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## Research article

## MONITORING URBAN EXPANSION AND LAND-USE/LAND COVER DYNAMICS IN BAUCHI METROPOLIS, NIGERIA

Aaron Andrew<sup>1\*</sup>

<sup>1</sup>Department of Geography and Environmental Management, University of Abuja, FCT, Abuja.

\*Corresponding author: Aaronnature@gmail.com

### ABSTRACT

Rapid urbanization has become a major driver of Land-Use and land cover (LULC) change, with significant environmental consequences in developing countries. This study assessed urban expansion and LULC dynamics in Bauchi Metropolis, Nigeria, from 1990 to 2020 using multi-temporal Landsat imagery integrated with Remote Sensing and Geographic Information System (GIS) techniques. Landsat 5 TM (1990), Landsat 7 ETM+ (2010), and Landsat 8 OLI/TIRS (2020) images were classified into five LULC classes using the Maximum Likelihood Classification algorithm. Classification accuracy was evaluated using confusion matrices, Overall Accuracy, User's Accuracy, Producer's Accuracy, and the Kappa coefficient. Overall Accuracy values of 85.20%, 90.60%, and 91.20%, with Kappa coefficients of 0.813, 0.836, and 0.744, confirmed the reliability of the classified maps. Built-up area expanded from 42.56 km<sup>2</sup> (35.5%) in 1990 to 96.15 km<sup>2</sup> (80.2%) in 2020, while water bodies declined from 13.91 km<sup>2</sup> to 3.86 km<sup>2</sup>. Transition matrix analysis identified vegetation as the principal source of urban expansion. The findings provide valuable evidence for sustainable urban planning, environmental conservation, and informed land management in rapidly urbanizing cities.

### KEYWORDS

Urban expansion; Land-Use/land cover change; Remote Sensing; Geographic Information System (GIS); Change detection; Transition matrix; Classification accuracy.

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## Introduction

Urban expansion is a major driver of land use/land cover (LULC) transformation, with significant implications for biodiversity, hydrological systems, ecosystem services, and sustainable land management. Rapid conversion of natural landscapes into built-up areas, particularly in developing countries, has intensified environmental degradation due to increasing population growth, urbanization, and inadequate land-use planning (Seto et al., 2012; Lambin & Meyfroidt, 2011). Across sub-Saharan Africa, and especially in Nigeria, urban growth has accelerated in recent decades, resulting in the widespread conversion of vegetation, agricultural land, and wetlands into residential, commercial, and infrastructural developments (Bloch et al., 2015; Güneralp et al., 2018).

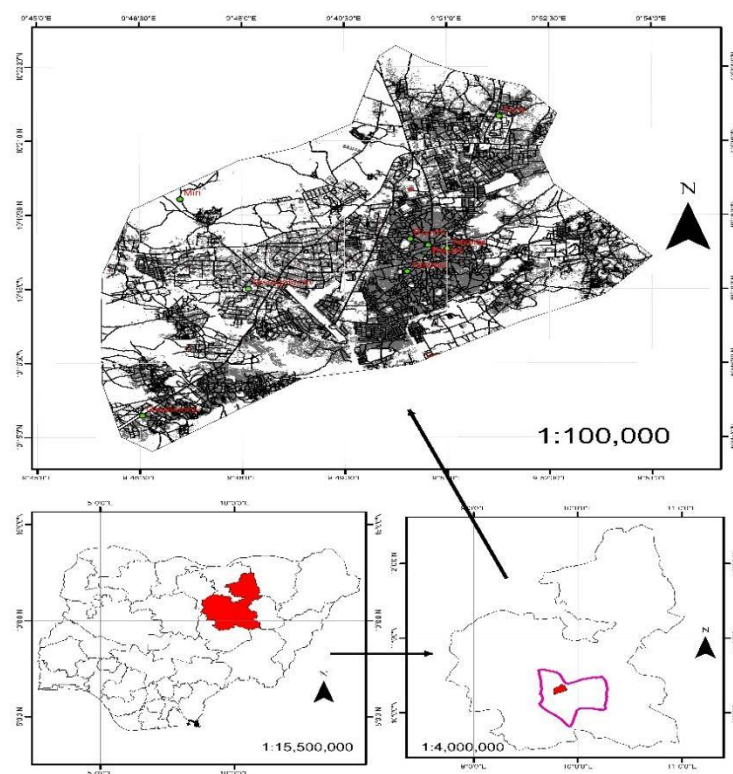
Bauchi Metropolis has experienced rapid physical expansion driven by population increase, commercial activities, infrastructure development, and government investment. This expansion has resulted in the continuous conversion of vegetation, water bodies, and other natural land cover types into built-up areas, placing increasing pressure on the urban environment. However, continuous monitoring of land use/land cover dynamics in the metropolis remains limited, constraining evidence-based urban planning and sustainable land management.

Remote Sensing and Geographic Information System (GIS) technologies have become indispensable tools for monitoring urban expansion because they provide reliable, cost-effective, and long-term observations of land cover change. The Landsat programme, with its continuous archive of satellite imagery, enables consistent assessment of landscape transformation over time, while GIS facilitates spatial analysis, change detection, and visualization of urban growth patterns (Jensen, 2015; Roy et al., 2014; Wulder et al., 2019).

Although several studies have examined urban expansion in Nigeria, relatively few have combined rigorous classification accuracy assessment with transition matrix analysis to evaluate the pathways of land cover conversion in Bauchi Metropolis. This study addresses this gap by integrating multi-temporal Landsat imagery, supervised image classification, classification accuracy assessment, post-classification change detection, and transition matrix analysis to assess urban expansion and LULC dynamics between 1990 and 2020. Specifically, the study aims to: (i) examine the spatial and temporal distribution of LULC classes; (ii) assess the magnitude and direction of land cover changes; (iii) evaluate the classification accuracy of the generated LULC maps; (iv) identify the major land cover transitions contributing to urban expansion; and (v) provide evidence to support sustainable urban planning and environmental management in Bauchi Metropolis.

