Urban Land-Use Change Detection Using Multi-Temporal Satellite Imageries: A Case Study of Isuikwuato Local Government Area in Abia State, Nigeria

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SUMMARY

It is necessary to have information about Land Use Land Cover (LULC) patterns change over time not only for urban planning purposes, but also for improving the management of the use of land resources. This study has demonstrated the importance of using Remote Sensing and GIS techniques to produce accurate LULC maps and change statistics in Isuikwuato Local Government Area (LGA) over the last two decades, which is valuable to monitor urban expansion effectively over time. A supervised Maximum Likelihood classification algorithm was applied to the Landsat images of 2000, 2015, and 2022 because it allows decisions about change to be made at the pixel level which minimizes the error criterion in the classified image over a large number of individual pixel classifications, the images were classified into a built-up area, open land, vegetation, and water bodies. Then, the classified images were used to determine land use/cover change between 2000 and 2015, and also between 2015 and 2022. The built-up class represents an urbanized area that provided an indicator of urban expansion. The results of LULC change detection of the study area showed that built-up area covered 25.902 km^2 in 2000, 33.326 km^2 in 2015 and 126.873 km^2 in 2022 or 5.93%, 7.63% and 29.06% of the study area respectively. This represents a net increase of 100.971km^2 in 22 years, which is mainly attributed to the rapid increase in population. During the period of 2000 to 2022, there was a decrease in both the vegetation and open land, which were converted to urban areas due to population growth. However, urban expansion had increased during the same period, which was considered as a key indicator that urban planning strategy should be given more attention. The increase in the built-up area is an indication of the rapid growth of the population and this may remain a challenge unless an environmentally friendly policy on land use is implemented to harmonize the demand and diminish the impacts that arise from it. This study may be use as a useful benchmark, to foster better decisions and improve policies in land use within the framework of a sustainable land use planning system.

KEYWORDS: *Urban Land Use/Land Cover (LULC) classification, Change Detection, Multi-Temporal Satellite Imageries, Remote Sensing, and GIS.*

1. INTRODUCTION

The urban areas of any country are by no means static. It changes overtime. As days and years go by, the urban landscape is altered. Development as well as growth in infrastructural amenities, affects the land use land cover. Globally, rapid population growth is intense in cities and is a major factor in land-use change (Onilude and Vaz, 2021). Man's dependence on the physical environment for his basic needs has led to land transformation, alteration, and modification, resulting in severe degradation and destruction of the abiotic and biotic components of the environment (Ujoh et al. 2010). According to Oseni et al. (2020), every parcel of land on the Earth's surface is unique in the cover it possesses. Land use and land cover are distinct yet closely linked characteristics of the Earth's surface. The use to which man put land includes among others grazing, agriculture, urban development, logging, and mining among many others, whereas land cover categories comprise cropland, forest, wetland, pasture, roads, and urban areas, among others. The term land cover originally referred to the kind and state of vegetation, such as forest or grass cover but its scope has been broadened in subsequent usage to include other things such as human structures, soil type, biodiversity, surface, and groundwater (Oseni et al. 2020).

Land Use / Land Cover generally refers to the categorization or classification of human activities and natural elements on the landscape within a specific time frame based on established scientific and statistical methods of analysis of appropriate source materials. Land use/land cover changes are very dynamic and have to be monitored at regular intervals for sustainable environmental development. Comprehensive information on the spatial distribution of the land use/land cover categories and the pattern of their change is a prerequisite for planning, utilization, and management of the land resources of the country.

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Olaleye et al. 2012). Change detection is an important process in monitoring and managing natural resources and urban development because it provides a quantitative analysis of the spatial distribution of the activities of interest. Olaleye et al.(2012) identified four aspects of land-use change detection that are important: (i) Detecting the changes that have occurred (change/no-change), (ii) Identifying the nature of the change, (iii) Measuring the areal extent of the change and (iv) Assessing the spatial pattern of the change.

Remote Sensing (RS) and Geographic Information System (GIS) have been recognized as powerful and effective tools and widely applied in detecting the Spatial-temporal dynamics of land use and land cover (Ujoh et al. 2011).The study was aimed at analyzing the urban land use and land cover changes in Isuikwuato Local Government Area over the last two decades using geospatial technologies. This aim was achieved through the following objectives:

i. Producing the land use land cover map of the study area for the years 2000, 2015, and 2022.
ii. Carrying out change detection analysis vis-a-vis determination of the trend, nature, and rate of land use and land cover change of the study area.

