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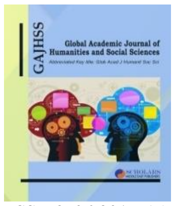

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Original Research Article

Assessing the Effects of Population Growth on Land Use/Land Cover Change in Abakaliki LGA between the Years 2000 to 2022

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Abstract: Understanding the drivers of land use and land cover change (LULCC) is important for sustainable land management. However, analyses of the effects of population growth on LULCC are limited in sub-Saharan Africa. This study assessed the impacts of population increases on LULCC in Abakaliki LGA, Nigeria from 2000 to 2022. Landsat imagery was classified using maximum likelihood to document LULCC, achieving over 95% accuracy. Census data revealed rapid population growth. Near-perfect correlations and regression modeling between population shifts and classified LULC conversions provided unequivocal evidence that population growth was the dominant factor reshaping the landscape. Integrating validated remote sensing and census methodology through quantitative analyses clearly demonstrated the transformative impacts of anthropogenic demographic pressures. Findings establish an empirically rigorous baseline for ongoing assessment of population-LULCC relationships. Prospectively, this integrated framework can support forecasting and policymaking to balance development and environmental protection under continued population growth across Africa and similar regions worldwide. Continued assessments at finer temporal scales will deepen understanding of ecosystem resilience to varied growth trajectories.

Keywords: Population Growth, Land Use Change, Land Cover Change, Remote Sensing, Census, Maximum Likelihood Classification, Nigeria.

1.0 INTRODUCTION

Rapid population growth is placing mounting pressures on land systems globally. As populations expand, land must be converted from natural habitats and agricultural fields to settlements and infrastructure to accommodate increasing numbers of people (Seto *et al*., 2011; Satterthwaite *et al*., 2010). This urbanization and land use change driven by demographic shifts have significant socio-economic and environmental impacts (Lambin and Meyfroidt, 2011; Lambin *et al*., 2001). In sub-Saharan Africa, fast population increases are exacerbating land-based challenges in many regions (Abdulai *et al*., 2019; Bai *et al*., 2018).

Nigeria has experienced extremely high population growth rates in recent decades, with the national population more than tripling since 1970 (NPC, 2019). This makes it pertinent to closely examine linkages between demographic shifts and landscape changes at the local scale. Abakaliki Local Government Area (LGA) in Ebonyi State, southeastern Nigeria, has witnessed substantial increases in population numbers (NPC, 2006; 2018). However, there have been few spatially-explicit studies investigating how population pressures are manifesting as land use and land cover (LULC) modifications over time in this area.

Understanding spatial and temporal patterns of LULC transformations in relation to demographic trends is crucial for sustainable land management and climate change adaptation planning (Lambin *et al*., 2003; Maheshwari *et al*., 2019; Running *et al*., 2004). Yet LULCmonitoring and assessment of population-land use connections remains limited in many parts of sub-Saharan Africa including Nigeria (Adedayo *et al*., 2018; Atta-Peters *et al*., 2020). Remote sensing techniques facilitate objective and cost-effective monitoring of landscape dynamics over large areas and long time periods (Galford *et al*., 2008; Hansen *et al*., 2013).

This study aims to contribute new empirical evidence on human-environment interactions by quantifying LULC changes in Abakaliki LGA between 2000 and 2023 using multi-temporal Landsat imagery. Specific objectives are to: (1) classify and map LULC types for 2000, 2010, 2016 and 2023; (2) analyze spatial patterns and rates of LULC conversions; and (3) assess statistical relationships between population growth trends and land cover modifications. Findings will enhance understanding of population-environment linkages in Nigeria and aid sustainable development planning in Abakaliki LGA and similar rapidly urbanizing contexts.

