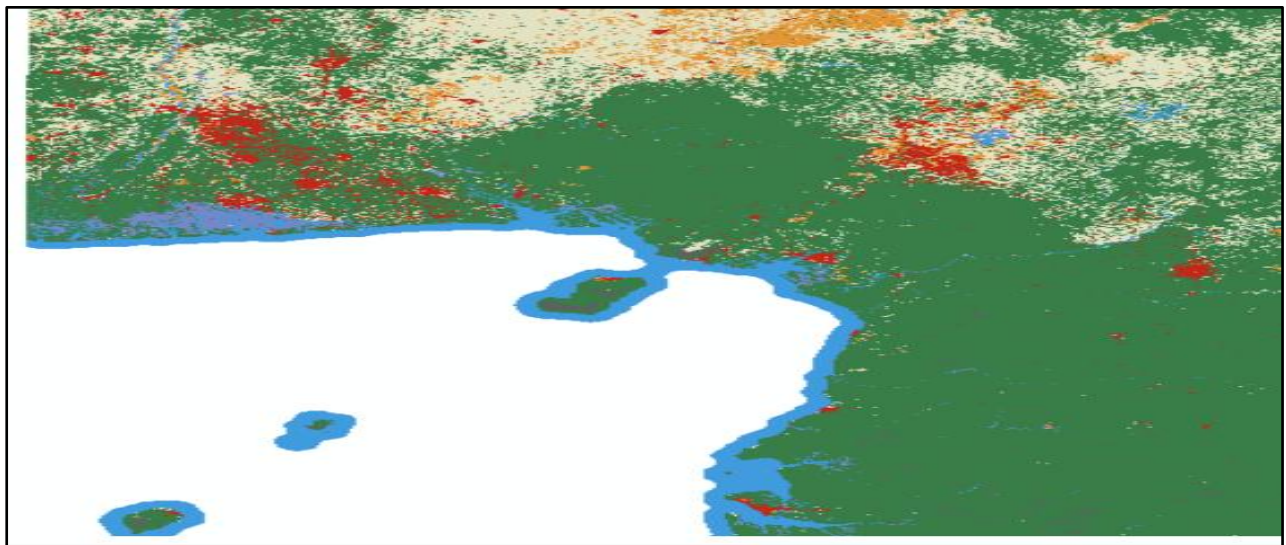


Figure 6: Esri Land Cover classification tiles and spatial distribution

ii) Clipping tool: The Clip Tool cuts out an input layer to a defined feature boundary. Like a cookie-cutter, the output is a new clipped layer. The clipping layer must be a polygon. But the input layer could be points, lines, or polygons.

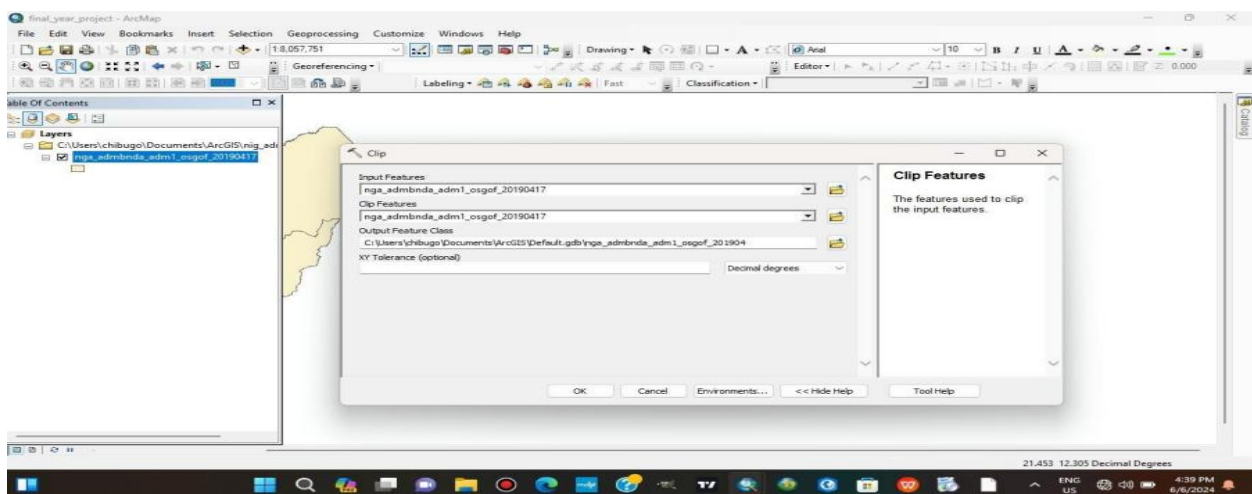


Figure 7: Added data of the administrative boundary of Nigeria into ArcMap 10.8 and clipped out the study area, which is Anambra State

iii) Extraction tool: The Extract by Mask tool in ArcGIS is a geoprocessing tool used to create a new dataset by clipping an existing dataset using a mask layer. This tool is particularly useful when you want to isolate specific areas or features within a larger dataset.

