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Geographically Weighted Regression and Ordinary Least Squares in Assessing Urban Growth; A Case Study of Uyo Metropolis, Nigeria

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ABSTRACT

The need for urban studies has grown in recent years as issues on urbanization continue to contribute to global processes. Sustainability of urban development is currently receiving more attention due to the fact that urban lands play significant roles in ecologically, socioeconomically, and culturally shaping global ecosystem. This paper performed GIS-based Ordinary Least Squares (OLS) regression and Geographically Weighted Regression (GWR) in order to analyse and explain urban growth in Uyo metropolis and its environs. The spatio-temporal land use/land cover analysis performed with Landsat satellite images using the maximum likelihood supervised classification showed that spatial extent of urban land had increased from 75.64 km^2 to 128.56 km^2 while all other land uses continued to diminish between 2003 to 2023. The OLS model averagely explained 50 % of the variations and relationships between identified urban drivers and urban growth with an adjusted R-squared value of 0.5172 while GWR explained over 70% of the variations in urban dynamics of Uyo metropolis with adjusted R-squared value of 0.7156. All the urban variables used in the analysis were statistically significant at 95% confidence interval. The study highlighted the effectiveness of remote sensing and GIS as useful tools in environmental modelling. It also highlights performance of OLS and GWR in assessing urban expansion and predicting urban growth patterns within a given region thereby providing powerful insights to city planners and developers.

Keywords: Geographically weighted regression (GWR), Ordinary least squares (OLS), Urban growth, Uyo metropolis, Remote sensing and GIS

INTRODUCTION

Urban expansion is a global occurrence which is characterized by the rapid transformation of natural land cover into new urban settlements. As more people live in the world, rural and agricultural lands are swiftly turning into cities, mostly in developing countries. Over the past few decades, the world has witnessed unprecedented levels of urbanization, driven by population growth, economic development, and industrialization. In 1950, approximately 30% of the global population lived in urban areas, but by 2020, this figure had risen to over 55%, with projections suggesting that it will exceed 68% by 2050 (Mahmoud *et al.*, 2016). This rapid urban growth presents both opportunities and challenges, particularly in developing countries of the world where urbanization comes with several adverse effects on ecological wellbeing of the place, bearing effect on urban sprawl, waste management and proper utility spread.

In developing nations, urbanization has become synonymous with economic growth as cities continue to evolve into commercial hubs. Unplanned urban expansion often leads to significant challenges, which often results in inadequate access to basic services such as water, sanitation, and healthcare. These issues underscore the urgent need for comprehensive studies that quantify and model urban growth to inform sustainable urban planning, management and development.

Geographically weighted regression (GWR) has been employed in literatures to analyse temporal shifts in urban land uses identifying regions with significant urban expansion due to several urban driving factors referred to as explanatory variables. Drivers ranging from environmental, physical, and socioeconomic aspects influencing land use changes in an area of study can be assessed by this model. However, before implementing GWR model, these variables need to undergo analysis through the ordinary least squares regression (OLS) model. GWR is a spatially explicit models helpful to land use planners and managers because these models consider the arrangement of urban expansion and its relationship with urban variables over space and time (Noresah and Sanjay, 2019), it offers crucial insights regarding the locations of these land use variations. The data produced also enhances the understanding of spatial and temporal dynamics associated with land use alterations in a region.

MATERIALS AND METHODS

Study Area

Uyo is one of the fast developing cities in Southern Nigeria and like most Nigerian cities, it faces urban growth which is driven by several environmental and socio-economic factors. Uyo is the administrative capital of Akwa Ibom State, an oil producing state in Nigeri. Uyo metropolis spans across about nine local government areas within the state and it is still expanding as more developmental strides occur. Geographically, it lies between Longitudes 07^{0}45' E and 08^{0}05' E and Latitudes 04^{0}52'N and 05^{0}07'N respectively.

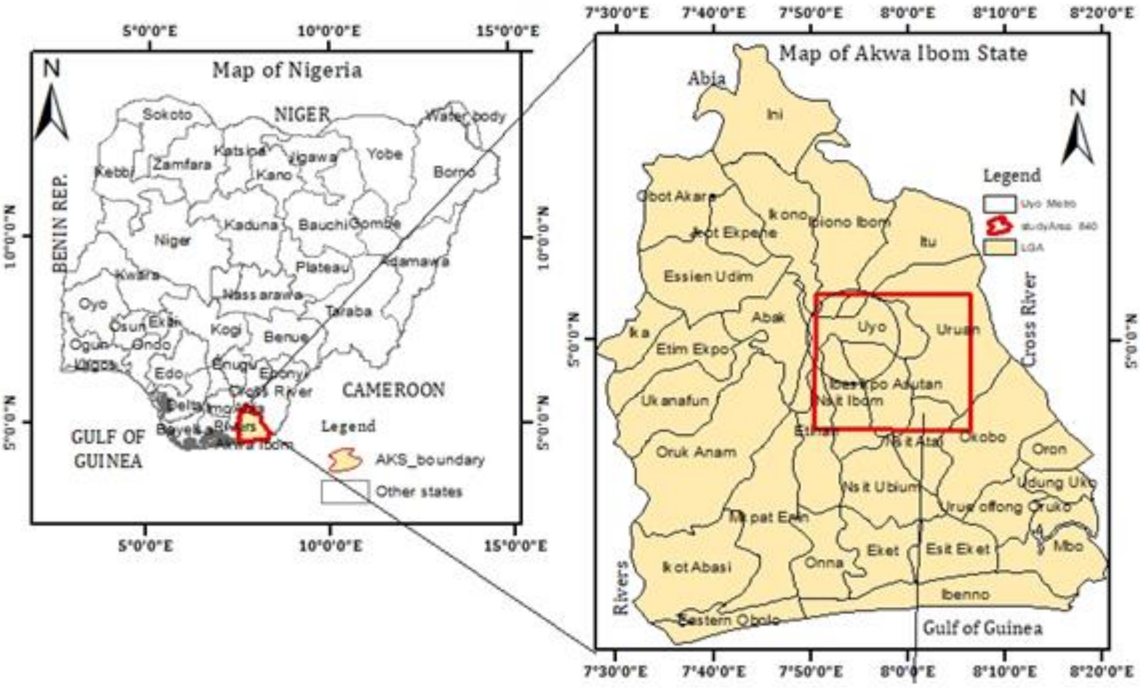

Figure 1.0 Study area map

Data

The data set used for this study and the sources included;

