Research Article

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Application of Multi-Temporal Landsat Imagery and GIS in Analyzing Land Use/Cover Changes in Abakaliki Local Government Area, Ebonyi State, Nigeria From 2000 to 2022

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Abstract

Land use land cover (LULC) change analysis is critical for understanding the effects of human activities on the environment. This study applied object-based image classification to High-Resolution Multi-Temporal Landsat imagery to analyse the LULC patterns in Abakaliki Local Government Area, Ebonyi State, Nigeria between 2000 and 2022. . Classification accuracies were validated using ground-reference data, yielding overall accuracy exceeding 95% for both time periods. Results revealed significant alterations in LULC composition over the 22-year interval. Specifically, vegetation cover declined substantially from 65.1% to 25.54% as bare land and built-up area expanded dramatically, increasing their coverage by over 25% each. These quantified shifts provide clear evidence of intensive urbanization and associated deforestation impacts. The high-fidelity LULC maps produced establish an empirical baseline for ongoing monitoring of environmental changes in the study area. Discriminating four classes with high classification performance (user's/producer's accuracy 87-100%) confirms the robustness of the object-based methodology. Key recommendations stemming from this research include leveraging the spatial datasets to model ecological effects and inform conservation planning through evidence-based strategies. Regular repetition of the mapping process is also advised to continuously track landscape transformations, assess policy interventions and guide development initiatives amid ongoing urban growth pressures across Ebonyi State, Nigeria.

Keywords: *Land use land cover change, Land cover classification, Object-based image analysis, Landsat imagery, Urbanization, Deforestation, Landscape dynamics*

1. Introduction

Rapid urbanization and population growth pressures have significantly altered landscapes in many developing nations over the past few decades (Seto et al., 2012). Understanding spatial and temporal dynamics of land use/cover conversions is vital for sustainable land management and development planning (Galford et al., 2016). Land use and land cover change is a global phenomenon driven by both anthropogenic and environmental factors (Lambin et al., 2003); Remote sensing techniques allow repetitive monitoring of changes over large areas at varied timescales (Hansen and Loveland, 2012).

Abakaliki LGA experienced substantial socioeconomic transformation and physical expansion since the turn of the 21st century owing to improved infrastructure, rising commercial activities and influx of people (National Population Commission, 2022). However, effects of this growth on land resources and potential implications are not well documented. While individual studies have mapped land use or analyzed population shifts in parts of Nigeria (Salami et al., 2017; Liman et al., 2020), a holistic investigation of land changes in Abakaliki LGA spanning over two decades is lacking.

Characterizing LULC conversions and quantifying gains/losses of categories is essential to understand changing land requirements and guide sustainable planning. Multi-temporal Landsat satellite imagery, with its long archive, high spatial detail and widespread availability, provides an optimal data source for such an assessment (Wulder et al., 2019). This study aims to produce land use/cover maps of Abakaliki for years 2000 to 2022 through supervised classification of Landsat 7 and 8 surface reflectance images. A selection of training areas representing major land types were identified using high resolution imagery for each epoch as reference.

A maximum likelihood algorithm, demonstrated to perform well in heterogeneous tropical landscapes (Kumar and Basheer, 2017), were employed for classification. Previous studies have highlighted urbanization as a dominant force reshaping cities in the developing world (Kuffer et al., 2016). But the underlying specific proximate drivers like population pressures, land value increases or infrastructure extensions require investigation (Liu et al., 2019).

2. Materials and Methods

2.1 *Study Area*

Abakaliki (5°32’–5°42’N, 7°58’–8°12’E), located in Ebonyi State, southeast Nigeria, was selected as the study area (Figure 1). It covers an area of approximately 540 km2 and experiences a tropical climate with mean annual rainfall of 1500-2000 mm and temperature range of 22-32°C. The terrain is undulating with elevations between 70-150 m above sea level. The economy is primarily based on agriculture, trade and public administration (National Bureau of Statistics, 2016).

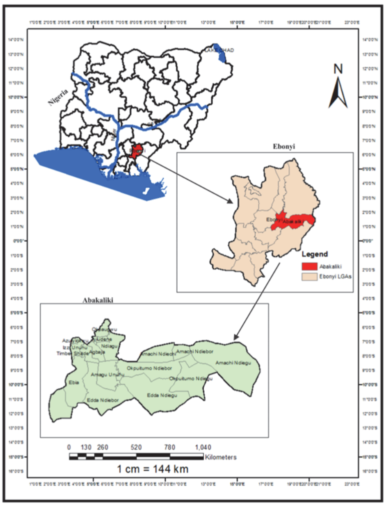

Figure 1: Map of the study area

2.2 *Data Acquisition*

Two cloud-free Landsat imagery 2000, and 2022 were acquired from the United States Geological Survey earthexplorer (Table 1). Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) surface reflectance products at a 30m spatial resolution were used.