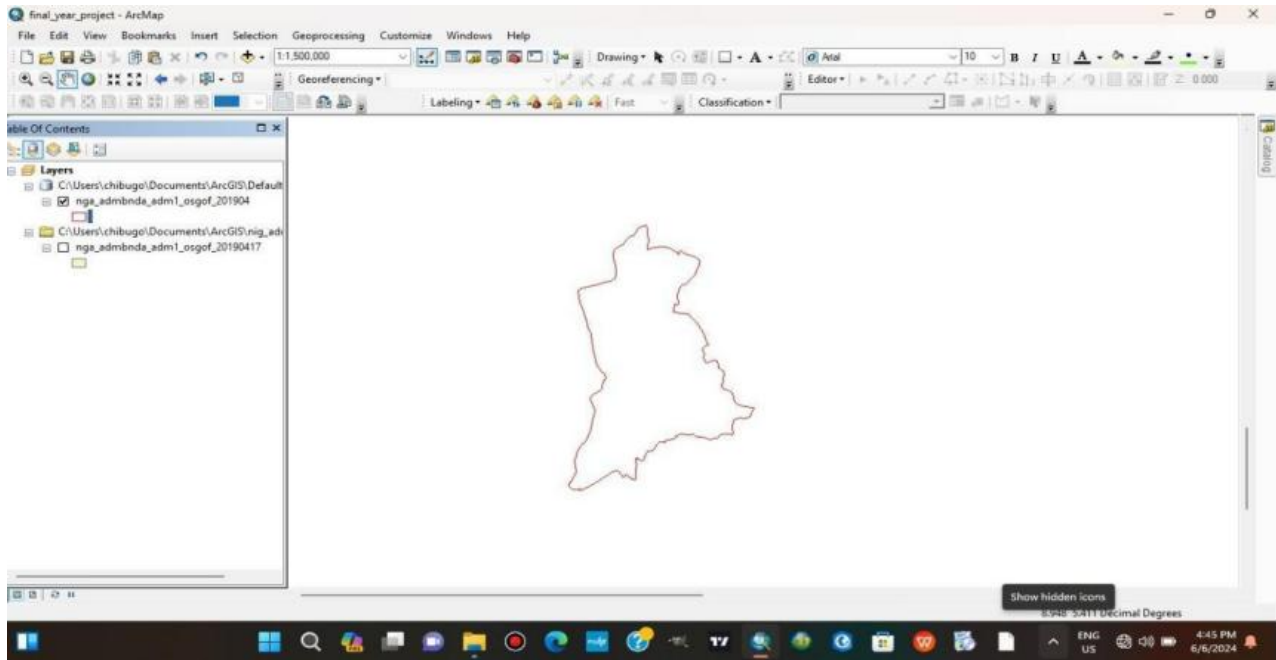


Figure 8: The hollow red area is the clipped-out study area with the Clip tool in the Geoprocessing tab

iv) Data integration: This involves combining data from multiple sources into a unified dataset for analysis and visualization. Figure 3.10 shows the integration of administrative boundary and Sentinel-2 imagery (see Figure 3.10). This process is essential for understanding complex relationships and patterns within geographic information.