2. THE STUDYAREA

Isuikwuato Local Government Area (LGA) in Abia State is situated in the Southeast geopolitical zone of Nigeria. The name Isu-Ikwu-Ato translates from Igbo as 'three Isu families or lineage' and refers to the three lineages descended from the Isu people, in what is now a local government area. Geographically, Isuikwuato Local Government Area is located between 5^{o}30'00" E and 7^{o} 30'00" N and is made up of several towns and villages such as Ohaise, Imenyi, Ezere, Uturu, Umunnekwu, Mbaugwu, Isu Amawu, and Ndiagidi (Figure

1.). According to the 2021 world statistical data, the Isuikwuato LGA has an estimated population of 151,700 inhabitants (United Nations -World Population Prospects), spread over a total area of 374.80km^2 with a population density of 404.8 per square kilometer with the vast majority of the area's dwellers being from the Igbo ethnic division. The notable landmarks in the area include the Abia state University Uturu and the Uhuchukwu cave in AhabaImenyi. The Local Government Area is the site of the Abia State University Uturu, Gregory University, and several post-secondary schools. Isuikwuato has natural resources such as iron ore and kaolin. The major land use/ land cover present in the study site are built-up, water bodies, vegetation such as trees, shrubs, farmland and open lands.

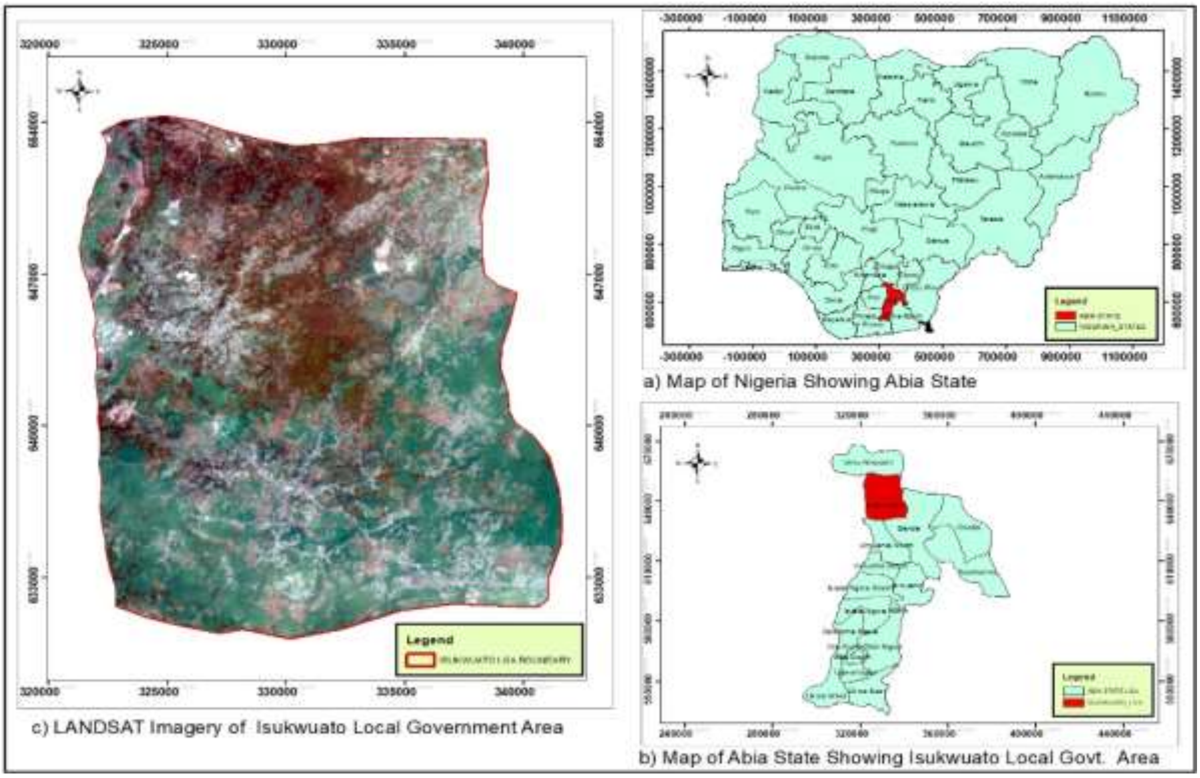

Figure1: *Location map of the study area (a) in Nigeria (b) in Abia state and(c) Land sat imagery of Isuikwuato Local Government Area*

Table 1: Data sources

S/N	Data	Acquisition date	Scale	Source

1	Landsat 7 ETM	2000-12-17	30m ™	U.S. Geological Survey(USGS)
2	Landsat 8 OLI_TIRS	2015-01-17	30m ™	U.S. Geological Survey(USGS)
3	Landsat 8 OLI_TIRS	2022-02-05	30m ™	U.S. Geological Survey(USGS)
4	Google Earth Imagery	2022-06-25		Google Earth
5	Administrative Map of Nigeria			OSGOF
6	Road Network			Geofabrik

Source: Author's work (2022)

In this study, ArcGIS 10.7 software was used for pre - processing, processing of the data and visualization of the maps/results. While Franson Converter software was employed to transform the various datasets to a uniform coordinate system (WGS84-UTM zone 32N projection).