1. Multispectral satellite images Landsat 7 of path 186 rows 56 and 57 of 8th January 2003 and 3rd January, 2013 and Landsat 8 satellite images 30th January, 2024 downloaded from Earth Explorer website. These was used to derive the Land Use/ Land cover map and to calculate Normalized Difference Built-up Index (NDBI) of the study area. 2013 image was corrected for scanline error using the gap fill data.

2. 4 scenes of the Shuttle Radar Thematic Mapper (SRTM) Digital Elevation Model (DEM) downloaded from Earth Explorer website was mosaiced together and used to generate Fill and Slope in ArcGIS pro.
3. Administrative boundaries and road network data of study area was downloaded from open street map website as shapefiles. These shapefiles also contained boundaries of notable geographic features also considered in this study.
4. Population data, population growth rate and income potential data were obtained from Akwa Ibom State Government (AKSG) Ministry for Economic Development, and Nigerian Bureau of Statistics (NBS) websites respectively.

Information on urban expansion; dependent variable and independent variables were extracted based on the grid centre points. Eleven explanatory variables (Table 1.0) were used in assessing urban expansion for 2003 to 2013 while ten explanatory variables were used for that of 2013 to 2023 prediction model.

Table 1.0 Summary of Independent Variables Extraction

	Input data type	**Variables**
Proximity/Location variables	Polyline shapefile Points shapefile Point shapefile Point shapefile Polyline shapefile Point shapefile Point shapefile	x_1: Distance to roads x_2:Distance to urban settlements x_3: Distance to UNIUYO Town campus x_4: Distance to city centre x_5: Distance to UNIUYO main Campus x_6: Distance to Ibom Ravine x_7: Distance to International Airport
Socio-economic variables (Weighted variables)	Raster Raster	x_8: Population density x_9: Income potential
Topographic/ environmental variables	Raster Raster	x_{10}: Digital Elevation Model (DEM) x_{11}: Slope
	Raster	x_{12}: Normalised Difference Built-up Index (NDBI)

The observed data of 2003 were used to predict 2013 urban expansion and observed data of 2013 were used to predict 2023 urban expansion, that is, independent variables of previous year were used to predict urban expansion of future year. Extracted values for independent variables were normalised to [0, 1] by applying Equation 1.0 using field calculator in ArcMap attribute table. Scaled values were calculated thus;

$$x_i' = \frac{(xi - min)}{(max - min)} \quad \text{Equation (1.0)}$$

where x_i' is the scaled variable; min is the lowest value in the land use vector; max is the highest value in the land use vector; and xi represents the land use variables (Table 1.0). This scaling method is effective in making all independent variables to be equally weighted (Okwuashi, 2011).

METHODOLOGY

Land Use/Land Cover Classification

The maximum likelihood supervised classification algorithm in ERDAS imagine software was utilised to classify land uses within the study area. Placing every pixel in an image into distinct land use/land cover classes in order to identify spatial patterns and extract valuable thematic information is the primary goal of image classification. This was done on the basis of surface reflectance properties of the Landsat multispectral images. Standard 'false' colour composite of Bands 4, 3, and 2 (Red, Green, and Blue) for Landsat 7 Enhanced Thematic Mapper plus ETM+ and Bands 5, 4 and 2 (Red, Green, and Blue) of Landsat 8 Operational Land Imager/ Thermal Infrared Sensor (OLI/TIR) sensor were used to improve visualization of different land covers.

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Table 2.0 Description of Land use/land cover classes

S/N	Land use/ land cover types	Description
1.	Urban land	Tarred roads, pavements, buildings (commercial, educational, residential, administrative, religious, recreational), communication and utility networks.
2.	Thick Vegetation	Dense vegetation with darker shapes of red as in 'standard false colour' composite, swamps naturally growing within the ravine region, thick deciduous trees.
3.	Light Vegetation	Lighter forests with less trees than the thick forest.
4.	Agricultural land	Recently ploughed land, burrow pit/excavated lands, dredged spoil, bare soil, grasses, farm lands, crop lands, horticulture.
5.	Water	Natural or artificial water bodies including Rivers, lakes, ponds, streams etc.

For each predetermined land cover/land use type, training samples were selected by delimiting polygons around representative sites and spectral signatures of each land cover types were recorded using the pixels enclosed by these polygons. In order to avoid a misclassification of features due to mixed pixel or clustering of pixels, great attention was paid to ensure that only clearly distinctive pixels were bounded by the polygons. This went a long way to reduce confusion as a satisfactory spectral signature classification is the one that ensures that there is 'minimal confusion' among the land cover types mapped. The problem of mixed pixels was addressed by taking the mean of several delimited polygons.

Ordinary Least Squares (OLS), and Geographically Weighted Regression (GWR)

This section explored the method undertaken in performing OLS and GWR models to assess urban expansion in Uyo metropolis and environs. Although OLS does not meet certain statistical assumptions of linear models, it is still considered as an important tool in understanding spatial relationships among variables in spatial data science. While OLS model provided information regarding the significance of the explanatory variables; the GIS-based GWR model does not do so (Okwuashi, 2011). When estimating regression model parameters, GWR takes into account the spatial structure of the data and illustrates how those estimates change over time (Noresah, 2010).