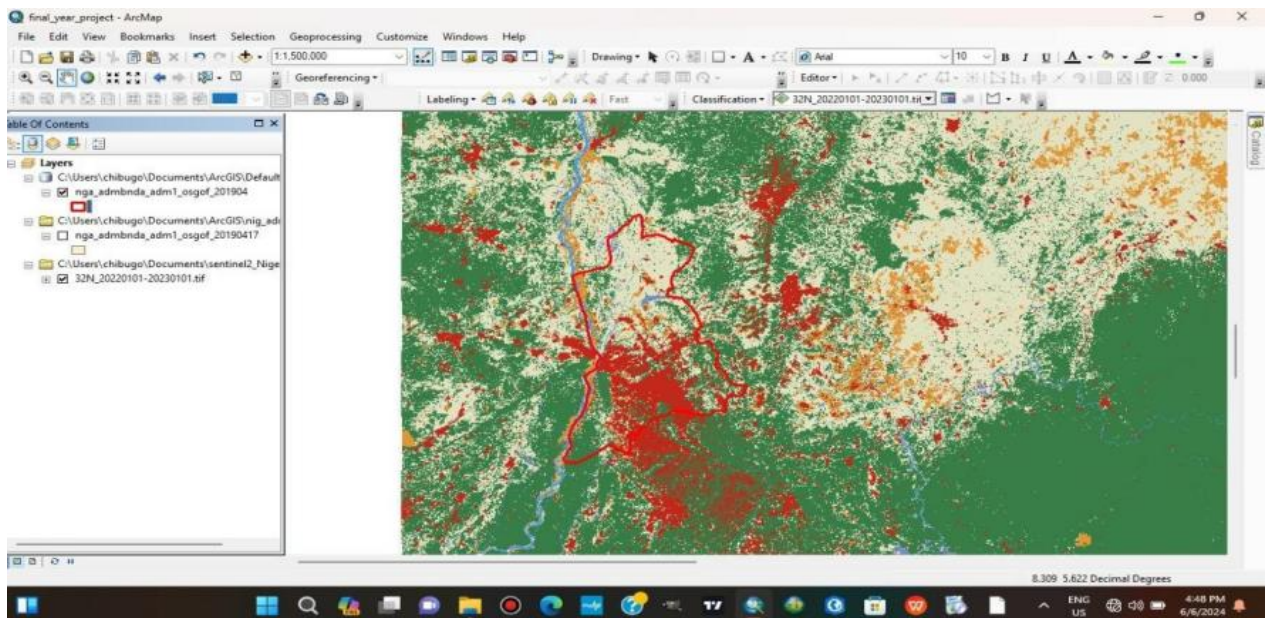


Figure 9: Showing imagery and the administrative boundary layered on each other

Because this study utilizes a pre-existing AI-generated secondary product, subsequent point verification using ArcGIS Earth and the generation of a confusion matrix were conducted to assess the thematic mapping accuracy of the Esri dataset over the study area.

v) Data analysis: This involves the application of statistical, spatial, and analytical techniques to extract meaningful information from geographic data. It helps us understand spatial patterns, relationships, and trends that might not be apparent through simple visualization. By effectively utilizing data analysis techniques in GIS, we can unlock the full potential of geographic data and gain valuable insights into our world. Some benefits of data analysis include:

- i) Reveals hidden patterns, relationships, and trends in spatial data.
- ii) Supports informed decisions based on data-driven insights.
- iii) Identifies potential issues and solutions more effectively.

To quantify the spatial distribution of each land-cover class within Anambra State, attribute table fields were populated and calculated using spatial formulas (multiplying pixel counts by resolution factors to derive square kilometers, followed by proportional calculations to determine percentage shares).