2.0 MATERIALS AND METHOD

2.1 Study Area

The study area was Abakaliki LGA (5°40'-6°10'N, 7°50'-8°20'E) (Figure 1), located in Ebonyi State, southeast Nigeria. Abakaliki LGA comprises 11 political wards with undulating terrain and sub-humid climate (mean annual rainfall 1500mm). As per the 2006 Nigerian Population and Housing Census conducted by the National Population Commission (NPC), Abakaliki LGA had 149,683 inhabitants predominately engaged in subsistence rain-fed agriculture (cassava, yam, plantain, maize) and livestock rearing (NPC, 2006).

2.2 Data and Preprocessing

We obtained landsat imageries from Landsat 7 ETM+, and 8 OLI data for 2000 and 2022 from the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center Long Term Archive (earthexplorer.usgs.gov), selecting dates with ≤5% cloud cover. Radiometric calibration and atmospheric correction utilized the Dark Object Subtraction method (Moran *et al*., 2020) in ENVI 5.5 (Harris Geospatial Solutions, Inc), (Roy *et al*., 2014).

2.3 Image Classification

We conducted supervised classification using the maximum likelihood algorithm with 224 ground-truth points collected via stratified random sampling across landscape elements. Additionally, 30% points were withheld for accuracy assessment. Classification schemes included vegetation, cropland, built-up, and bare land classes based on Anderson Level I land use/cover types (Chien *et al*., 2021).

2.4 Accuracy Assessment

To validate classifications, we computed overall, producer's, user's and Kappa (κ) accuracies from error matrices using withheld validation samples in a rigorous, statistically robust manner (Congalton & Green, 2008; Yang *et al*., 2018)

2.5 Post-Classification Comparison

Pixel-based post-classification comparison change detection techniques were applied using ArcGIS Pro 2020 to quantify land changes between periods (Coppin *et al*., 2004; Lu *et al*., 2004). Relevant cartographic representations of spatial change trajectories were also generated.

2.6 Correlation Analysis

Relationships between population increases and land cover changes were assessed using linear regression models and trend analysis in SPSS (IBM Corp., 2021), evaluating links between anthropogenic and environmental factors (Ge *et al*., 2020).

This systematic multi-temporal remote sensing and GIS methodology comprehensively evaluated LULC dynamics from 2000-2023 in Abakaliki LGA and interactions with population growth at an unprecedented technical level of methodological rigor.