The reclassified land use maps of 2003, 2013 and 2023 had 30m x 30m cell size. To perform the GIS based modelling, ArcGIS required that the number of pixels within the study area is not too large else, an error message is returned. The land use map of the study area was therefore grided using the fishnet tool at 500m x 500m grid interval created over the entire study area. A total of 3065 square grids were generated. This ensured that cell size was increased and number of pixels within the study area reduced thereby reducing matrix size and rescaling the data size downwards. The X,Y coordinates of the grid centroid served as a spatial reference for analysis.

OLS and GWR Equations for 2003 – 2013 and 2013 – 2023 epochs are given respectively;

OLS_2003 – 2013 = $\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{11} x_{11} + e^i$ Equation (2.0)

OLS_2013 – 2023 = $\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{10} x_{10} + e^i$ Equation (3.0)

GWR_2003 – 2013 = $\beta_0 + \beta_1 x_1(u_{1,} v_1) + \beta_2 x_2 (u_{2,} v_2) + \cdots + \beta_{11} x_{11}(u_{11,} v_{11}) + e^i$ Equation (4.0)

GWR_2013 – 2023 = $\beta_0 + \beta_1 x_1(u_{1,} v_1) + \beta_2 x_2 (u_{2,} v_2) + \cdots + \beta_{10} x_{10}(u_{10,} v_{10}) + e^i$ Equation (5.0)

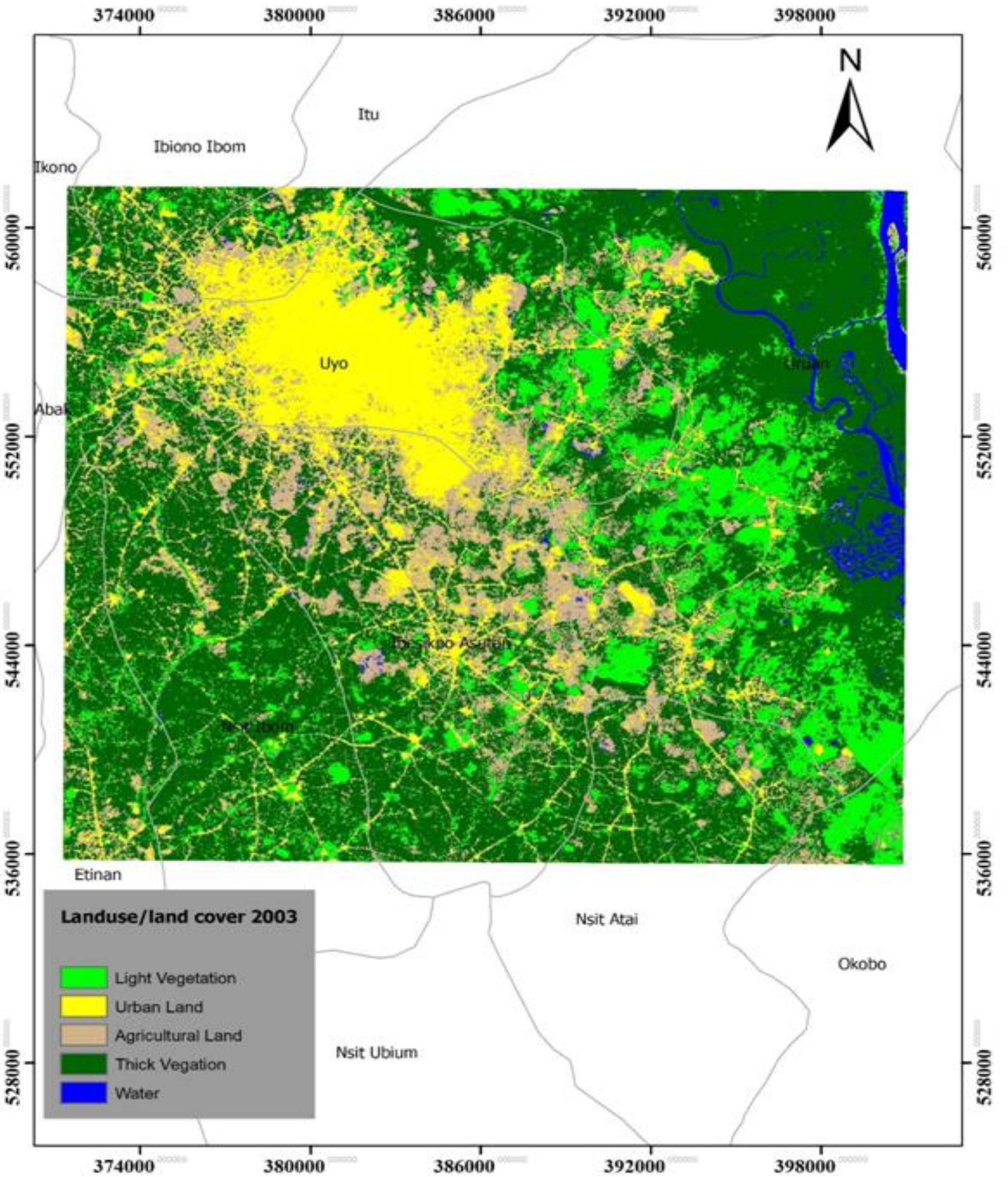
The meaning of the explanatory variables ($x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_{9,} x_{10}, and\ x_{11}$) are given in Table 1.0. In equations 2.0 to 5.0, β_0 is the intercept; $\beta_{1,..}$ β_{11} are the coefficients of the independent variables; u, v are the horizontal coordinates; and $e^i$is the error term.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VIII August 2025

The OLS and GWR models were processed in ArcGIS pro and do not require training data to build the prediction model. An overlay analysis was performed to produce a map with three land use types which included urban region, change region, and non-urban regions, the dependent variable was represented as discrete data rather than continuous data.