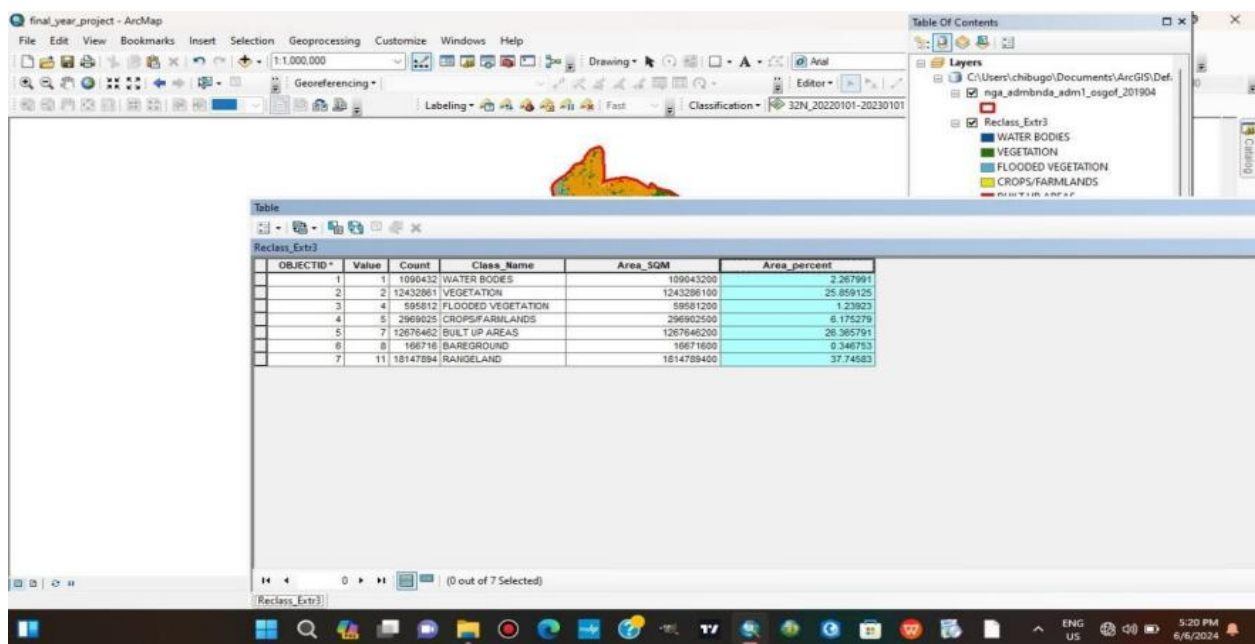


Figure 10: Showing the result of the attribute table of the calculation done

2.4 Accuracy assessment, ground truthing and confusion matrix

To validate the thematic accuracy of the pre-classified Esri Land Cover dataset over Anambra State, point verification was conducted using ArcGIS Earth as a reference platform in combination with ArcMap 10.8. While the Esri raster product utilizes a 7-class standardized schema, the accuracy assessment evaluated 5 primary classes where validation points were successfully sampled. The evaluated classes correspond to:

- i) Water bodies: Lakes, ponds, shallow water, streams, and rivers.
- ii) Vegetation: Closed-canopy natural forests, woodlands, and heavy multi-layered natural vegetation.
- iii) Flooded vegetation: Areas characterized by periodic or seasonal inundation, wetlands, and swamp ecosystems.
- iv) Crops/farmlands: Active croplands, managed arable lands, and cultivated agricultural plots.
- v) Built-up areas: Rural and urban settlements, residential, commercial, and industrial zones.
- vi) Bare ground: Open spaces, exposed soil, rocky outcrops, and surfaces lacking vegetative cover.
- vii) Rangeland: Open shrublands, herbaceous vegetation, and extensive bush fallow systems resulting from rotational shifting cultivation (grouped following standard global remote sensing taxonomies for scrub-herbaceous transition zones; Karra et al., 2021).

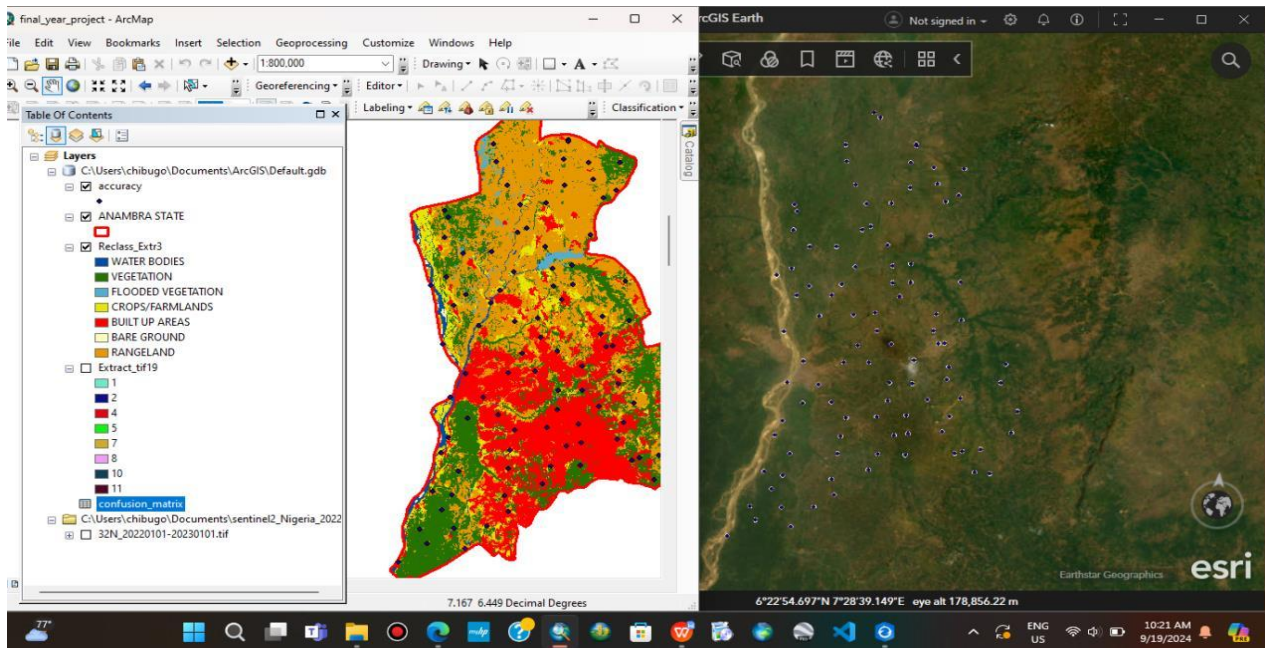


Figure 11: Side-by-side validation workflow between ArcMap 10.8 and ArcGIS Earth, with accuracy points loaded over Anambra State.