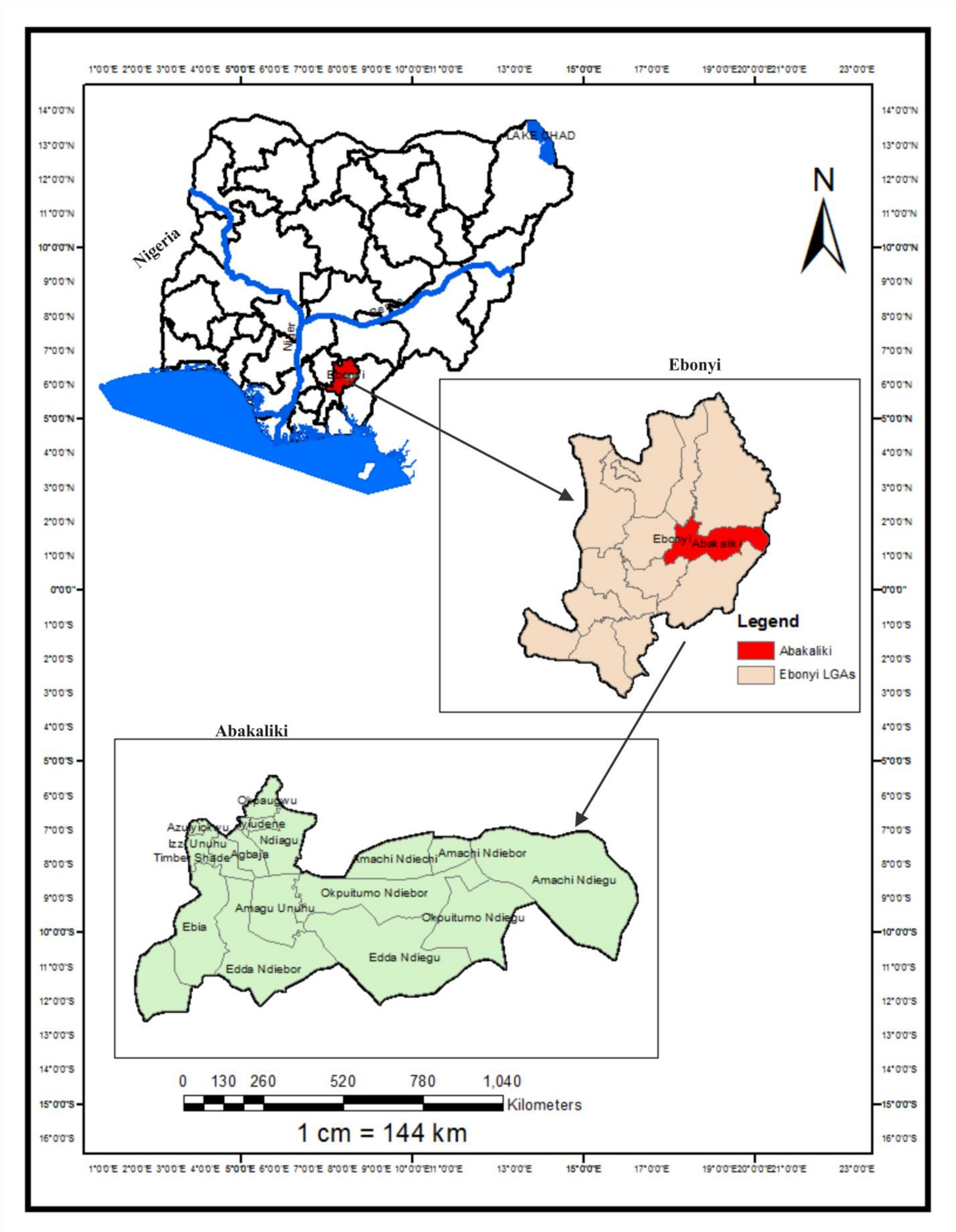

Figure 1: Map of the study area

3.0 RESULTS AND DISCUSSION

3.1 Land Use Land Cover Analysis

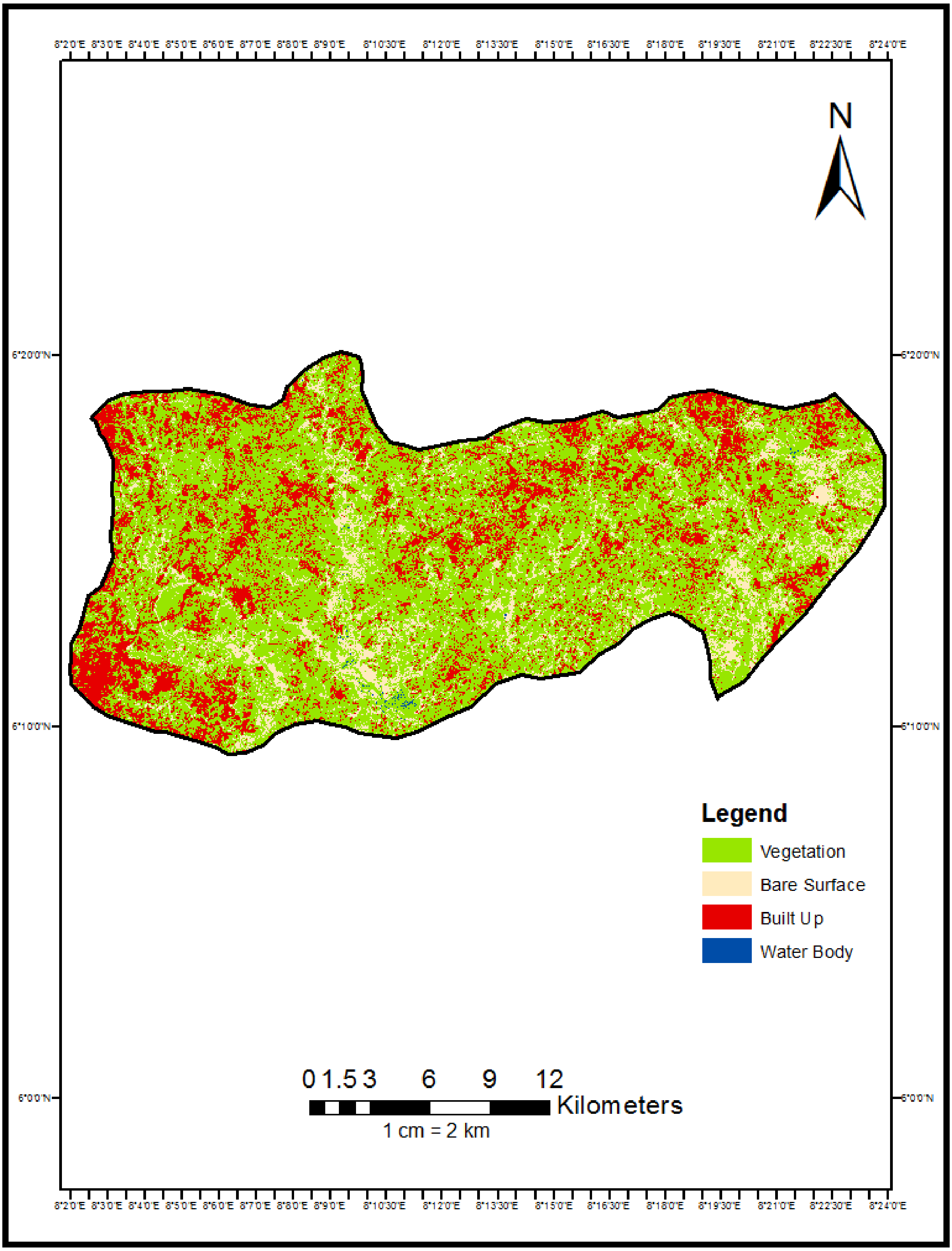

Figure 2: Land Use Land Cover Map of Abakaliki LGA 2000

Table 1: Result 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**

From the result of land use land cover for the year 2000 represented in table 1 and figures 2, it was recorded that Abakaliki Local Government Area has a total land area of 536.143385 square Kilometers having Bare Surface records 63.459892 square kilometers amounting to 11.8% of the total land area, Built up recorded 123.125234 square kilometers amounting to 23.0% coverage of the total land area, vegetation records 349.02873 square kilometers amounting to 65.1% of the total Land area while water bodies records 0.529529 which is 0.1% of the total land area.