## Study Area

Bauchi Metropolis is located in Bauchi State, northeastern Nigeria, and lies approximately between latitudes  $10^{\circ}12'N$  and  $10^{\circ}22'N$  and longitudes  $9^{\circ}45'E$  and  $9^{\circ}55'E$ . The metropolis covers approximately 119.87 km<sup>2</sup> and serves as the administrative, commercial, educational, and political headquarters of Bauchi State. Owing to its strategic location and growing economic importance, the metropolis has experienced rapid population growth and physical expansion over the past three decades, leading to significant changes in Land-Use and land cover patterns (Usman and Mohammed, 2012).



**Figure 1. The Study Area**

The study area experiences a tropical wet-and-dry (Sudan Savannah) climate, with a rainy season from May to October and a dry season from November to April. Mean annual rainfall ranges from 900 to 1,200 mm, while average temperatures vary between  $22^{\circ}C$  and  $34^{\circ}C$ . The area is characterized by ferruginous tropical soils and Sudan Savannah vegetation, although urban expansion and agricultural activities have significantly modified the natural vegetation. The terrain is generally undulating with isolated rock outcrops and seasonal drainage channels that influence settlement patterns and urban growth (Abdullahi et al., 2009). Economically, the metropolis is driven by commerce, public administration, education, transportation, agriculture, and small-scale manufacturing. Rapid population growth, increasing housing demand, and infrastructure development have accelerated the conversion of natural land cover to built-up areas, making Bauchi Metropolis an ideal case study for urban expansion and land use/land cover change analysis using Remote Sensing and GIS.

## Materials and Methods

### Research Design

This study adopted a geospatial change detection approach integrating Remote Sensing and Geographic Information System (GIS) techniques to assess the spatial and temporal dynamics of land use/land cover (LULC) change and urban expansion in Bauchi Metropolis between 1990 and 2020. The methodology comprised multi-temporal Landsat image acquisition, image pre-processing, supervised classification, classification accuracy assessment, post-classification change detection, transition matrix analysis, and spatial interpretation of LULC dynamics. This integrated approach enabled reliable quantification of the magnitude, direction, and patterns of urban expansion (Singh, 1989).

### Data Sources

The study utilized three cloud-free Landsat surface reflectance images (1990, 2010, and 2020) obtained from the United States Geological Survey (USGS) Earth Explorer. Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI/TIRS images with less than 5% cloud cover were selected to ensure reliable classification and temporal consistency. All images were Collection 2 Level-2 Surface Reflectance products projected to UTM Zone 32N (WGS 84; EPSG:32632), with a multispectral spatial resolution of 30 m. The characteristics of the satellite imagery are presented in Table 1.

**Table 1. Details of Satellite Imagery Used**

| S/N | Satellite & Sensor   | Acquisition Date | Scene / Product ID            | Cloud Cover (%) | Processing Level                      | Spectral Bands / Composites                                             | Coordinate Reference System (CRS) / Projection | Spatial Resolution                                          | Map Scale | Source               |
|-----|----------------------|------------------|-------------------------------|-----------------|---------------------------------------|-------------------------------------------------------------------------|------------------------------------------------|-------------------------------------------------------------|-----------|----------------------|
| 1   | Landsat 5 (TM)       | 1990-12-15       | LT05_L1TP_187054_19901215_... | < 5%            | Level-1TP / Collection 2 Level-2 (SR) | Bands 1-5, 7 (Visible, NIR, SWIR); RGB: 5,4,3 or 4,3,2                  | UTM Zone 32N / WGS 84 (EPSG: 32632)            | 30 m (Thermal: 120 m resampled to 30 m)                     | 1:80,000  | USGS / EarthExplorer |
| 2   | Landsat 7 (ETM+)     | 2010-01-10       | LE07_L1TP_187054_20100110_... | < 5%            | Level-1TP / Collection 2 Level-2 (SR) | Bands 1-5, 7 (30 m); Band 8 (Panchromatic, 15 m); Band 6 (Thermal)      | UTM Zone 32N / WGS 84 (EPSG: 32632)            | 30 m (Panchromatic: 15 m; Thermal: 60 m resampled to 30 m)  | 1:80,000  | USGS / EarthExplorer |
| 3   | Landsat 8 (OLI/TIRS) | 2020-02-05       | LC08_L1TP_187054_20200205_... | < 5%            | Level-1TP / Collection 2 Level-2 (SR) | Bands 1-7, 9 (30 m); Band 8 (Panchromatic, 15 m); Bands 10-11 (Thermal) | UTM Zone 32N / WGS 84 (EPSG: 32632)            | 30 m (Panchromatic: 15 m; Thermal: 100 m resampled to 30 m) | 1:80,000  | USGS / EarthExplorer |

Source: Author's Analysis

### Image Pre-processing

Satellite images were pre-processed to ensure radiometric and geometric consistency prior to classification following standard Remote Sensing procedures (Jensen, 2015; Lillesand et al., 2015). Pre-processing involved radiometric and atmospheric correction, layer stacking, image enhancement, clipping to the Bauchi Metropolis boundary, and geometric verification. The Landsat 7 ETM+ (2010) image was corrected for Scan Line Corrector (SLC)-off gaps using the USGS Phase 2 gap-filling algorithm based on local histogram matching and neighbourhood interpolation. Visual inspection confirmed satisfactory gap correction and spatial consistency, ensuring reliable image classification.

### Image Classification

Land use/land cover classification was performed using the Supervised Maximum Likelihood Classification (MLC) algorithm, a widely applied method for medium-resolution satellite imagery (Lillesand et al., 2015). Training samples were developed from field observations, high-resolution Google Earth imagery, existing land use information, and expert knowledge of the study area. Five land use/land cover classes were identified: Built-up Area, Water Bodies, Rock Area, Bare Surface, and Vegetation. The classified maps for 1990, 2010, and 2020 formed the basis for the classification accuracy assessment, change detection, and transition matrix analyses.

### Classification Accuracy Assessment

To evaluate the reliability of the classified Land-Use/land cover maps, a post-classification accuracy assessment was conducted using confusion matrices derived from reference data. A total of 500 validation points were proportionally distributed among the five land cover classes for each study year based on their respective areal extents.