2.4.1 Reference data provenance and sampling

- i) Reference validation points comprising a total sample size of $N = 100$ points were compiled using field survey coordinate records and high-resolution historical satellite imagery accessed interactively via ArcGIS Earth.
- ii) Traditional physical field surveys were not conducted for this study; instead, ground-truth reference data were established through systematic visual interpretation, point coordinate extraction, and verification against high-resolution reference imagery in ArcGIS Earth.
- iii) The 100 validation points were distributed proportionally across the active classes in the confusion matrix (Water bodies: 6 points, Vegetation: 28 points, Crops/Farmlands: 5 points, Built-up areas: 27 points, Rangeland: 34 points).
- iv) Because the evaluation tests a pre-existing Esri global deep-learning product, all reference validation points remained independent of the underlying AI training pipeline.

2.4.2 Steps involved in accuracy verification

- i) Accuracy point coordinate data (imported as CSV/Excel files containing spatial coordinates and observed land-cover types) were loaded into ArcGIS Earth.
- ii) The pre-processed Esri land-cover raster was imported into ArcMap 10.8, ensuring spatial reference systems matched.
- iii) The 3D visualization capabilities of ArcGIS Earth were utilized alongside ArcMap 10.8 to visually inspect and compare ground truth points against the classified pixels.
- iv) Discrepancies were analyzed through visual inspection, attribute comparisons, and spatial accuracy metric calculations using ArcToolbox.

2.4.3 Confusion matrix analysis

A confusion matrix (error matrix) was generated to evaluate the thematic performance of the dataset. Rows represent actual reference classes from ground truthing, while columns represent the predicted classes from the Esri raster. Below are the accuracy metrics calculated:

- i) Overall accuracy: The proportion of correctly classified pixels relative to the total number of evaluated pixels.
- ii) Producer's accuracy: The proportion of reference pixels correctly identified as a specific land-cover type.

- iii) User's accuracy: The proportion of pixels classified into a specific category that actually match the ground truth.
- iv) Kappa coefficient: A statistical measure accounting for chance agreement between the reference points and the classification map.

Table

confusion_matrix

	ClassValue	OBJECTID *	C_1	C_2	C_5	C_7	C_11	Total	U_Accuracy	Kappa
▶	C_1	1	6	0	0	0	0	6	1	0
	C_2	2	0	21	0	2	3	26	0.807692	0
	C_5	3	0	0	5	0	0	5	1	0
	C_7	4	0	3	0	25	0	28	0.892857	0
	C_11	5	0	4	0	0	31	35	0.885714	0
	Total	6	6	28	5	27	34	100	0	0
	P_Accuracy	7	1	0.75	1	0.925926	0.911765	0	0.88	0
	Kappa	8	0	0	0	0	0	0	0	0.834825

Figure 12: Image displaying the row/column totals, user's accuracy, producer's accuracy, and the overall Kappa Coefficient.

2.4.4 Accuracy metrics and mathematical formulations

To evaluate the thematic quality of the classification map, standard error matrix metrics were mathematically defined and implemented as follows:

- i) User's accuracy: Indicates, for each classified category on the map, the proportion of pixels that represent that land cover on the ground, and it measures commission errors as presented in Table 4.

$$\text{User's accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of classified pixels in that category (row total)} \times 100} \quad (1)$$

$$\text{Water bodies} = \frac{6}{6} \times 100 = 100\%$$

$$\text{Vegetation} = \frac{21}{26} \times 100 = 80\%$$

$$\text{Crops/farmland} = \frac{5}{5} \times 100 = 100\%$$

$$\text{Built up area} = \frac{25}{28} \times 100 = 89\%$$

$$\text{Range land} = \frac{31}{35} \times 100 = 88\%$$

- ii) Producer's accuracy: Indicates, for each land cover class, the proportion of reference pixels that were correctly classified (Measures omission errors). It measures how well real-world land cover types can be classified (see Table 5).

$$\text{Producer's accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of reference pixels in that category} \times 100} \quad (2)$$

$$\text{Water bodies} = \frac{6}{6} \times 100 = 100\%$$

$$\text{Vegetation} = \frac{21}{28} \times 100 = 75\%$$

$$\begin{aligned} \text{Crops/farmland} &= \frac{5}{5} \times 100 = 100\% \\ \text{Built up areas} &= \frac{25}{27} \times 100 = 92\% \end{aligned}$$

$$\text{Range land} = \frac{31}{34} \times 100 = 91\%$$

iii) Overall accuracy: This is the percentage of correctly classified pixels across all categories.

$$\text{Overall accuracy (OA)} = \frac{\text{Total number of corrected classified pixels (diagonal)} \times 100}{\text{Total number of reference pixels}} \quad (3)$$

$$\text{Therefore, Overall accuracy (OA)} = \frac{88 \times 100}{100} = 88\%$$

iv) Kappa coefficient: A chance-corrected agreement statistic that evaluates the extent to which map classification correctness surpasses expected random agreement, serving as a complementary metric to overall accuracy.