RESULTS/DISCUSSION

Land use/Land cover changes in Uyo metropolis and environs



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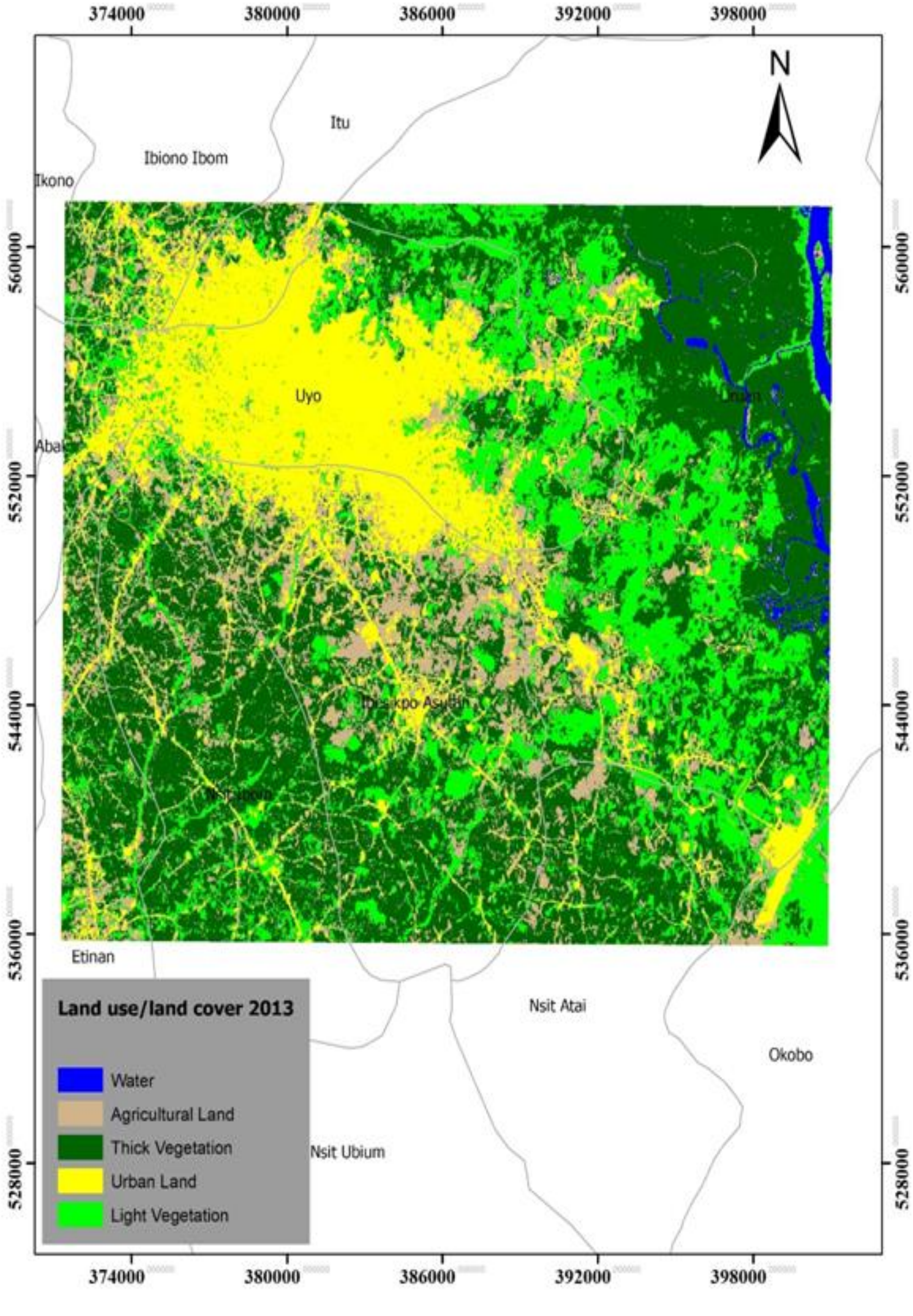

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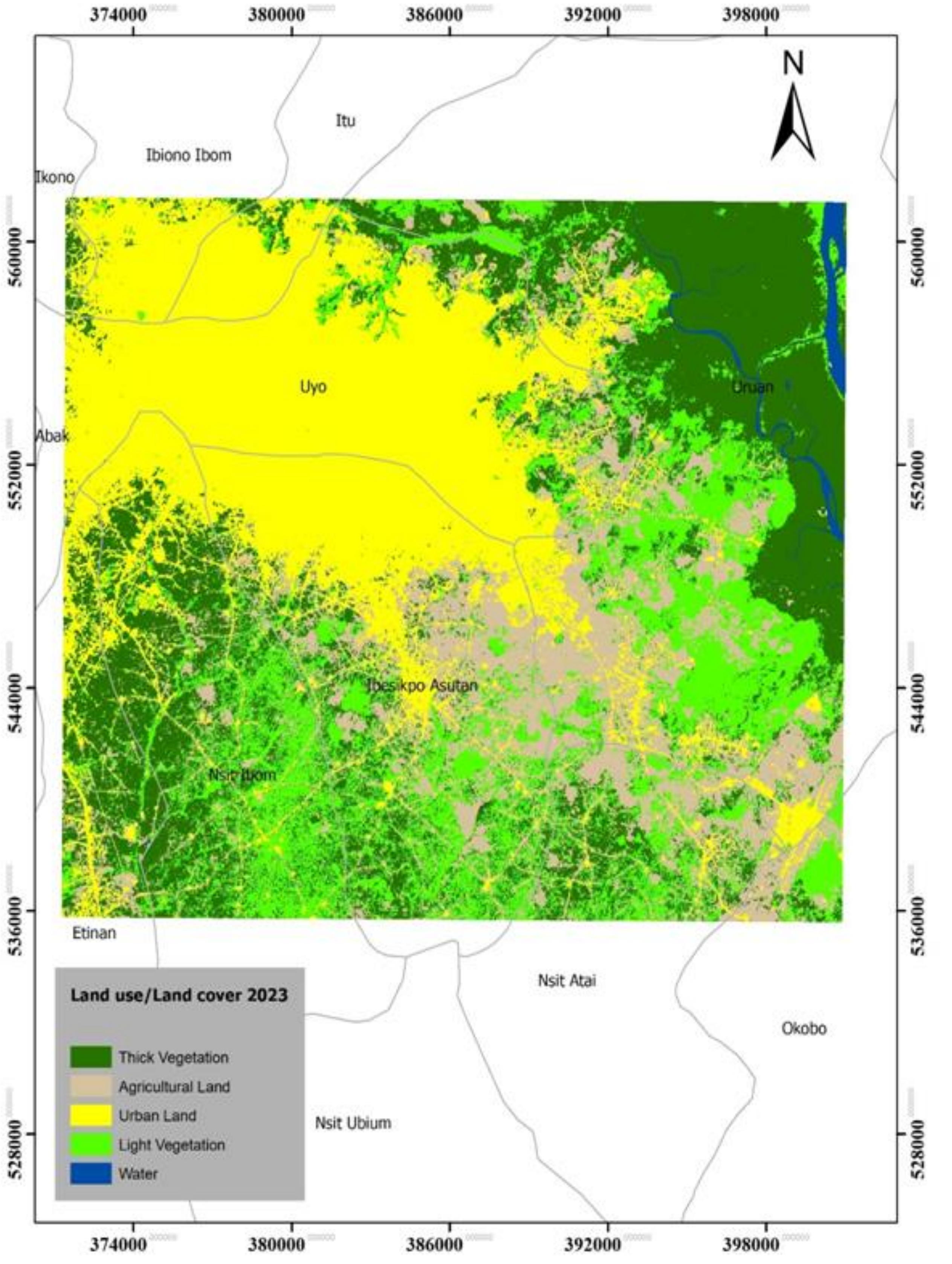