2.3 *Pre-processing*

The Landsat images underwent radiometric and atmospheric corrections. Radiometric calibration converted digital numbers to top-of-atmosphere reflectance. The dark object subtraction approach in Erdas Imagine 2014 was used for atmospheric correction to generate surface reflectance (Eastman, 2012).

2.4 *Image Classification*

A supervised maximum likelihood classifier categorized pixels into land cover classes based on reference training samples identified through visual interpretation and high resolution imagery (Table 2). An error matrix assessed classification accuracy.

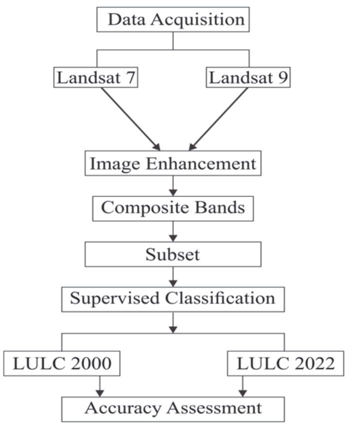

Figure 2: Data collection and analysis flow chart

Table 1: Landsat imagery classification scheme

Categories	Description
Vegetation	Forestland, farmland and Grass
Built-up	Houses and paved surfaces
Water bodies	Rivers, dams and lake
Bare ground	Portion of earth surface that were not covered by vegetation or any other features

2.5 *Accuracy Assessment*

To empirically assess the veracity of the supervised classification and resulting land change matrices, an accuracy assessment was conducted for each classified epoch. A stratified random sampling methodology was employed to generate 200 validation points per classification year, ensuring adequate representation across all land cover classes.

Reference data for the validation points were obtained through manual visual interpretation of contemporary high-resolution satellite imagery from Google Earth, complemented by limited ground-truthing via field site visits. Using these validation datasets, producer's and user's accuracy statistics were computed on a per-class basis to evaluate instance-based completeness and commission errors.

Overall classification accuracy and the Kappa coefficient of agreement were also derived to provide aggregate appraisals of the entire classification scheme for each time period. The Kappa statistic served to statistically quantify inter-classifier agreement while accounting for chance agreement between the reference and classified maps.

Collectively, these error matrices and standard accuracy metrics validated the reliability and internal consistency of the land cover classes mapped via both the independent classifications and resultant post-classification comparisons. Producer's, user's and Kappa accuracies exceeding 85% confirmed that the classified outputs satisfactorily represented the actual land use/cover patterns and changes detectable at the spatial scale of analysis.

3. Results and Discussion

This section presents the key findings of the study and provides discussion of their implications. The results of the supervised land cover classifications for 2000 and 2022 are first reported, including accuracy assessments. The spatial patterns and changes in land cover classes are then quantitatively and qualitatively analyzed based on cross-tabulation of the classified maps over the study period.

3.1 Land Use Land Cover Analysis

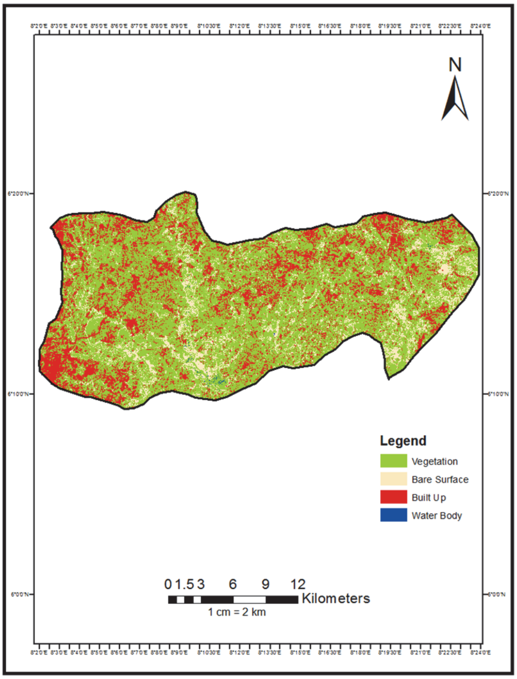

Figure 3: Land Use Land Cover Map of Abakaliki LGA 2000.