3. DATA PROCESSING

The datasets used for this study were from different data sources and thus are in different coordinates systems. Therefore, these datasets were transformed into a uniform coordinates system using the Franson Converter Software. Spatial consistency was attained by processing all data to a spatial resolution of 30 m and WGS84-UTM zone 32N projection. The shape file of the study area was extracted from the Administrative Map of Nigeria and all images were clipped out according to the study area. Then, the composite image bands were generated which allows the right band combinations that reflect different surface features for the selection of training. Thereafter, the Land sat image of the respective period was classified into four land cover types (vegetation, built-up area, open land, and water bodies) using the Maximum Likelihood Classification (MLC) algorithm (Ujoh et al. 2010; Ghosh et al.2014). The Maximum-likelihood allows decisions about change to be made at the pixel level, which minimizes the error criterion in the classified image over a large number of individual pixel classifications. Based on the prior knowledge of the study area, the classification scheme was developed using the modified Andersons land use/ land cover classification scheme (Anderson et al. 1976). Thus, the respective class was given a numerical value from 1 – to 4 (Table2). Polygons were used for training samples of each class and for built-up lands, a total of 98 training samples were used, for vegetative covers it was 110 training samples while open lands it was 98 training samples and water bodies have a training sample of 48 samples. The training samples were acquired based on a combination of visual interpretation of pan sharpen landsat images of 2000, 2015 and 2022, ground truthing information, Google Earth Imagery and local knowledge of the study area.

Table 2: Land use and land cover classification scheme

Code	LULC Category	Description
1.	Built-up lands	All residential, commercial, and industrial areas, village settlements, and transportation infrastructure

2	Vegetation covers	Trees, shrub land and semi-mature vegetation, deciduous, coniferous, and mixed forests, palms, orchids, herbs, gardens, and grasslands
3	Open lands	Fallow land, earth and sand land infillings, construction sites, excavation site, solid waste landfills, open space and exposed soil, rocky areas, dry grasses, etc.
4	Water bodies	River, permanent open water, lakes, ponds, canals, and Reservoirs

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Source: Author's work (2022)

3.1 Data Analysis

One of the common post-processing steps applied to satellite images is classification. In most cases, classification is performed to reveal the patterns in land cover in the area of interest. Since a satellite image is made up of pixels, image classification aims at semi-automatically categorizing pixels into different land covers. The Maximum Likelihood classification, which is the most widely, used per-pixel method by taking into account spectral information of land cover classes, was applied in this study. The maximum likelihood classifier considers not only the cluster centers but also the shape, size and orientation of clusters. This is achieved by calculating a statistical distance based on the mean values and covariance matrix of the clusters.

Furthermore, the accuracy assessment process compares the classified image to another data source called ground truth data which is considered to be of superior accuracy (Olofsson et al. 2014). For this study, high-resolution Google Earth image was used as base map for the ground truthing. Having provided satisfactory measure of accuracy, the classified images were utilized to analyze land use/cover change and how much change has occurred and the trend of change. Also, Digital change detection analysis was carried out using the most widely used method which is Post Classification Change Detection (PCCD) method which can generate a thematic map for each date and provide specific "from to" change information. The first step for Post Classification Change Detection was to stack multi temporal images into one single vector(X).Suppose there are two images dated time i and time j available for the detection of land-use changes, these two images can be referred to as two-pixel vectors (see Eqn. 1a –1c):

$$X_i = [X_{i1}, X_{i2}, \ldots \ldots \ldots .., X_{in}] \quad (1a)$$

$$X_j = [X_{j1}, X_{j2}, \ldots \ldots \ldots .., X_{jn}] \quad (1b)$$

$$X_{mt} = [X_{i1}, X_{i2}, \ldots \ldots \ldots .., X_{in}, X_{j1}, X_{j2}, \ldots \ldots \ldots .., X_{jn}] \quad (1c)$$

Where X_{i1} to X_{in} and X_{j1} to X_{jn} are the brightness values of the pixel X in bands from 1 to n for the time i and j, respectively. X_{mt} is a stack of multi temporal images, mt = multi-temporal

Comparison of the land use/cover maps and their statistics assisted in identifying changes, and determining the trend, rate, and magnitude of change between 2000, 2015, and 2022(Figure 2 and Table 3).