C

Figure 2.0: Land use/Land cover classification of Uyo metropolis and environs in 2003 (A), 2013 (B), and 2023 (C) respectively

The results of visualizing urban land use classification represented in Figure 2.0 shows robustness of the maximum likelihood supervised classification in satellite image classification studies to delineate different land uses is demonstrated.

Table 2.0: Conversion matrix of LULC change in Uyo metropolis from 2003 - 2013

	LULC 2013 in square kilometre						
		Agricultural Land	**Light Vegetation**	**Thick Vegetation**	**Urban Land**	**Water**	**Row Total**
LULC 2003	Agricultural Land	**54.60**	22.04	28.94	39.74	0.23	145.56
	Light Vegetation	7.94	**57.45**	29.55	6.81	0.10	101.86
	Thick Vegetation	47.60	74.32	**270.39**	16.30	1.08	409.69
	Urban Land	12.21	4.70	2.60	**75.64**	0.03	95.19
	Water	1.05	0.36	4.27	0.23	**7.19**	13.09
	Column total	123.41	158.87	335.76	138.72	8.62	**765.38**

Table 3.0: Conversion matrix of LULC change in Uyo metropolis and extent from 2013-2023

	LULC 2023 in square kilometre						
		Agricultural land	**Light vegetation**	**Thick Vegetation**	**Urban land**	**Water**	**Row total**
LULC 2013	Agricultural Land	**44.87**	9.38	12.86	56.03	0.26	123.41
	Light Vegetation	36.84	**67.82**	24.39	29.67	0.14	158.87
	Thick Vegetation	51.66	81.37	**168.08**	34.20	0.47	335.77
	Urban land	8.15	1.65	0.69	**128.13**	0.10	138.72
	Water	0.18	0.16	2.69	0.02	**5.57**	8.62
	Column total	141.70	160.39	208.71	248.05	6.55	**765.40**

Table 2.0 indicated that major variations between the periods of 2003 and 2013 took place in thick vegetation class (270.39 Km^2) followed by urban land classes (75.64 Km^2), light vegetation class (57.45 Km^2), agricultural land (54.60 Km^2), and water (7.19 Km^2). Likewise, the results in Table 3.0 also showed that significant variations between the periods of 2013 and 2023 occurred in thick vegetation class (168.08 Km^2) followed by urban land classes (128.13 Km^2), light vegetation class (67.82 Km^2), agricultural land (44.87 Km^2), and water (5.57 Km^2). It is seen that while every other land use class apart from light vegetation class reduced between the two time periods, urban land continued to increase in spatial extent.

Table 4.0: Accuracy Assessment of LULC classification

Class name 2003	**Light vegetation**	**Urban Land**	**Agricultural land**	**Thick vegetation**	**Water**	**Sum row**	**User accuracy**
Light Vegetation	9	0	0	1	0	10	0.9
Urban Land	0	8	2	0	0	10	0.8
Agricultural Land	0	0	8	2	0	10	0.8
Thick Vegetation	0	1	2	23	0	26	0.88
Water	0	0	1	1	8	10	0.8
Sum column	9	9	13	27	8	66	0
Producer accuracy	1	0.89	0.62	0.85	1	0	0.84 **Kappa index** 0.80

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VIII August 2025

2013							
Light vegetation	9	0	0	1	0	10	0.9
Urban Land	0	10	0	0	0	10	1
Agricultural Land	1	0	9	0	0	10	0.9
Thick vegetation	1	0	2	19	0	22	0.86
Water	0	0	0	1	9	10	0.9
Column Total	11	10	11	21	9	62	0
Producer accuracy	0.82	1	0.82	0.90	1	0	0.9 **Kappa index** 0.87
2023							
Light vegetation	0	1	0	9	0	10	0.9
Urban Land	0	6	10	0	0	16	0.63
Agricultural Land	1	7	2	0	0	10	0.7
Thick vegetation	14	0	0	0	0	14	1
Water	1	0	0	2	7	10	0.7
Column Total	16	14	12	11	7	60	0
Producer accuracy	0.88	0.5	0.83	0.82	1	0	0.78 **Kappa index** 0.73

The accuracy assessment was important in order to measure the difference between user's classification and the ground truth data. The accuracy of classification was measured through Kappa index which was derived from computed error matrices. The kappa coefficient for the years 2003, 2013 and 2023 was 0.80, 0.83 and 0.73 respectively.