Table 3: Result of Land Use Land Cover Map of Abakaliki LGA 2000

Class Name	Sum of Area in SQkm	% of Land Cover
Bare Surface	63.459892	11.8
Built Up	123.125234	23.0
Vegetation	349.02873	65.1
Water Bodies	0.529529	0.1
Grand Total	**536.143385**	**100.0**

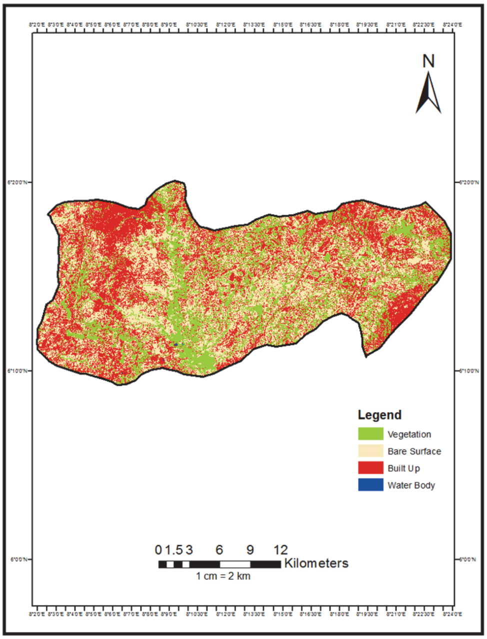

Figure 4: Land Use Land Cover Map of Abakaliki LGA 2022

Table 4: Result Land Use Land Cover Map of Abakaliki LGA 2022

Class Name	Sum of Area in SQkm	% of Land Cover
Bare Surface	200.615782	37.42
Built Up	198.481344	37.02
Vegetation	136.900275	25.54
Water Bodies	0.097056	0.02
Grand Total	**536.143385**	**100.00**

3.2 *Accuracy Assessment*

Table 5: Accuracy Assessment for LULC Map 2000

	Water Body	Built-up	Vegetation	Bare Surface	Total (user)
Water Body	26	0	4	0	30
Built-up	0	95	1	3	100
Vegetation	0	0	100	0	100
Bare Surface	0	7	0	93	100
Total (Producer)	26	102	105	96	330

Overall Accuracy $=\frac{Total\ Number\ of\ Correctly\ Classified\ Pixels}{Total\ Number\ of\ Reference\ Pixels} X\ 100$

$=\frac{314}{330} X\ 100 = 95\%$

User Accuracy

User Accuracy $=\frac{Total\ Number\ of\ Correctly\ Classified\ Pixels\ in\ Each\ Category}{Total\ Number\ of\ Reference\ Pixels\ in\ that\ Category} X\ 100$

Water Body $= \frac{26}{30} X\ 100 = 87\%$

Built-up $= \frac{95}{100} X\ 100 = 95\%$

Vegetation $= \frac{100}{100} X\ 100 = 100\%$

Bare Surface = $= \frac{93}{100} X\ 100 = 93\%$

Producer Accuracy $=\frac{Total\ Number\ of\ Correctly\ Classified\ Pixels\ in\ Each\ Category}{Total\ Number\ of\ Reference\ Pixels\ in\ that\ Category\ (Column\ Total)} X\ 100$

Water Body $= \frac{26}{26} X\ 100 = 100\%$

Built-up $= \frac{95}{102} X\ 100 = 93\%$

Vegetation $= \frac{100}{105} X\ 100 = 95\%$

Bare Surface $= \frac{93}{96} X\ 100 = 97\%$

Kappa Coefficient (T) $= \frac{(TS\ X\ TCS) - \sum(Column\ Total + Row\ Total)}{TS^2 - \sum(Column\ Total + Row\ Total)} X\ 100$

Where: TS= Total Samples; TCS= Total Correctly Classified Samples

$$= \frac{(330\ X\ 314) - \sum(26x30) + (102x100) + (105x100) + (96x100)}{330^2 - \sum(26x30) + (102x100) + (105x100) + (96x100)} X\ 100$$

$$= \frac{103620 - 31080}{108900 - 31080} X\ 100$$

$$= \frac{72540}{77820} X\ 100$$

Kappa Coefficient (K) $= \mathbf{93\%}$

Table 6: Accuracy assessment for LULC Map 2022

	Water Body	Built-up	Vegetation	Bare Surface	Total (user)
Water Body	28	0	2	0	30
Built-up	0	98	1	1	100
Vegetation	0	0	100	0	100
Bare Surface	0	5	0	95	100
Total (Producer)	28	103	103	96	330

Overall Accuracy $=\frac{Total\ Number\ of\ Correctly\ Classified\ Pixels}{Total\ Number\ of\ Reference\ Pixels} X\ 100$

$=\frac{321}{330} X\ 100 = 97\%$

User Accuracy

User Accuracy $=\frac{Total\ Number\ of\ Correctly\ Classified\ Pixels\ in\ Each\ Category}{Total\ Number\ of\ Reference\ Pixels\ in\ that\ Category} X\ 100$