$$\text{Kappa coefficient } T = \frac{(TS \times TCS) - \sum (Col.tot \times Row.tot)}{T^2 - \sum (Col.tot \times Row.to)} \times 100 \quad (4)$$

Where,

TS = Total number of samples; TCS = Total corrected samples; Col.tot = Column total

Row.tot = Row total

And T = Total (user Value)

Substituting the values in the above equation, we have,

$$T = \frac{(100 \times 88) - \{(6 \times 6) + (28 \times 26) + (5 \times 5) + (27 \times 28) + (34 \times 35)\}}{10,000 - \{(6 \times 6) + (28 \times 26) + (5 \times 5) + (27 \times 28) + (34 \times 35)\}} \times 100$$

Therefore kappa coefficient = 83%

3.0 Results and Discussion

This section shows the results and discussion of the findings from the processing of the spatial data acquired for this study.

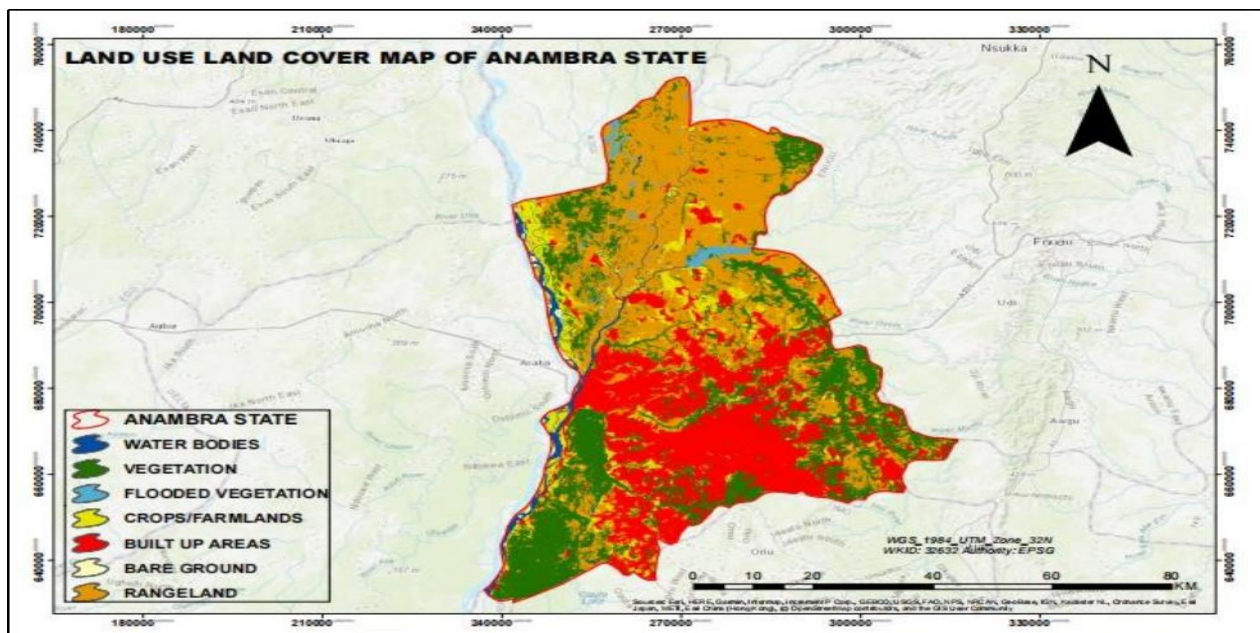


Figure 13: Land cover map of Anambra State

The total raster-derived land area evaluated for Anambra State covers 4,807,920,200m² (4,807.92 km²), presenting a minor 0.74% variance from standard administrative records (4,844 km²) due to grid quantization and raster edge-fitting. Water occupied a land mass of 2.27%, vegetation occupied 25.86%, flooded vegetation occupied 1.24%, crops/farmlands occupied 6.18%, built-up areas occupied 26.37%, bare ground occupied 0.35%, and rangeland occupied 37.75% of the land mass.