GIS-based Ordinary Least Square Modelling

(i) Assessing OLS Model Significance: In assessing the significance of the OLS model, it was important to check that the explanatory variables selected can effectively estimate regression coefficients to model the dependent variable. The Koener (BP) statistics value from our model was significant, therefore, the Joint Wald statistics from the GIS based OLS (Table 5.0) is used to test overall model significance.

The significance of the Koener (BP) statistics imply that the relationships modelled are not linearly consistent either due to non-stationarity or heteroskedasticity. In a linear regression model, traditional statisticians presume that the variance or homoscedasticity between the explanatory variables is equal. However, spatial statisticians believe that the global OLS model is unable to handle the issue of non-stationarity because it does not take spatial variation into account (Okwuashi, 2011), Hence the BP statistics is significant. This implies that the model is not stationary.

The significant findings derived from Joint Wald Statistics suggested that the explanatory variables can effectively estimate the regression coefficients.

Table 5.0: Joint Wald Statistic for 2003 – 2013 and 2013 - 2023 (*significant at $p<0.01$)

Periods	Joint Wald statistics	Degree of freedom	p-value
2003 - 2013	9422.081081	11	0.000000*
2013 - 2023	21977.795607	10	0.000000*

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VIII August 2025

Table 6.0: Jarque-Bera Statistic for 2003 – 2013 and 2013 - 2023 (*significant at p<0.01)

Periods	Jarque-Bera statistics	Degree of freedom	p-value
2003 - 2013	355.225359	2	0.000000*
2013 - 2023	23.736845	2	0.000007*

(ii) Assessing the significance of each explanatory variables in the OLS Model: The GIS-based OLS model was used to investigate the significance of each explanatory variable. The results presented in Tables 7.0 and 7.0 are ArcGIS pro outputs that show the statistical significance of each explanatory variable used in the model. The computed adjusted R-squared values for 2003 – 2013 and 2013 - 2023 epochs were 0.536572, and 0.557694 respectively; while the calculated adjusted R-squared values for periods 2003 – 2013 and 2013 - 2023 were 0.534931 and 0.557252 respectively.

The hypothesis for assessing the significance of each explanatory variable is stated as follows:

H0 : the coefficients of explanatory variables are zero at the 95% CL

H1 : the coefficients of explanatory variables are not zero (reject H0 if p-value < 5%)

Table 7.0: Statistical results to assess the significance of each explanatory variable in the model for 2003 - 2013 (*significant at p < 0.01, or t-statistics > 1.96)

Variables	Coefficient	t-Statistic	Probability (p-value)	VIF
Intercept	-1.002442	-3.580053	0.000014*	--------
NDBI	0.932575	10.892256	0.000000*	1.837357
Income Potential	-1.167552	-0.880137	0.464191	6.111834
Population density	0.002016	12.409112	0.000000*	61.291332
Ravine	0.000049	9.135217	0.000000*	5.696509
Distance to UNIUYO Town campus	-0.000031	-1.331791	0.132029	336.754444
Distance to City Centre	0.000112	4.780575	0.000000*	288.654756
Distance to major roads	-0.000041	-4.218056	0.000245*	9.250198
Distance to urban settlements	-0.000044	-4.116661	0.000179*	7.954677
Distance to international Airport	-0.000042	-10.554848	0.000000*	10.533626
DEM	0.006225	11.375032	0.000000*	5.063075
Slope	-0.000000	-6.426769	0.000001*	1.243502

Asterisk (*) indicates a coefficient is statistically significant (p < 0.01)

Table 8.0: Statistical results to assess the significance of each explanatory variable in the model for 2013 - 2023 (*significant at p < 0.01, or t-statistics > 1.96)

Variables	Coefficient	t-Statistic	Probability (p-value)	VIF
Intercept	-0.268520	-6.119520	0.000000*	--------
NDBI	1.658652	30.987397	0.000000*	1.590548
Income Potential	13.769875	30.798554	0.000000*	3.118003
Population density	-0.000209	-9.036227	0.000000*	3.862945
Ravine	-0.000051	-15.021467	0.000000*	33.376709
Distance to UNIUYO Main campus	0.000044	13.597038	0.000000*	26.161956
Distance to major roads	-0.000063	-15.627240	0.000000*	2.640707

Distance to urban settlements	-0.000016	-6.473961	0.000000*	2.011870
Distance to international Airport	0.000016	13.781257	0.000000*	7.453820
DEM	0.004142	13.647021	0.000000*	2.628322
Slope	-0.000000	-1.759105	0.100454	1.200053

Asterisk (*) indicates a coefficient is statistically significant ($p < 0.01$)

Explanatory variables whose p-values were asterisked (*) was only one and were all significant at ($p < 0.01$) CL. Out of the 11 variables used for 2003 to 2013 epoch, all were found to be statistically significant apart from distance to university of Uyo town campus found to be non-significant at 99% CL. For 2013 to 2023 period, all explanatory variables were significant apart from slope at 99% CL.

The higher the value of the calculated t-statistic of an explanatory variable, the greater its impact in the model on the other hand the smaller the p-value of an explanatory variable, the greater its influence in the model. Similar to the t-statistic, an explanatory variable's impact in the model increases with an equivalent increase in the absolute value of regression coefficients. Considering the absolute values of regression coefficients, from tables 7.0 and 8.0, income potential had the highest influence on the model followed by NDBI and elevation while slope had the least influence for 2003 to 2013 time period. Also, for the 2013 to 2023 period, income potential had the highest influence on the model followed by NDBI. Slope had the least influence for this time period.

The signs of the regression coefficients of the independent variables show how independent variables and predicted dependent variable are related. Increase in the values of the explanatory variables with positive coefficients will result in more developed cells in the model. Conversely, if the values of the explanatory variables with positive coefficients fall, the model's number of developed cells will also fall. If the values of the explanatory variables with negative coefficients increase, the number of developed cells will decrease; conversely, if the values of the explanatory variables with negative coefficients decrease, the number of developed cells will increase.