The performance of the classification was evaluated using four standard accuracy metrics:

**i. Overall Accuracy (OA)**, which represents the proportion of correctly classified validation samples relative to the total number of samples.

$$OA = \frac{\sum_{i=1}^k x_{ii}}{N}$$

- $x_{ii}$  = Number of correctly classified points for class  $i$  (values along the diagonal)
- $N$  = Total number of validation points in the confusion matrix
- $k$  = Total number of classes

**ii. Producer's Accuracy (PA)**, which measures the probability that a reference pixel was correctly classified.

$$PA_i = \frac{x_{ii}}{x_{+i}}$$

- $x_{ii}$  = Number of correctly classified points for class  $i$
- $x_{+i}$  = Column total for class  $i$  (total number of reference points for that class)

**iii. User's Accuracy (UA)**, which indicates the probability that a pixel classified into a given category actually belongs to that category on the ground.

$$UA_i = \frac{x_{ii}}{x_{i+}}$$

- $x_{ii}$  = Number of correctly classified points for class  $i$
- $x_{i+}$  = Row total for class  $i$  (total number of predicted map points for that class)

**iv. Kappa Coefficient ( $\kappa$ )**, which measures the level of agreement between the classified image and the reference data after accounting for agreement occurring by chance.

$$K = \frac{P_o - P_e}{1 - P_e}$$

$$P_e = \frac{\sum_{i=1}^k (x_{i+} \times x_{+i})}{N^2}$$

- $P_o$  = Observed Agreement (equal to the Overall Accuracy)
- $P_e$  = Expected Chance Agreement
- $x_{i+}$  = Total row count for class  $i$
- $x_{+i}$  = Total column count for class  $i$

**Table 2. Rating Criteria of Kappa Statistics**

| No. | Kappa Statistics | Strength of Agreement |
|-----|------------------|-----------------------|
| 1   | <0.00            | Poor                  |
| 2   | 0.00 - 0.20      | Slight                |
| 3   | 0.21 - 0.40      | Fair                  |
| 4   | 0.41 - 0.60      | Moderate              |
| 5   | 0.61 - 0.80      | Substantial           |
| 6   | 0.81 - 1.00      | Almost perfect        |

Source: Rwanga et al. (2017)

These indices are widely accepted for evaluating classification performance in remote sensing studies. Overall Accuracy values greater than 85% and Kappa coefficients exceeding 0.80 generally indicate strong classification reliability suitable for Land-Use/land cover change analysis.

Tables 3a-3c present the confusion matrices together with the Overall Accuracy, Producer's Accuracy, User's Accuracy, and Kappa coefficient for each classification epoch.

### Land Use/Land Cover Change Detection

Land use/land cover (LULC) changes were assessed using the Post-Classification Comparison (PCC) technique by comparing the independently classified images for 1990, 2010, and 2020. The area (km<sup>2</sup>) and percentage coverage of each land cover class were computed to quantify changes in spatial extent, persistence, gains, and losses over the study period. Percentage land cover was calculated as:

$$\text{Percentage Land Cover} = (\text{Area of Land Cover Class} / \text{Total Area of Study Area}) \times 100$$

The resulting statistics were used to determine increases, decreases, persistence, and overall patterns of landscape transformation.

### Land Use/Land Cover Transition Matrix Analysis

Transition matrix analysis was performed to quantify the magnitude and direction of land cover conversions between 1990–2010 and 2010–2020. The matrices identified the major transition pathways contributing to urban expansion and provided a detailed assessment of landscape transformation beyond conventional change detection.

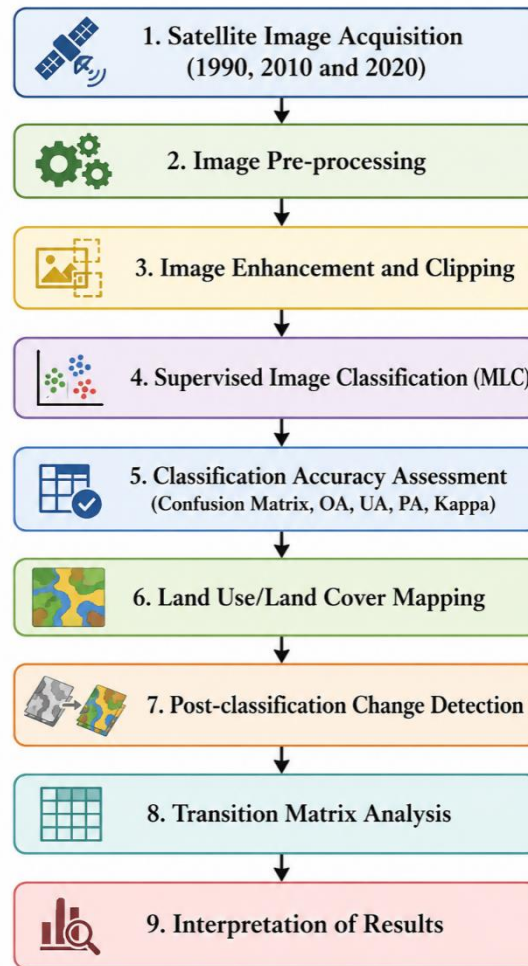
### Methods of Data Analysis

Spatial analyses were conducted using Remote Sensing and GIS software. The analytical procedures included supervised image classification, classification accuracy assessment, post-classification comparison, area computation, overlay analysis, and transition matrix analysis. Descriptive statistics (frequencies, percentages, and area calculations) were used to summarize land use/land cover changes and interpret the magnitude, direction, and environmental implications of urban expansion in Bauchi Metropolis.

### Conceptual Framework of the Methodology

The methodological workflow adopted in this study is summarized below:

Satellite Image Acquisition (1990, 2010 and 2020)



*Figure 2. methodological workflow*

## Results and Discussion

### Classification Accuracy Assessment

#### Classification Accuracy for the 1990 Epoch

The confusion matrix for the 1990 classification (Table 3a) yielded an Overall Accuracy of 85.20% and a Kappa coefficient of 0.813, indicating strong agreement between the classified image and the reference data. These values demonstrate that the classified map reliably represents the spatial distribution of Land-Use/land cover classes in Bauchi Metropolis for the baseline year.