4. RESULTS ANDDISCUSSION

4.1 Classification Results

Using the maximum likelihood algorithm, land cover maps were generated for all study years (figure 2) and area estimates and statistics were computed. For each of the maps, four distinct land use/cover classes were identified; these are vegetation, built-up area, open land, and water bodies. The vegetation is depicted in green, built-up areas in red, open land in light yellow and water bodies in blue. The class statistics for each year are presented in Table 3. Computation of the area occupied by each class in their respective year allowed for detecting an increase and or reduction in land use/cover. From the quantitative analysis, are duction in open land and vegetation land cover is detected between 2000 and 2022, compared to the built-up area that has shown extensive growth.

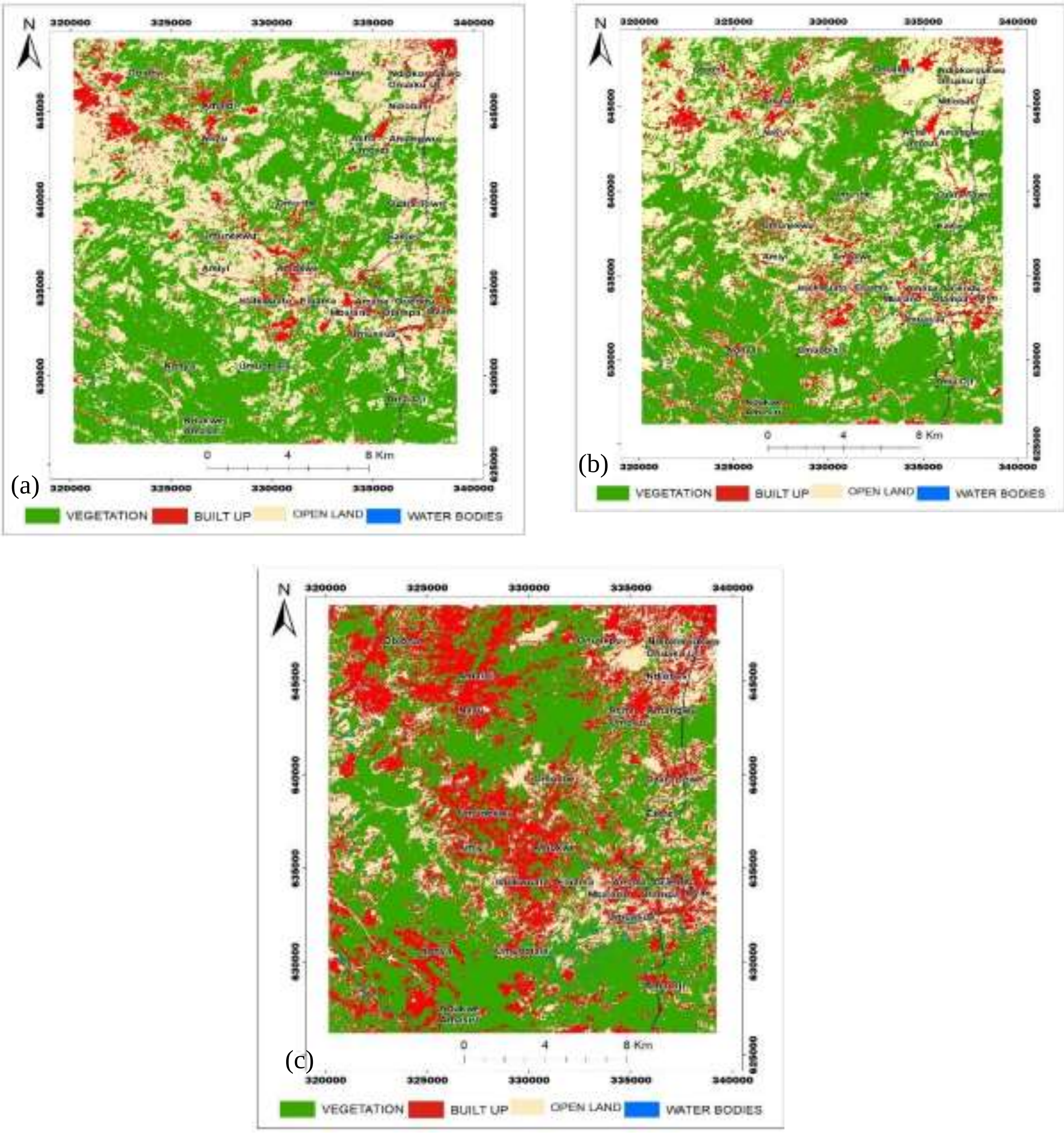

Figure 2: classified maps of (a) 2000, (b) 2015, and (c) 2022

Table 3: Land use/cover class statistics

Land use/cover	Area coverage (in km²)					
	2000	**%**	**2015**	**%**	**2022**	**%**
Vegetation	235.833	54.01	227.663	51.37	225.128	51.78
Built up	25.902	5.93	33.326	7.63	126.873	29.06
Open land	174.841	40.04	175.385	40.17	83.738	19.18
Water bodies	0.050	0.01	0.252	0.06	0.887	0.20
Total	436.626		436.626		436.626	

Source: Author's Work (2022)

4.2. Classification Accuracy Assessment

A minimum of 90 pixels were considered stratified by each land cover type. Relatively stable features such as road intersections and landmarks were used for the sampling of control pixels. The results of this accuracy assessment are presented in Table 4, 5 and 6 as land cover/use change confusion (error) matrices for 2000, 2015 and 2022. The column of confusion (error) matrices contains the classes of pixel in ground-truth or validation set. While the row show the classes that pixels have been assigned to. The diagonal show pixels classified correctly by the classifier. According to Olaleye et al. (2012), the land-cover classification accuracy of 85% and above is considered accurate. For kappa statistic, kappa coefficient within the range of 0.8 to 1 indicates very good lands cover/ use classification (McHugh, 2012). The overall accuracy for classification is 86.723 percent, 95.870 percent, and 89.017 percent for epoch 2000, 2015, and 2022 respectively and Kappa coefficient is 0.818, 0.932, and 0.847 for time stamp of 2000, 2015, and 2022. In the context of classification error as expressed in the error matrices, more built-up class pixels were misclassified or wrongly as other classes. This trend was consistent across the time epoch of the study.