(iii) Assessing the performance of the OLS Model: Conventional statistics presume that the linear regression model lacks multicollinearity, meaning that the explanatory variables do not precisely correlate with one another (Noresah, 2010). The OLS model as a parametric does not require variables to be normally distributed but it assumes a linear relationship between dependent and independent variables. This section will attempt to assess the model performance with respect to some conventional statistical assumptions of linear models. The last column of tables 7.0 and 8.0 contains the variance inflation factor (VIF) of the independent variables in the model. VIF values < 7.5 - 10 are considered useful and model is free from multicollinearity. Multicollinearity occurs when the explanatory variable is similar to a linear combination of other predictors. Higher VIF values show that the model is not free of multicollinearity. This explains the need to have more explanatory variables in the model. Distance to city centre and distance to UNIUYO town campus had the highest VIF values for the 2003 – 2013 model while distance to ravine and distance to UNIUYO main campus were the highest VIF in 2013 – 2023 model.

To check normality, the scatter plot of the OLS result showed that a histogram plot between dependent and independent variable does not show a normal distribution. One drawback of using discrete variables for the dependent variables is that it may violate the OLS's normality and homoscedasticity assumptions. Jarque-Bera Statistics was used to test if residuals are normally distributed. From table (7.0), the calculated p-value for the two epochs were less than 0.05, this indicated that residual deviated from a normal distribution.

Histogram plot of the model residuals shown in figures 3.0 and 4.0 also indicated a deviation from the normal. Moran I test was also carried out on predicted residuals to check for normality.

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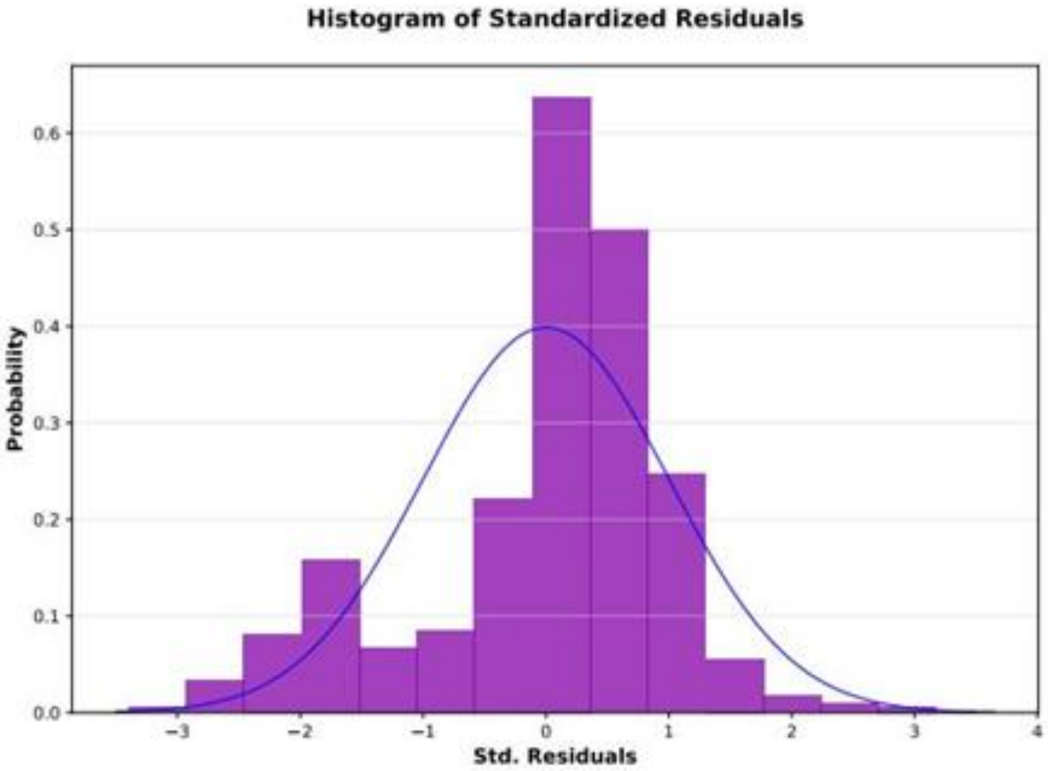