Producer's Accuracy ranged from 73.56% for Bare Surface to 93.10% for Water Bodies, while User's Accuracy varied from 75.29% for Bare Surface to 93.10% for Water Bodies. Built-up Area achieved a Producer's Accuracy of 91.01% and a User's Accuracy of 88.52%, indicating that urban features were accurately identified with relatively limited commission and omission errors. In contrast, the comparatively lower accuracies recorded for Bare Surface and Rock Area suggest the occurrence of spectral confusion among exposed soils, weathered rock surfaces, and sparsely vegetated areas, which commonly exhibit similar spectral responses in medium-resolution Landsat imagery.

**Table 3a. Classification Accuracy for the 1990 Epoch**

| Predicted \ Reference     | Built-up Area | Water Bodies  | Rock Area     | Bare surface  | Vegetation    | Row Total | User's Acc.   |
|---------------------------|---------------|---------------|---------------|---------------|---------------|-----------|---------------|
| Built-up Area             | <b>162</b>    | 1             | 8             | 10            | 2             | 183       | <b>88.52%</b> |
| Water Bodies              | 1             | <b>54</b>     | 0             | 2             | 1             | 58        | <b>93.10%</b> |
| Rock Area                 | 7             | 0             | <b>55</b>     | 6             | 4             | 72        | <b>76.39%</b> |
| Bare Surface              | 6             | 2             | 5             | <b>64</b>     | 8             | 85        | <b>75.29%</b> |
| Vegetation                | 2             | 1             | 3             | 5             | <b>91</b>     | 102       | <b>89.22%</b> |
| <b>Column Total (Ref)</b> | <b>178</b>    | <b>58</b>     | <b>71</b>     | <b>87</b>     | <b>106</b>    | 500       |               |
| <b>Producer's Acc.</b>    | <b>91.01%</b> | <b>93.10%</b> | <b>77.46%</b> | <b>73.56%</b> | <b>85.85%</b> |           |               |

Overall Accuracy: 85.20%

Expected Agreement (Pe): 0.2079

Kappa Coefficient (K): 0.813

The Overall Accuracy obtained for the 1990 epoch compares favourably with findings reported by Enoguanbhor et al. (2024) for urban Land-Use mapping in the Abuja City-Region, where Overall Accuracy exceeded 85% following supervised classification of Landsat imagery. Similarly, Pirnazar et al. (2018) reported Overall Accuracy values ranging between 84% and 89% in their assessment of urban expansion using Landsat data, emphasizing that classifications exceeding the 85% threshold are generally considered suitable for temporal change analysis. The results are also consistent with the recommendations of Congalton and Green (2019), who emphasized that Overall Accuracy values above 85% provide sufficient confidence for environmental monitoring and Land-Use change investigations.

The high classification accuracy achieved for the 1990 epoch therefore provides a reliable baseline for evaluating subsequent Land-Use/land cover changes within Bauchi Metropolis.

### Classification Accuracy for the 2010 Epoch

The classification accuracy improved considerably in 2010, producing an Overall Accuracy of 90.60% and a Kappa coefficient of 0.836, representing the highest classification agreement among the three study periods. The improvement suggests that the classification procedure successfully distinguished the various land cover classes despite the use of Landsat 7 ETM+ imagery, which required gap-filling following the Scan Line Corrector (SLC)-off failure.

**Table 3b. Classification Accuracy for the 2010 Epoch**

| Predicted \ Reference     | Built-up Area | Water Bodies  | Rock Area     | Bare surface  | Vegetation    | Row Total | User's Acc.   |
|---------------------------|---------------|---------------|---------------|---------------|---------------|-----------|---------------|
| Built-up Area             | <b>254</b>    | 2             | 3             | 1             | 14            | 274       | <b>92.70%</b> |
| Water Bodies              | 2             | <b>28</b>     | 0             | 0             | 1             | 31        | <b>90.32%</b> |
| Rock Area                 | 4             | 0             | <b>7</b>      | 1             | 1             | 13        | <b>53.85%</b> |
| Bare Surface              | 2             | 1             | 1             | <b>4</b>      | 2             | 10        | <b>40.00%</b> |
| Vegetation                | 11            | 1             | 0             | 0             | <b>160</b>    | 172       | <b>93.02%</b> |
| <b>Column Total (Ref)</b> | <b>273</b>    | <b>32</b>     | <b>11</b>     | <b>6</b>      | <b>178</b>    | 500       |               |
| <b>Producer's Acc.</b>    | <b>93.04%</b> | <b>87.50%</b> | <b>63.64%</b> | <b>66.67%</b> | <b>89.89%</b> |           |               |

Overall Accuracy: 90.60%

Expected Agreement (Pe): 0.4266

Kappa Coefficient (K): 0.836

Producer's Accuracy values ranged from 63.64% for Rock Area to 93.04% for Built-up Area, whereas User's Accuracy varied from 40.00% for Bare Surface to 93.02% for Vegetation. The relatively lower User's Accuracy observed for Bare Surface may be attributed to the spectral similarity between recently cleared land, exposed rock, and developing urban surfaces. Nevertheless, the excellent classification performance achieved for Built-up Area and Vegetation indicates that the dominant land cover categories were successfully delineated.

The superior Overall Accuracy obtained for 2010 agrees with the observations of Maxwell et al. (2018), who demonstrated that careful image pre-processing, rigorous training sample selection, and appropriate classification algorithms substantially improve thematic classification accuracy. Likewise, Belgiu and Drăguț (2016) observed that supervised classification approaches remain highly effective for urban Land-Use mapping when supported by representative training datasets and quality-controlled image pre-processing.

### Classification Accuracy for the 2020 Epoch

The 2020 classification achieved the highest Overall Accuracy of 91.20%, while the corresponding Kappa coefficient was 0.744, indicating substantial agreement between the classified image and the reference data. Although the Kappa coefficient was slightly lower than that obtained for 2010, the Overall Accuracy demonstrates that the classified map provides a highly reliable representation of contemporary Land-Use/land cover conditions in Bauchi Metropolis.