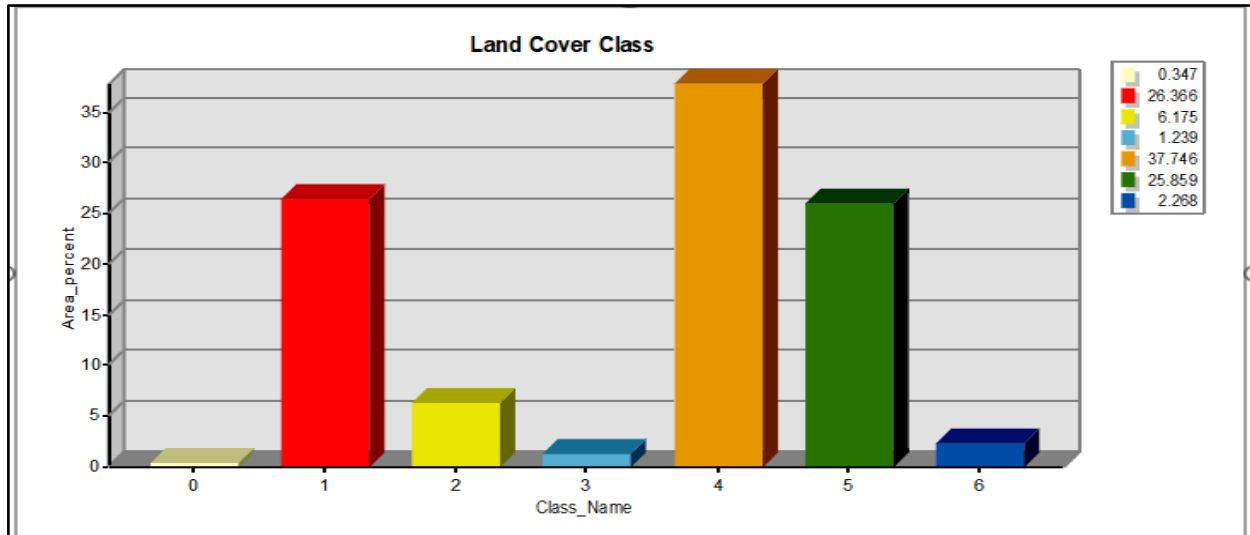


Figure 14: Showing spatial distribution of land cover classes using a vertical bar chart

Table 1: Land Cover Classes and Results

S/N	Land cover classes	Area in square meters (sq.m)
1	Water bodies	109,043,200
2	Vegetation	1,243,286,100
3	Flooded vegetation	59,581,200
4	Crops/farmlands	296,902,500
5	Built-up areas	1,267,646,200
6	Bare grounds	16,671,600
7	Range land	1,814,789,400

The result of the classified land cover map of Anambra State showed the individual contribution of the various land cover classes. It is observed that range lands have the highest percentage (37.75%), while the least is the bare ground (0.35%). From the map, it was seen that the range lands occupied the most land mass of the state with the value 1,814,789,400 sq.m, followed by built up areas with 1,267,646,200 sq.m, then vegetation with 1,243,286,100 sq.m, crops/ farmland has 296,902,500 sq.m, the water body with an area of 109,043,200 sq.m, flooded vegetation with an area of 59,581,200 sq.m and then finally, bare ground with an area of 16,671,600 sq.m.

Area covered by vegetation, built-up area, water(river), bare earth, farmland, range land, and flooded vegetation was calculated, and the count value was used to get the total area. This shows the various spaces they occupy. The following query was used to calculate their various areas:

$$\text{Area} = ([\text{count}]10 \times 10) \quad (5)$$

Where the count represents the number of points or features that are located at each individual spatial position, and the cell size X, Y (Homogeneous DN values) is represented by 10*10, indicating the image resolution,

which is 10m. Table 2 shows the percentage of each land cover class and their areas. The area percentages were obtained using the following query:

$$\text{Area \%} = (\text{area} \times 100 \div \text{sum of area}) \quad (6)$$

Table 2: Area and Percentage of Land Cover Classes

S/N	Land cover classes	Area (sq.m)	Calculating percentage	Percentage (%)
1	Water bodies	109,043,200	$(109,043,200 \times 100 / 4,807,920,200)$	2.27
2	Vegetation	1,243,286,100	$(1,243,286,100 \times 100 / 4,807,920,200)$	25.86
3	Flooded vegetation	59,581,200	$(59,581,200 \times 100 / 4,807,920,200)$	1.24
4	Crops/farmlands	296,902,500	$(296,902,500 \times 100 / 4,807,920,200)$	6.18
5	Built-up areas	1,267,646,200	$(1,267,646,200 \times 100 / 4,807,920,200)$	26.37
6	Bare grounds	16,671,600	$(16,671,600 \times 100 / 4,807,920,200)$	0.35
7	Range land	1,814,789,400	$(1,814,789,400 \times 100 / 4,807,920,200)$	37.75
	Total	4,807,920,200		100.00

The land cover mapping of Anambra State reveals a complex interplay between human activities and natural processes. The spatial distribution of built-up areas and agricultural lands alongside natural vegetation provides an essential 2023 baseline for regional management. The proportion of vegetative cover and built-up spaces highlights critical areas for environmental planning, while the presence of flooded vegetation maps areas subject to periodic or seasonal inundation. Understanding the spatial extent of these wetland and seasonally saturated zones provides a baseline for regional land management and infrastructure siting.