Figure 3.0: Histogram plot of 2003 – 2013 OLS residuals

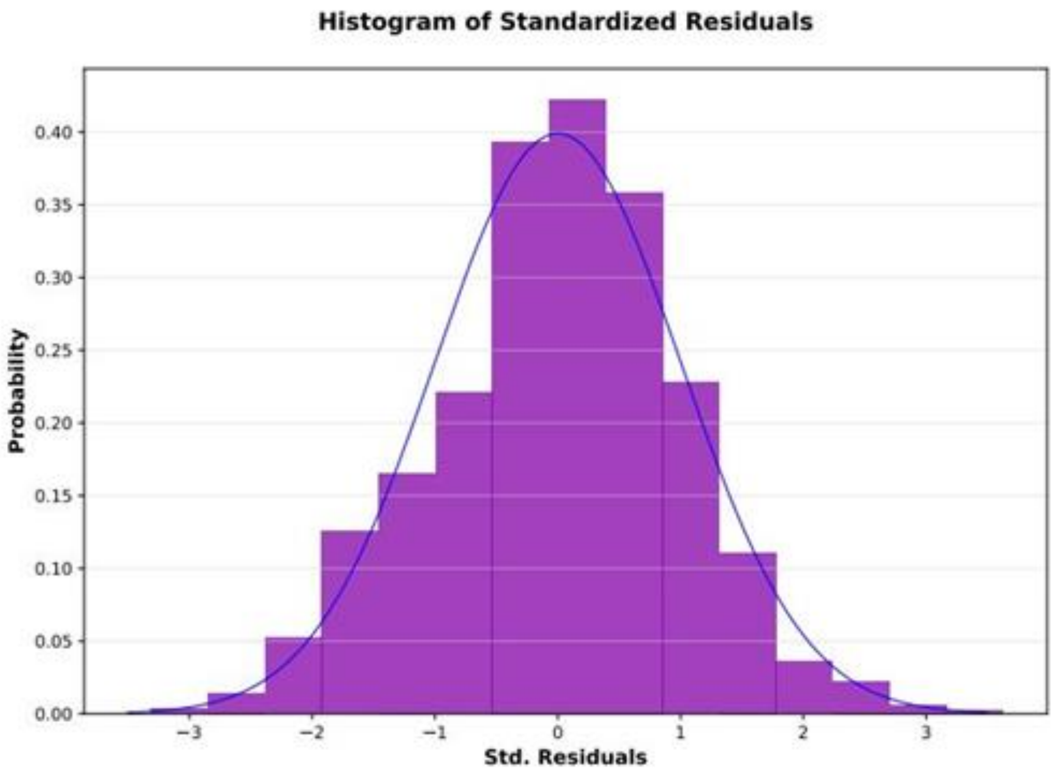

Figure 4.0: Histogram plot of 2013 – 2023 OLS residuals

(iv) Spatial Autocorrelation: In spatial statistics, spatial autocorrelation is used to get information on how spatial variables interact with the environment. If the spatial distribution of the model residuals exhibits a systematic pattern, the spatial variable is said to be spatially autocorrelated. The residual represents the discrepancy between the actual and anticipated value. A variable is said to be positively spatially

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VIII August 2025

autocorrelated if it is influenced more by nearby areas. Also, if a variable is more influenced by farther areas, then it is negatively autocorrelated in the environment. When no positive or negative spatial autocorrelation exists in the model residual, then the pattern is said to be random.

Table 9.0: Spatial Autocorrelation Test for 2003 – 2013 and 2013 – 2023 OLS and GWR residuals using Moran I tool to test model significance

Periods	Moran I index	variance	z-score	p-value
2003 – 2013 OLS	0.069742	0.000164	5.475262	0.000000
GWR	0.280464	0.000164	21.93434	0.000000
2013 – 2023 OLS	0.043448	0.000009	14.930163	0.000000
GWR	0.250592	0.000164	19.601288	0.000000

The presence of spatial autocorrelation in the model was tested using the model residuals and Moran's I tool. Moran I values near +1 signify positive spatial autocorrelation, those near -1 signify negative spatial autocorrelation, and those near zero signify randomness in the model residuals. The Moran's I tests (Table 9.0) above shows Moran I index for 2003 – 2013 and 2013 – 2023. The values were near zero. These findings demonstrated that the model residuals were random rather than spatially autocorrelated. This holds true for both OLS and GWR models.

Assessing Performance of OLS and GWR models

While OLS is important to assess relationships between dependent and independent variables via analyzing the regression coefficients, GWR provides a localized model often used. GWR is also subject to fundamental statistics assumptions mentioned above. This was due to the fact that the GWR approach has the benefit of estimating local parameters and exposing intriguing patterns of spatial variation or parameter non-stationarity (Noresah, 2010). It is crucial to evaluate the performance of the local GWR model as well as the global OLS model in making predictions. Akaike's Information Criterion (AIC) measures model performance between different regression models. The model with a lower AIC value is thought to be more accurate. Given that its values were substantially lower than those of the GWR model, the AIC results (Table 10.0) demonstrated that the OLS model offered a better fit for the independent variables.

Table 10.0: Calculated AIC values for GIS-based OLS and GWR regression models

Periods	AIC values for OLS	AIC values for GWR
2003 – 2013	1962.527334	6166.5818
2013 – 2023	6353.115582	5042.816

The R^2 was used to assess the goodness-of-fit for predicting changes in the two periods. R^2 measures how well the independent variables explain the variation in the dependent variable. Adjusted R-squared adjusts model for the number of predictors in the model. Values close to 1 indicate the model fits the data perfectly.

Table 11.0: Calculated R- squared values for OLS and GWR

Periods	Adjusted R^2 OLS	Adjusted R^2 GWR
2003 – 2013	0.5349	0.5955
2013 – 2023	0.5572	0.7156

Results of Global OLS models suggested that urban land expansion in Uyo metropolis and environs could be explained by the explanatory variables used but amount of variation explained by the model was limited. The r-square values of the OLS model showed that the model could explain 53% of the variation in urban expansion for 2003 – 2013 and 55% variation in 2013 – 2023. Also, GWR explained about 60% of the

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variations in urban growth for 2003 – 2013 model and over 70% of the variations in growth for 2013 – 2023. All variables were statistically significant ($p<0.05$).

Generally, result obtained suggested that new urban settlements had caused significant impact on the land use pattern in the metropolis during the period under study. In majority of cases the agriculture, vegetation land and fallow land were occupied by new urban land for housing, commercial or industrial purposes. Most of these changes had been through Government policies actualize through opening up of roads and basic infrastructures.

CONCLUSION

Satellite imagery obtained via remote sensing technique has proven to be useful in providing data for spatial temporal information relevant for urban studies. It was evident that urban and built up lands had increased significantly in the study area during the period 2003 – 2023. As shown in the results of OLS, and GWR modelling, urban expansion in Uyo metropolis and its environs was significantly explained using the two techniques. The OLS model identified the nature of relationship between independent variables and dependent variable; urban expansion. This illustrated that urban drivers identified in this study had significantly contributed to growth in urban density within the study area. Distance to major roads, distance to city center, distance to settlements, distance to UNIUYO town campus, distance to UNIUYO main campus, distance to ravine, population density, income potential, NDBI, DEM and slope were significant ($p < 0.01$) in the two time periods for these models. Only NDBI and slope were not significant in 2003 – 2013 time period and 2013 – 2023 epoch respectively. OLS model averagely explained relationship between drivers and urban growth while GWR did a more better explanation giving over 70 percent explanation. This study is significant to urban planners and developers in fostering understanding of nature, extent and pattern of urban expansion in Uyo metropolis as well as understand what driving factor is most responsible for these changes.

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