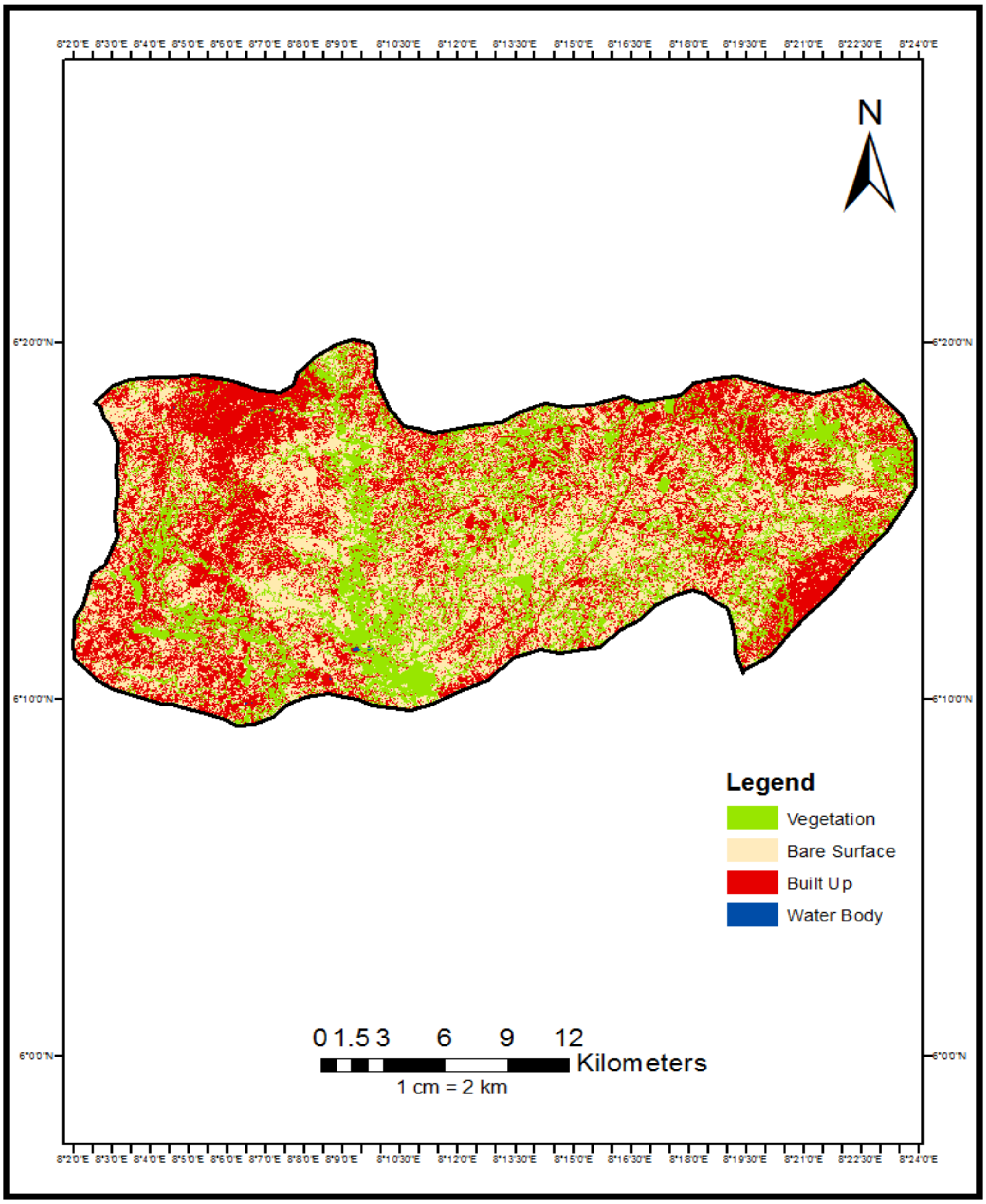

Figure 3: Land Use Land Cover Map of Abakaliki LGA 2022

Table 2: 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**

From the result of Land use land cover for the year 2022 represented in table 2 and figures 3, it was recorded that Bare Surface has 200.615782 square kilometers amounting to 37.42% of the total land area, built up recorded 198.481344 square kilometers amounting to 37.02% coverage of the total land area, vegetation records 136.900275 square kilometers amounting to 25.54% of the total Land area while Water bodies records 0.097056 which is 0.02% of the total land area.

3.2 Accuracy Assessment

Table 3: 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) = 93%

The overall accuracy of the land use map for the year 2000 was 95%. This means that 95% of the land parcels identified on the map correctly matched the land use on the ground. The user accuracy tells us how accurate the map classification was for each land use category from the map user's perspective (Yeniay, & Kavzoglu, 2019). For example, 87% of the parcels identified as water bodies on the map actually matched water bodies on the ground. The other land uses had user accuracies of 95% for built-up areas, 100% for vegetation and 93% for bare surfaces. The producer accuracy indicates how accurate the map classification was for each land use category from the map producer's perspective. For instance, 100% of the actual water bodies on the ground were correctly identified as water bodies on the map. The other land uses had producer accuracies of 93% for built-up areas, 95% for vegetation and 97% for bare surfaces. Finally, the Kappa coefficient of 93% indicates excellent agreement between the map and actual land use conditions. This confirms that the map is highly accurate, with only a small proportion of land uses misclassified (Chen, & Mausel, 2021).