The loss of vegetation cover can also exacerbate soil erosion, leading to sedimentation in water bodies and reducing agricultural productivity. The spatial distribution of flooded vegetation highlights areas subject to seasonal water retention. This information provides useful baseline intelligence for agricultural planning, environmental monitoring, and regional infrastructure development.

The identification of water bodies is crucial for water resource management, ensuring access to clean water for domestic, agricultural, and industrial use. However, the spatial proximity of agricultural lands to water bodies highlights areas where land-use interactions warrant careful catchment management and environmental monitoring.

3.1 Accuracy assessment

While the regional area inventory (Table 2) accounts for all seven standardized classes of the Esri dataset, the quantitative accuracy assessment and confusion matrix (Table 3) focus on the five primary classes (Water bodies, Vegetation, Crops/farmlands, Built-up areas, and Rangeland). Minor classes, namely Bare ground (0.35% of total area) and Flooded vegetation (1.24% of total area), did not register sufficient spatial presence

to capture random validation points within the $N = 100$ sample size and were thus excluded from the error matrix calculations to maintain statistical reliability.

To perform the quantitative accuracy assessment, a total of $N = 100$ reference sample points were generated using a stratified random sampling design across the study area. The samples were distributed across the validated classes based on their proportional spatial footprint, yielding class-specific sample sizes as follows: Water bodies ($n = 6$), Vegetation ($n = 28$), Crops/farmlands ($n = 5$), Built-up areas ($n = 27$), and Rangeland ($n = 34$). These sample locations were cross-verified against high-resolution reference imagery corresponding to the 2023 baseline period to establish ground truth. Class-specific reference totals and error distributions are detailed in the confusion matrix (Table 3). Furthermore, while overall accuracy measures the proportion of correctly classified pixels, the Kappa coefficient is included as a supplementary chance-corrected measure of agreement to provide a robust evaluation of classification performance

3.1.1 Confusion matrix result

The confusion matrix results comparing the predicted classes against the ground-truth reference points are presented in Table 3.

Table 3: Confusion Matrix

	Water bodies	Vegetation	Crops/farmlands	Built-up areas	Range land	Total (user)
Water bodies	6	0	0	0	0	6
Vegetation	0	21	0	2	3	26
Crops/farmlands	0	0	5	0	0	5
Built-up areas	0	3	0	25	0	28
Range land	0	4	0	0	31	35
Total (user)	6	28	5	27	34	100

The resulting classification metrics derived from the error matrix are summarized below:

i) User's accuracy: Water bodies achieved 100%, vegetation achieved 80%, crops/farmlands achieved 100%, built-up areas reached 89%, and rangeland scored 88% (Table 4).

Table 4: User's Accuracy

S/N	Land cover category	Correctly classified	Total classified (row total)	User's accuracy (%)
1	Water bodies	6	6	100
2	Vegetation	21	26	80
3	Crops/farmland	5	5	100
4	Built-up areas	25	28	89
5	Range land	31	35	88

ii) Producer's accuracy: Water bodies recorded 100%, vegetation recorded 75%, crops/farmlands recorded 100%, built-up areas reached 92%, and rangeland reached 91% (Table 5).

Table 5: Producer's Accuracy

S/N	Land cover category	Correctly classified	Reference pixels (total)	Producer's accuracy (%)
1	Water bodies	6	6	100
2	Vegetation	21	28	75
3	Crops/farmland	5	5	100
4	Built-up areas	25	27	92
5	Range land	31	34	91

iii) Overall accuracy & Kappa coefficient: The overall classification accuracy reached 88%, supported by a Kappa coefficient of 83%, indicating strong spatial agreement between the Esri land-cover dataset and the reference validation points.

4.0 Conclusion

This study established a validated 2023 high-resolution land-cover baseline for Anambra State, utilizing 10-meter Sentinel-2 derived imagery and geospatial processing. The spatial inventory revealed that rangelands (37.75%) and built-up areas (26.37%) dominate the landscape, reflecting active post-COVID urbanization and rotational agricultural fallow systems, while vegetation accounts for 25.86%. The quantitative accuracy assessment validated the spatial model with an overall accuracy of 88% and a Kappa coefficient of 83%, confirming the reliability of high-resolution classification frameworks over traditional coarse-resolution alternatives.

These findings provide actionable evidence for urban planners, environmental regulators, and agricultural policymakers in southeastern Nigeria. Specifically, the precise spatial delineation of built-up expansion and wetland dynamics offers a foundation for mitigating soil erosion, managing watershed pressures, and regulating suburban sprawl. Future research should integrate multi-temporal datasets to monitor longitudinal land-cover transitions and evaluate micro-climate impacts driven by rapid infrastructure growth across the region.

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