**Table 3c. Classification Accuracy for the 2020 Epoch**

| Predicted \ Reference     | Built-up Area | Water Bodies  | Rock Area     | Bare surface  | Vegetation    | Row Total | User's Acc.   |
|---------------------------|---------------|---------------|---------------|---------------|---------------|-----------|---------------|
| Built-up Area             | <b>382</b>    | 2             | 2             | 9             | 6             | 401       | <b>95.26%</b> |
| Water Bodies              | 1             | <b>14</b>     | 0             | 1             | 0             | 16        | <b>87.50%</b> |
| Rock Area                 | 3             | 0             | <b>4</b>      | 1             | 0             | 8         | <b>50.00%</b> |
| Bare Surface              | 10            | 0             | 1             | <b>24</b>     | 1             | 36        | <b>66.67%</b> |
| Vegetation                | 5             | 0             | 0             | 2             | <b>32</b>     | 39        | <b>82.05%</b> |
| <b>Column Total (Ref)</b> | <b>401</b>    | <b>16</b>     | <b>7</b>      | <b>37</b>     | <b>39</b>     | 500       |               |
| <b>Producer's Acc.</b>    | <b>95.26%</b> | <b>87.50%</b> | <b>57.14%</b> | <b>64.86%</b> | <b>82.05%</b> |           |               |

Overall Accuracy: 91.20%

Expected Agreement (Pe): 0.6558

Kappa Coefficient (K): 0.744

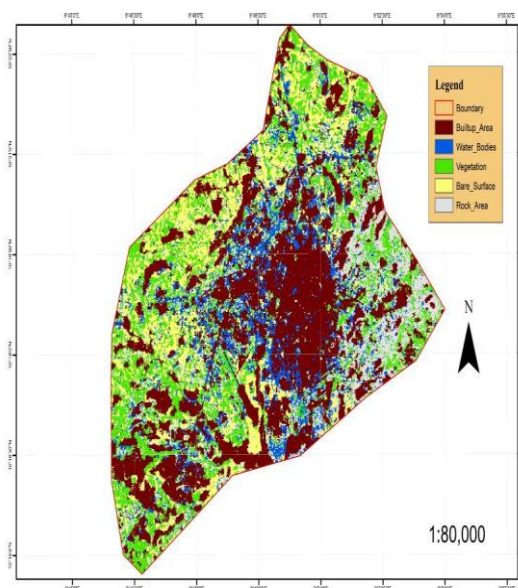
Built-up Area recorded exceptionally high Producer's and User's Accuracies of 95.26%, reflecting the increasing spatial dominance and spectral distinctiveness of urban features within the metropolis. Water Bodies also achieved high classification accuracies, whereas Rock Area and Bare Surface recorded comparatively lower values, largely because of persistent spectral confusion among exposed land cover types. Similar challenges have been documented in Landsat-based urban classification studies, particularly where bare soils, weathered rocks, and construction sites exhibit overlapping spectral signatures.

The slightly lower Kappa coefficient despite the higher Overall Accuracy is most likely attributable to the increasing dominance of Built-up Area within the study area. As noted by Foody (2020), Kappa statistics may decline under highly imbalanced class distributions even when Overall Accuracy improves because the expected agreement by chance increases with class dominance. Consequently, the observed reduction in the Kappa coefficient should not be interpreted as a decline in classification quality but rather as a statistical consequence of changing land cover composition.

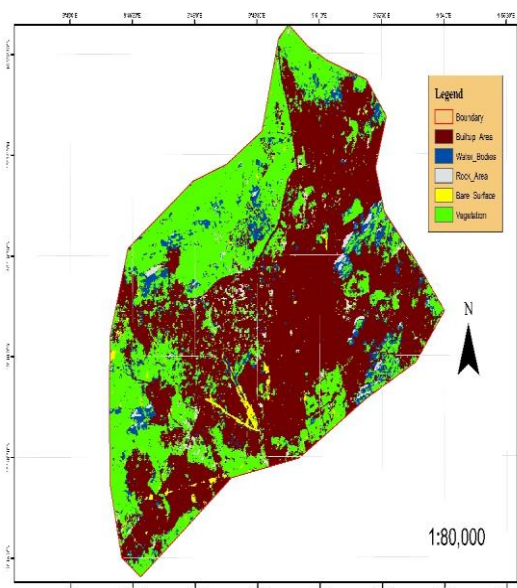
Comparable Overall Accuracy values have been reported by Enoguanbhor et al. (2024), and Maxwell et al. (2018) in studies investigating urban expansion using medium-resolution satellite imagery. The consistency of these findings further confirms the robustness of the classification methodology adopted in the present study.

### Spatio-temporal Dynamics of Land-Use/Land Cover in Bauchi Metropolis (1990-2020)

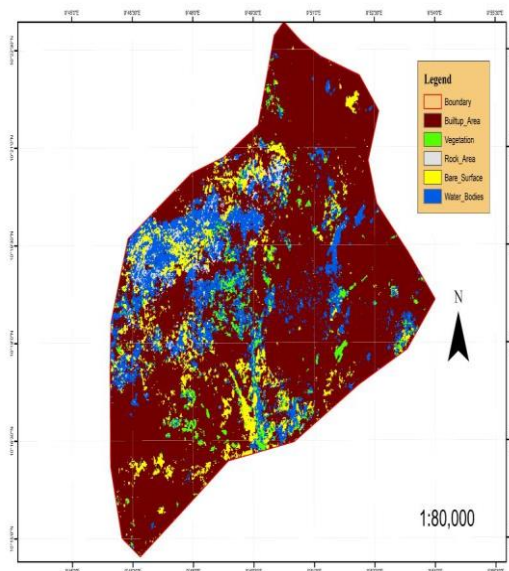
The classified Landsat images revealed substantial changes in the spatial distribution of Land-Use/land cover (LULC) classes within Bauchi Metropolis between 1990 and 2020. Five major Land-Use/land cover categories, Built-up Area, Water Bodies, Rock Area, Bare Surface, and Vegetation were identified for each epoch. The temporal changes in their spatial extent reflect the influence of rapid urbanization, population growth, infrastructure development, and increasing anthropogenic pressure on the natural environment.



**Figure 3: LULC of Bauchi Metropolis 1990**



**Figure 4: LULC of Bauchi Metropolis 2010**



**Figure 5: LULC of Bauchi Metropolis 2020**

Overall, the study demonstrates a progressive transformation of the landscape from predominantly natural land cover to an increasingly urbanized environment. During the thirty-year study period, Built-up Area consistently expanded, while Water Bodies and Rock Area declined continuously. Vegetation exhibited an initial increase between 1990 and 2010 before experiencing a substantial decline by 2020, whereas Bare Surface showed fluctuating changes associated with different phases of urban development. The detailed area and percentage distribution of each Land-Use/land cover class are presented in Table 4, while the corresponding spatial patterns are illustrated in Figures 3-5.