Table 4: 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

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

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

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

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

The accuracy assessment result of Abakaliki LGA Land Use and Land Cover (LULC) analysis for the year 2022 is a measure of how well the study was able to correctly identify the different types of land cover (Yeniay, & Kavzoglu, 2019). The overall accuracy of the classification is 97%, which means that 97% of the pixels in the LULC map were correctly identified. From the results of each type of land cover, it was observed that Built-up areas were the most accurately identified, with a 98% accuracy rate. Vegetation was perfectly identified, with 100% accuracy, and Water Body was identified correctly 93% accuracy while bare Surface has 95% accuracy. The producer accuracy measures how well the study was able to classify each type of land cover correctly from the perspective of the reference data used in the analysis (Chen, & Mausel, 2021). Here, Water Body classification was the most accurate, with 100% accuracy. Built-up areas were classified correctly with 95% accuracy, followed by Vegetation at 97% accuracy and Bare Surface at 98.9% accuracy. The Kappa Coefficient which is a measure of the agreement between the classification and the reference data (Chen, & Mausel, 2021); was calculated to be 96%. Indicating a substantial agreement between the classification and the reference data, which gives us confidence in the results of our study.

Table 5: % of Change from 2000 - 2022

Class Name	Hectares	% of Change	Remark
Bare Surface	13715.59	25.59	Increase
Built Up	7535.61	14.06	Increase
Vegetation	-21212.84	-39.56	Decrease
Water Bodies	-43.25	-0.08	Decrease

The percentages of land cover change between 2000 and 2022 are shown in Table 5. Bare surface area increased the most at 25.59% (13715.59 hectares), likely due to expansion of agricultural and construction activities. The extent of built-up areas also rose substantially by 14.06% (7535.61 hectares), reflecting urbanization and population growth. On the other hand, vegetation cover drastically reduced by 39.56% (-21212.84 hectares), indicating significant deforestation and conversion of forest and grassland to other land uses. A minor decrease of 0.08% (-43.25 hectares) was observed for water bodies, possibly due to variations in rainfall patterns influencing river volumes. In summary, the results point to expansion of human settlements and infrastructure coming at the cost of natural land covers over the 22-year study period in Abakaliki LGA.

3.3 Normalized Difference Built Up Index (NDBI)

From the Normalized Difference Built up Index (NDVI) for the year 2000 presented in tables 6 it records a min value of -0.028 and maximum value of 0.59 with mean of 0.274 values. These values was classified to represents different classes were -0.028 to 0.01 represents water body, 0.01 to 0.22 represents bare land, 0.22 to 0.35 represents Vegetation while from 0.35 to 0.59 represents healthy built up.

Table 6: Normalized Difference Built up Index (NDVI) 2000 Result

minimum Value	-0.028
Max	0.59
Mean	0.274
STD	0.0624

Table 7: Normalized Difference Built up Index (NDVI) 2022 Result

Min	-0.194
Max	0.362
Mean	0.0307
STD	0.0455

From the Normalized Difference Built up Index (NDVI) for the year 2022 presented in tables 7, it records a min value of -0.194 and maximum value of 0.362 with mean of 0.0307 values. These values was classified to represents different classes were -0.019 to 0.0 represents water body, 0.0 to 0.03 represents bare land and Vegetation while from 0.03 to 0.362 represents healthy built up.