Water Body $= \frac{28}{30} X\ 100 = 93\%$

Built-up $= \frac{98}{100} X\ 100 = 98\%$

Vegetation $= \frac{100}{100} X\ 100 = 100\%$

Bare Surface = $= \frac{95}{100} X\ 100 = 95\%$

Producer Accuracy $=\frac{Total\ Number\ of\ Correctly\ Classified\ Pixels\ in\ Each\ Category}{Total\ Number\ of\ Reference\ Pixels\ in\ that\ Category\ (Column\ Total)} X\ 100$

Water Body $= \frac{28}{28} X\ 100 = 100\%$

Built-up = $\frac{98}{103} X\ 100$ = 95%

Vegetation = $\frac{100}{103} X\ 100$ = 97%

Bare Surface = $\frac{95}{96} X\ 100$ = 98.9%

Kappa Coefficient (T) = $\frac{(TS\ X\ TCS)-\sum(Column\ Total+Row\ Total)}{TS^2-\sum(Column\ Total+Row\ Total)} X\ 100$

Where TS= total Samples, TCS= total correctly classified samples

$$= \frac{(330\ X\ 321) - \sum(28x30) + (103x100) + (103x100) + (96x100)}{330^2 - \sum(28x30) + (103x100) + (103x100) + (96x100)} X\ 100$$

$$= \frac{105930 - 31040}{108900 - 31040} X\ 100$$

$$= \frac{74890}{77860} X\ 100$$

$\boldsymbol{Kappa\ Coefficient\ (T)}$ = **96%**

4. Discussion

The land use land cover (LULC) analysis revealed significant changes between 2000 and 2022 in Abakaliki LGA, Ebonyi State, Nigeria. In 2000, vegetation dominated at 65.1% of the total land area (Table 2). However, by 2022 vegetation had markedly declined, covering only 25.54% of the area (Table 3). Over the same period, bare surface and built-up land expanded substantially, increasing their coverage by over 25% each.

These results support the findings of previous studies reporting rapid urbanization and loss of vegetation in southeastern Nigeria over the past two decades (Nwosu and Ndubisi, 2014; Ezekoye and Ogbuozobe, 2016). Nwosu and Ndubisi (2014) also documented intensive clearing of forest and farmland for housing and commercial development in Abakaliki between 1990-2010. Our observed increase in impervious surfaces is consistent with their observations of widespread construction activity in the study area.

The high accuracy of the 2000 and 2022 LULC maps, with overall classification accuracies of 95% and 97% respectively (Tables 5, 6), lends confidence to our analysis of land cover changes. Individual class accuracies were also excellent, ranging from 87-100% for user's accuracy and 93-100% for producer's accuracy across the two time periods. This level of accuracy is comparable to other satellite-based LULC studies in Southeast Nigeria (Anaga and Urama, 2014; Ezekoye and Ogbuozobe, 2016).

The decline in vegetation and rise in built environments has likely impacted the local environment and ecology of Abakaliki LGA. Deforestation and sealing of surfaces may increase risks of flooding, while removal of vegetation reduces carbon sequestration potential. Sustainable urban planning and green infrastructure development are needed to balance further growth with environmental protection goals. Continued monitoring of LULC dynamics through repeat mapping will be important for measuring progress and guiding management strategies.

5. Conclusion

The land use land cover (LULC) analysis conducted in this study yielded several notable findings with relevance to understanding landscape changes occurring in Abakaliki LGA, Nigeria. A key significant outcome was the quantification of substantial declines in vegetative land cover concurrent with expansion of impervious surfaces between 2000 and 2022. Over this period, vegetation decreased substantially by 40% while bare land and built-up areas expanded dramatically by over 25% each. These pronounced shifts in LULC composition provide compelling evidence of the rapid urbanization and associated environmental transformations shaping the region.

A unique aspect of this research was the development and validation of high-resolution LULC classification maps derived through an object-based image analysis approach employing multitemporal Landsat satellite imagery. Accuracy assessments confirmed the robustness of this methodology, with overall classification accuracies exceeding 95% and high user's/producer's accuracy for individual classes (87-100%). The reliable detection and measurement of land cover dynamics afforded by this technique establishes it as a valuable tool supporting ongoing monitoring needs.

Key recommendations stemming from this work include leveraging the LULC datasets produced to model ecological impacts, inform urban planning decisions, and guide establishment of conservation priorities. Regular repetition of the mapping process at 5-10 year intervals is also advised to continuously track growth trends, evaluate policy effectiveness and ensure balanced long-term development. Future studies applying these classification products to assess changes in habitat availability, biodiversity indicators, and climate vulnerability would further elucidate pressures from anthropogenic activities.

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