**Table 4. Land-Use/Land Cover Distribution in Bauchi Metropolis (1990-2020)**

| Land-use/Land Cover Class | 1990 Area (km <sup>2</sup> ) | 1990 (%)   | 2010 Area (km <sup>2</sup> ) | 2010 (%)   | 2020 Area (km <sup>2</sup> ) | 2020 (%)   |
|---------------------------|------------------------------|------------|------------------------------|------------|------------------------------|------------|
| Built-up Area             | 42.5588                      | 35.5       | 65.4863                      | 54.6       | 96.1471                      | 80.2       |
| Water Bodies              | 13.9146                      | 11.6       | 7.7515                       | 6.4        | 3.8609                       | 3.2        |
| Rock Area                 | 17.0913                      | 14.3       | 2.4724                       | 2.1        | 1.7107                       | 1.4        |
| Bare Surface              | 20.7424                      | 17.3       | 1.5086                       | 1.3        | 8.8105                       | 7.4        |
| Vegetation                | 25.564                       | 21.3       | 42.6523                      | 35.6       | 9.3419                       | 7.8        |
| <b>Total</b>              | <b>119.8711</b>              | <b>100</b> | <b>119.8711</b>              | <b>100</b> | <b>119.8711</b>              | <b>100</b> |

### Built-up Area

Built-up Area recorded the most significant increase among all Land-Use/land cover classes during the study period. The area occupied by Built-up land expanded from 42.56 km<sup>2</sup> (35.5%) in 1990 to 65.49 km<sup>2</sup> (54.6%) in 2010 and further to 96.15 km<sup>2</sup> (80.2%) in 2020. This represents a net increase of 53.59 km<sup>2</sup>, equivalent to an overall growth of approximately 126% relative to its 1990 extent. The average annual rate of expansion during the thirty-year period was approximately 1.79 km<sup>2</sup> per year, with the most rapid growth occurring between 2010 and 2020 when the built-up area increased by 30.66 km<sup>2</sup>, equivalent to an average annual expansion of approximately 3.07 km<sup>2</sup> per year.

The marked increase in built-up land may reflect the rapid urbanization experienced by Bauchi Metropolis over the past three decades. As the administrative capital of Bauchi State, the city has witnessed sustained population growth, expansion of residential neighbourhoods, increased commercial activities, institutional development, and significant investment in transportation and public infrastructure. These socioeconomic developments have increased demand for land, leading to the progressive conversion of natural land cover into urban settlements. The accelerated expansion observed after 2010 further suggests that urban growth intensified during the last decade of the study period, possibly as a result of increasing rural-urban migration, economic diversification, and expansion of peri-urban settlements.

The findings are consistent with the global observations of Fatusin et al. (2019), who demonstrated that urban expansion in developing countries is largely driven by population increase, economic growth, and infrastructure development. Similarly, Güneralp et al. (2020) reported that cities across Sub-Saharan Africa are experiencing some of the fastest rates of spatial expansion worldwide, with urban growth increasingly occurring through outward expansion into surrounding natural landscapes rather than through urban densification.

### Water Bodies

Water Bodies exhibited a continuous decline throughout the study period, decreasing from 13.91 km<sup>2</sup> (11.6%) in 1990 to 7.75 km<sup>2</sup> (6.4%) in 2010 and further to 3.86 km<sup>2</sup> (3.2%) in 2020. This represents a net loss of 10.05 km<sup>2</sup>, equivalent to approximately 72.3% of its 1990 extent, with an average annual decline of 0.34 km<sup>2</sup> per year.

The persistent reduction in water bodies may indicate increasing anthropogenic pressure associated with urban expansion. As Bauchi Metropolis grew, wetlands, streams, and other surface water features were progressively encroached upon for residential, commercial, and infrastructural development. Seasonal climatic variability, sedimentation, and increased water abstraction may have also contributed to the observed decline. Similar reductions in urban surface water have been reported by Olalekan et al. (2020) in Lagos, and Mashi et al. (2025) in the Federal Capital Territory, where rapid urbanization altered natural drainage systems and reduced the extent of surface water resources.

The continued loss of water bodies has important environmental implications for Bauchi Metropolis. Reduced surface water can diminish freshwater availability, degrade aquatic ecosystems, and increase urban flood risk by disrupting natural

drainage pathways. These findings underscore the need for stronger protection of wetlands and riparian corridors, together with improved enforcement of land-use regulations to safeguard critical water resources as urban development continues.

### Rock Area

Rock Area experienced a substantial decline over the study period, decreasing from 17.09 km<sup>2</sup> (14.3%) in 1990 to 2.47 km<sup>2</sup> (2.1%) in 2010 and further to 1.71 km<sup>2</sup> (1.4%) in 2020. This represents a net loss of 15.38 km<sup>2</sup>, equivalent to approximately 90.0% of its 1990 extent, with an average annual decline of about 0.51 km<sup>2</sup> per year.

The marked reduction in rock areas suggests increasing human modification of the landscape as urban development expanded into previously undeveloped terrains. The construction of residential estates, road networks, and other infrastructure, together with quarrying and excavation activities, likely contributed to the conversion of rocky surfaces into built-up land. Similar observations were reported by Bernard et al. (2019) in Niger and Akpu et al. (2017) in Kaduna, where urban expansion increasingly encroached upon rocky and marginal landscapes as available developable land became limited.

The progressive loss of rock areas has important environmental implications, including alteration of the natural landscape, increased susceptibility to soil erosion, and disruption of local drainage patterns. These findings highlight the need for environmentally sensitive land-use planning that considers the ecological and geomorphological significance of rocky landscapes before approving future urban development.

### Bare Surface

Bare Surface exhibited a fluctuating pattern during the study period. The area declined sharply from 20.74 km<sup>2</sup> (17.3%) in 1990 to 1.51 km<sup>2</sup> (1.3%) in 2010 before increasing to 8.81 km<sup>2</sup> (7.4%) in 2020. Overall, the class recorded a net loss of 11.93 km<sup>2</sup> compared with its 1990 extent, although the increase between 2010 and 2020 indicates renewed exposure of land surfaces associated with ongoing urban development.