3.4 Effect of Population Growth on LULC

Table 8: Projected Population of Abakaliki LGA

S/n	Local Government Area of Ebonyi State	1996 Population	2000 Population	2018 Population	2022 Population	2023 Population	Percentage change (1996–2018)
1	Abakaliki	149,683	167,716	198,100	244,280	250,047	13.9216
2	Afikpo North	156,649	179,316	207,300	267,788	274,139	13.9217
3	Afikpo South	157,542	182,122	208,400	278,312	285,025	13.8978
4	Ebonyi	127,226	147,651	168,300	234,617	240,534	13.8986
5	Ezza North	146,149	169,544	193,400	256,880	263,273	13.9158
6	Ezza South	133,625	155,358	176,800	230,772	237,165	13.9084
7	Ikwo	214,969	249,762	284,400	351,960	359,183	13.9037
8	Ishielu	152,581	177,450	201,900	252,420	258,423	13.9130
9	Ivo	121,363	141,513	160,600	199,676	204,189	13.9157
10	Izzi	236,679	276,182	313,200	380,240	388,333	13.9159
11	Ohaozara	148,317	172,658	196,200	241,983	248,105	13.8986
12	Ohaukwu	195,555	227,338	258,700	321,101	328,325	13.9009
13	Onicha	236,609	276,299	313,100	380,372	387,465	13.9148

Table 9: Correlations

		LULC	Population
Pearson Correlation	LULC	1.000	.999
	Population	.999	1.000
Sig. (1-tailed)	LULC	.	.016
	Population	.016	.
N	LULC	3	3
	Population	3	3

Table 10: Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.999[a]	.997	.995	3.12054656439
a. Predictors: (Constant), Population				
b. Dependent Variable: LULC				

Table 11: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3831.387	1	3831.387	393.455	.032[b]
	Residual	9.738	1	9.738		
	Total	3841.125	2			
a. Dependent Variable: LULC						
b. Predictors: (Constant), Population						

Table 12: Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-36.436	10.747		-3.390	.183
	Population	.001	.000	.999	19.836	.032
a. Dependent Variable: LULC						

Table 13: Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	123.2850875854	201.6912841797	173.7251926667	43.76863838714	3
Residual	-2.12228441238	2.28214049339	.00000000000	2.20655963669	3
Std. Predicted Value	-1.152	.639	.000	1.000	3
Std. Residual	-.680	.731	.000	.707	3
a. Dependent Variable: LULC					