The initial decline in bare surfaces is attributable to the rapid conversion of vacant and exposed land into built-up areas during the early phase of urban expansion. The subsequent increase observed in 2020 is likely associated with land clearing for new residential layouts, road construction, and infrastructure development, where cleared sites remained temporarily exposed before full development. Similar trends have been reported by Pirnazar et al. (2018) and Mashi et al. (2025), who noted that fluctuations in bare surfaces are common in rapidly expanding urban areas because of continuous cycles of land clearing and construction.

The changing extent of bare surfaces reflects the dynamic nature of urban development in Bauchi Metropolis. While temporary increases in exposed land are often associated with construction activities, prolonged exposure can accelerate soil erosion, increase dust pollution, and reduce land quality. These findings highlight the importance of implementing effective land management practices, including prompt site rehabilitation and erosion control measures during urban development projects.

### Vegetation

Vegetation exhibited a dynamic pattern over the study period. The area increased from 25.56 km<sup>2</sup> (21.3%) in 1990 to 42.65 km<sup>2</sup> (35.6%) in 2010 before declining sharply to 9.34 km<sup>2</sup> (7.8%) in 2020. Overall, vegetation experienced a net loss of 16.22 km<sup>2</sup> between 1990 and 2020, representing a reduction of approximately 63.5% relative to its 2010 extent. The pronounced decline during the 2010–2020 period indicates that vegetation became the principal land cover affected by rapid urban expansion.

The increase in vegetation between 1990 and 2010 may be attributed to natural regeneration, afforestation initiatives, or differences in seasonal vegetation conditions at the time of satellite image acquisition. However, the substantial decline recorded between 2010 and 2020 suggests that increasing urban development, infrastructure expansion, and population growth accelerated the conversion of vegetated land into built-up areas. Similar patterns have been reported by Amaechi et al. (2023), who identified vegetation as one of the land cover types most vulnerable to urban expansion globally. In Nigeria, Enoguanbhor et al. (2024) and Jeminiwa et al. (2020) likewise observed that rapid urban growth resulted in significant losses of vegetation cover as cities expanded into peri-urban environments.

The continued reduction in vegetation poses serious environmental concerns, including declining biodiversity, increased surface temperatures, reduced carbon sequestration, and deterioration of ecosystem services. The findings underscore the need to incorporate urban green spaces, afforestation programmes, and the protection of existing vegetation

into urban planning policies to promote sustainable development and enhance the environmental resilience of Bauchi Metropolis.

### Land-Use/Land Cover Transition Matrix (1990-2010)

The Land-Use/Land Cover (LULC) transition matrix for the period 1990-2010 provides detailed information on the persistence of each land cover class and the magnitude of conversions between classes. Unlike the areal statistics presented in the preceding section, the transition matrix identifies the specific pathways through which landscape transformation occurred, thereby providing deeper insight into the processes driving urban expansion in Bauchi Metropolis. The transition matrix for the study period is presented in Table 5.

**Table 5. Land-Use/Land Cover Transition Matrix (1990-2010)**

| 1990 → 2010         | Built-up | Water  | Rock   | Bare Surface | Vegetation |
|---------------------|----------|--------|--------|--------------|------------|
| <b>Built-up</b>     | 26.7693  | 2.6633 | 1.7123 | 0.4889       | 10.8991    |
| <b>Water Bodies</b> | 9.1141   | 0.7883 | 0.1388 | 0.1527       | 3.7106     |
| <b>Rock Area</b>    | 9.1981   | 1.6193 | 0.2605 | 0.1400       | 5.8438     |
| <b>Bare Surface</b> | 9.4591   | 1.1808 | 0.0307 | 0.4314       | 9.6162     |
| <b>Vegetation</b>   | 10.9191  | 1.4906 | 0.3286 | 0.2944       | 12.4949    |

The results indicate that Built-up Area recorded the largest gross gain during the period, increasing primarily through the conversion of Vegetation (10.92 km<sup>2</sup>), Bare Surface (9.46 km<sup>2</sup>), Rock Area (9.20 km<sup>2</sup>), and Water Bodies (9.11 km<sup>2</sup>) into urban land. This pattern confirms that urban expansion occurred through the progressive conversion of both natural and semi-natural land cover classes into residential, commercial, and infrastructural developments. At the same time, 26.77 km<sup>2</sup> of existing built-up land remained unchanged, demonstrating a high level of persistence of established urban areas.

Among the natural land cover classes, Vegetation experienced the greatest conversion to Built-up Area, highlighting its role as the principal source of land for urban expansion during the period. Although vegetation also exhibited considerable persistence, the magnitude of its conversion indicates increasing development pressure on green spaces surrounding the metropolis. Similar findings were reported by Yakubu et al. (2020), who observed that urban growth in developing countries is predominantly achieved through the conversion of vegetated landscapes. In Nigeria, Enoguanbhor et al. (2024) likewise found that vegetation constituted the largest contributor to urban expansion within the Abuja City-Region due to rapid population growth and infrastructure development.

The transition matrix further shows that Bare Surface and Rock Area contributed substantially to the expansion of Built-up Area. This suggests that urban growth during the 1990-2010 period was not limited to vegetated land but also extended into exposed surfaces and rocky terrains as demand for developable land increased. Comparable trends have been reported by Mashi et al. (2025) and Makinde et al. (2021), who noted that expanding Nigerian cities increasingly utilize marginal lands, including rocky outcrops and previously undeveloped open spaces, for residential and infrastructural development.

Overall, the transition patterns indicate that the period between 1990 and 2010 was characterized by steady outward urban expansion accompanied by moderate landscape transformation. While a significant proportion of each land cover class remained unchanged, the increasing conversion of vegetation and other natural surfaces into built-up land reflects the early stages of accelerated urbanization in Bauchi Metropolis. These findings emphasize the need for proactive land-use planning to guide future urban growth while conserving environmentally sensitive land cover classes.

### Land-Use/Land Cover Transition Matrix (2010-2020)

The Land-Use/Land Cover (LULC) transition matrix for the period 2010-2020 reveals a marked intensification of landscape transformation compared with the preceding period. The matrix identifies the magnitude and direction of land

cover conversions and provides insight into the processes responsible for the accelerated urban expansion observed within Bauchi Metropolis. The transition matrix for this period is presented in Table 6.

**Table 6. Land-Use/Land Cover Transition Matrix (2010-2020)**

| 2010 → 2020         | Built-up | Water  | Rock   | Bare Surface | Vegetation |
|---------------------|----------|--------|--------|--------------|------------|
| <b>Built-up</b>     | 60.0154  | 2.0922 | 1.0572 | 4.0829       | 0.2192     |
| <b>Water Bodies</b> | 5.1801   | 0.0756 | 1.9172 | 0.3485       | 0.2199     |
| <b>Rock Area</b>    | 1.0669   | 0.4737 | 0.8941 | 0.0129       | 0.0231     |
| <b>Bare Surface</b> | 0.9077   | 0.0585 | 0.1510 | 0.3756       | 0.0143     |
| <b>Vegetation</b>   | 29.2010  | 1.1575 | 7.0803 | 3.9833       | 1.1698     |

The results indicate that Built-up Area continued to record the largest gross gain during the period, primarily through the conversion of Vegetation (29.20 km<sup>2</sup>), followed by Water Bodies (5.18 km<sup>2</sup>), Bare Surface (0.91 km<sup>2</sup>), and Rock Area (1.07 km<sup>2</sup>) into urban land. Furthermore, 60.02 km<sup>2</sup> of the built-up area remained unchanged, demonstrating a high level of persistence and confirming that previously developed areas continued to retain their urban character while new developments expanded into surrounding landscapes.

The transition matrix clearly indicates that Vegetation was the dominant source of urban expansion during the 2010-2020 period. The conversion of 29.20 km<sup>2</sup> of vegetation into built-up land was almost three times greater than the 10.92 km<sup>2</sup> recorded during the 1990-2010 period, highlighting a significant acceleration in the rate of vegetation loss. This finding suggests that, as available vacant and exposed lands became increasingly limited, urban development shifted towards the conversion of vegetated areas located mainly within the peri-urban fringe. Similar observations were reported by Seto et al. (2012), who noted that urban expansion in rapidly developing regions increasingly occurs through the replacement of natural vegetation. Likewise, Güneralp et al. (2020) emphasized that the expansion of cities in Sub-Saharan Africa is increasingly concentrated within peri-urban landscapes, resulting in widespread vegetation loss and ecosystem fragmentation.

Another notable finding is the continued conversion of Water Bodies into Built-up Area. The transition of 3.63 km<sup>2</sup> of water surfaces to urban land indicates increasing encroachment on wetlands and natural drainage systems. Comparable trends have been documented by Enoguanbhor et al. (2024) in the Abuja City-Region and Olalekan et al. (2020) in Lagos, where rapid urban growth resulted in the reclamation and modification of wetlands and floodplains for residential and commercial development. Such conversions have important environmental implications because they reduce natural flood storage capacity, disrupt hydrological processes, and increase the vulnerability of urban areas to flooding.

A comparison of the two transition periods demonstrates that urban expansion became substantially more aggressive between 2010 and 2020. While the 1990-2010 period was characterized by moderate conversion of multiple land cover classes, the latter decade was dominated by extensive transformation of vegetation into built-up land. This shift reflects the increasing scarcity of undeveloped land within the urban core and the outward expansion of the metropolis into previously vegetated peripheral areas. Similar patterns have been reported by Musa et al. (2017) and Koko et al. (2021), who observed that urban growth in Nigerian cities increasingly progresses from infilling within existing urban areas to outward expansion into peri-urban environments.

## Conclusion

This study employed multi-temporal Landsat imagery integrated with Remote Sensing and GIS techniques to assess Land-Use/land cover (LULC) dynamics and urban expansion in Bauchi Metropolis between 1990 and 2020. The high classification accuracies (85.20%, 90.60%, and 91.20%) and substantial Kappa coefficients confirmed the reliability of the classified maps for change detection. The results revealed significant landscape transformation, with Built-up Area

increasing from 42.56 km<sup>2</sup> (35.5%) in 1990 to 96.15 km<sup>2</sup> (80.2%) in 2020, while Water Bodies, Rock Area, and Vegetation generally declined due to increasing urban development.

Transition matrix analysis showed that vegetation was the principal source of land converted to Built-up Area, particularly between 2010 and 2020, indicating an acceleration of peri-urban expansion and increasing pressure on natural ecosystems. Overall, the study demonstrates that integrating Remote Sensing, GIS, classification accuracy assessment, and transition matrix analysis provides a robust framework for monitoring urban growth and landscape transformation. The findings offer valuable spatial information for sustainable land-use planning, environmental conservation, and evidence-based urban management in Bauchi Metropolis and other rapidly urbanizing cities.

## Recommendations

1. Planning authorities, particularly the Bauchi State Urban Development Board and the Bauchi State Ministry of Lands and Survey, should prioritize development control in peri-urban areas identified as major urban expansion hotspots to prevent unplanned growth and protect environmentally sensitive land.
2. Given the substantial loss of vegetation and water bodies during the study period, the Bauchi State Ministry of Environment should enforce buffer zones around wetlands and riparian corridors while promoting urban green spaces, afforestation, and ecosystem restoration to enhance environmental sustainability.
3. The Bauchi State Government should establish a Bauchi State Geographic Information Service (BAGIS) or a similar geospatial agency to coordinate land information management and undertake five-yearly Land-Use/land cover monitoring using Remote Sensing and GIS. Such an institution would provide reliable geospatial data to support evidence-based planning, development control, and environmental management.
4. Urban development should prioritize compact growth, urban renewal, and mandatory Environmental Impact Assessments (EIAs) to reduce encroachment on natural landscapes. Future studies should integrate socioeconomic drivers and predictive models, such as Cellular Automata-Markov (CA-Markov) and machine learning techniques, to improve urban growth forecasting and long-term land-use planning.

## Declarations

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### Conflict of interest

The author declare that there is no conflict of interest.

### Authors contribution

The author contributed to the conceptualisation, literature review, textual analysis, drafting, critical revision and approval of the final manuscript.

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