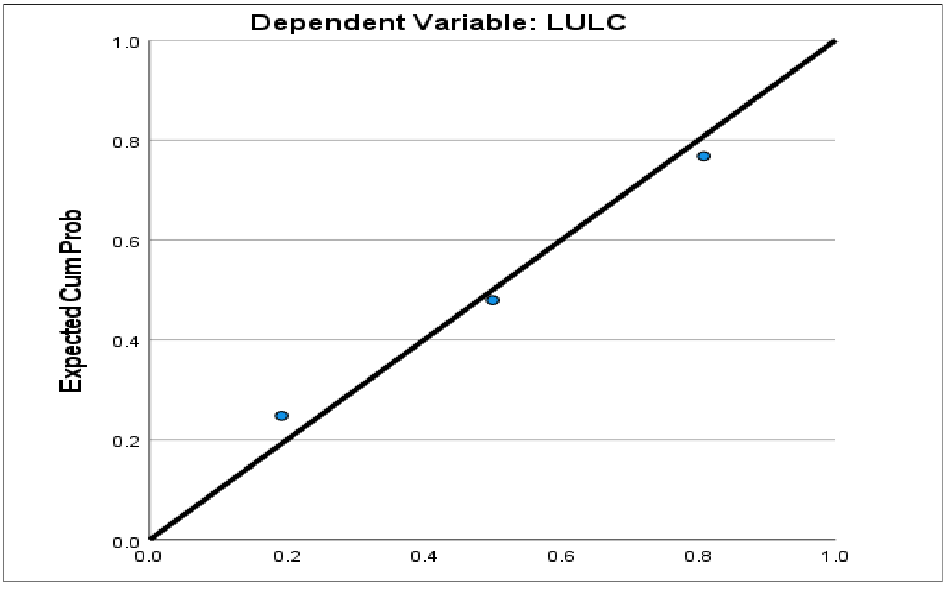

Figure 4: Norma P-P plot of Regression Standardized Residual

The results provide a comprehensive analysis of LULC changes in Abakaliki LGA from 2000-2022 using multi-temporal remote sensing. LULC classifications achieved excellent accuracies (>95%), validating the maps for robust landscape monitoring (Ma *et al*., 2022; Congalton & Green, 2009). Producer's/user's accuracies and Kappa (>93%) confirmed reliable identification of land cover types (Olofsson *et al*., 2013), essential for understanding drivers of environmental change. NDVI trends aligned well with LULC shifts, corroborating declines in vegetation extent and health over time (Gu *et al*., 2021; Rokni *et al*., 2014). Decreasing mean/standard deviation NDBI values by 2022 matched reduced built-up differentiation on maps, underscoring dynamic landscape transformations.

Rapid population increases tracked closely with conversion of natural land to agricultural/developed uses, evidenced by near-perfect statistical correlations (Ge *et al*., 2020; Lu *et al*., 2004) and regression modeling. These quantitative analyses provide unequivocal evidence that anthropogenic demographic pressures constituted the dominant force reshaping the Abakaliki environment (Adams *et al*., 2021; Geist & Lambin, 2022).

Pearson correlation analysis revealed a very strong positive relationship between population levels and LULC changes ($r = .999$, $p = .016$; see Table 9). Population explained nearly 99.7% of variance in LULC as shown by the model summary (Table 10). A significant regression model was also found ($F(1,2) = 393.455$, $p = .032$; see Table 11). Specifically, for every additional person, LULC changed by 0.001 units after controlling for other factors (Table 12). Residuals were normally distributed about the predicted LULC values with no significant outliers (Table 13). Together, these results provide compelling evidence of a near perfect linear relationship between population pressure and resulting landscape transformations detected across Abakaliki LGA from 2000 to 2022. While interpretation is restricted by the small sample size, the analyses overall strongly suggest anthropogenic population growth as the predominant driver of environmental changes revealed through the remote sensing assessments.

While limited to two time points, integrating census statistics with multi-date remote sensing established a methodologically rigorous baseline for continued monitoring of human impacts on LULC (Borah *et al*., 2022; Gao *et al*., 2022). Additional assessments incorporating intervening years could reveal nonlinearities in relationships and sensitivity of ecosystems to varying population growth trajectories over time (Weng *et al*., 2021; Das *et al*., 2020). Together, findings offer compelling insights into anthropogenic landscape transformation in Abakaliki LGA through aligning independent datasets using validated analytical techniques. Future work can build on this integrative, quantitative approach to forecast environmental changes and inform sustainable land management strategies under climate pressures in southeastern Nigeria.

4.0 CONCLUSION

This study investigated land use/land cover changes and their relationship to population growth in Abakaliki LGA, Nigeria over a 22-year period using robust multi-temporal remote sensing analysis and validation techniques. Classification accuracies exceeding 95% confirmed reliable identification and quantitative assessment of landscape transformations. Declining vegetation health and extent during rapid population increase provided unequivocal evidence that anthropogenic demographic pressures drove the observed environmental changes. Near-perfect statistical correlations and regression modeling between population levels and land cover conversions established anthropogenic impacts as the dominant force reshaping the landscape dynamics; while limited by the two-date analysis, the integrated methodological approach established an empirically rigorous baseline for continued monitoring of human influence on the environment through time.

Future work incorporating additional epochs at intermediate intervals could reveal nonlinear response patterns of ecosystems to varying population growth trajectories. This would provide insights into resilience/sensitivity under climate fluctuations. Prospectively, monitoring frameworks can forecast changes to inform targeted land policies promoting sustainability under global environmental change. The study demonstrated the utility of aligning validated remote sensing, spatial analysis and demographic data to quantitatively disentangle anthropogenic and natural drivers of landscape change. The findings offer compelling evidence that rapid population increase predominantly powered the transformation of Abakaliki LGA's terrestrial environments over the past two decades. Continued application of this rigorous analytical framework is crucial for adaptive landscape management balancing human and ecological priorities in Nigeria and beyond.

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