Accuracy (%) = Total True Sample / Total Sample Taken

Table 4: showing the classification accuracy assessment for 2000

Classification	Ground reference(pixel)					
	Built-up Land	Vegetation	Open Land	Water Bodies	Total	User's Acc. (%)
Built-up Land	79	11	8	0	98	80.612
Vegetation	4	96	10	0	110	87.273
Open Land	0	11	87	0	98	88.776
Water Bodies	0	0	3	45	48	93.75
Total	83	118	108	45	354	
Producer's Acc. (%)	95.180	81.356	80.556	100		
Overall Acc. (%)	86.723					
Kappa Coeff.	0.818					

Source: Author's Work (2022)

Table 5: showing the classification accuracy assessment for 2015

Classification	Ground reference(pixel)					
	Built-up Land	Vegetation	Open Land	Water Bodies	Total	User's Acc.(%)

Built-up Land	84	3	6	0	93	90.323
Vegetation	2	93	0	0	95	97.895
Open Land	0	2	94	0	96	97.917
Water Bodies	0	3	0	52	55	94.545
Total	86	101	100	52	339	
Producer's Acc.(%)	97.674	92.079	94	100		
Overall Acc. (%)	95.870					
Kappa Coeff.	0.932					

Source: Author's Work (2022)

Table 6: showing the classification accuracy assessment for 2022

	Ground reference(pixel)					
Classification	Built-up Land	Vegetation	Open Land	Water Bodies	Total	User's Acc. (%)
Built-up Land	93	4	1	0	98	80.6120
Vegetation	0	104	8	0	112	87.273
Open Land	19	6	80	0	105	88.776
Water Bodies	0	0	0	31	31	
Total	112	114	89	31		
Producer's Acc. (%)	83.036	91.228	89.888	100		
Overall Acc. (%)	89.017					
Kappa Coeff.	0.847					

Source: Author's Work (2022)

4.3 Urban Land-Use Changed Detection

Comparison of the land use/cover maps and their statistics assisted in identifying changes, and determining the trend, rate, and magnitude of change between 2000, 2015, and 2022 (Figure 3 and Table 7). In Figure 3, the rate of change in the respective land use/cover type across the years observed is shown. Between 2000 and 2022, the vegetation land cover and the open land have reduced from 54.01% to 51.56% translating to a loss of 10.705km^{2}of land and 40.04% to 19.18% (91.103km^2) of open land respectively. Whereas the built-up area increased from 5.93% to 29.06% (100.971km^2). Unlike the other land cover categories, a subtle increase and variation of percentage water body (0.011% to 0.058% and 0.203%) was observed between 2000, 2015 to 2022 in the study area. This may be attributed to erroneous classification of other land cover/land use as water body or increase of artificially made water bodies especially in the rainy season.

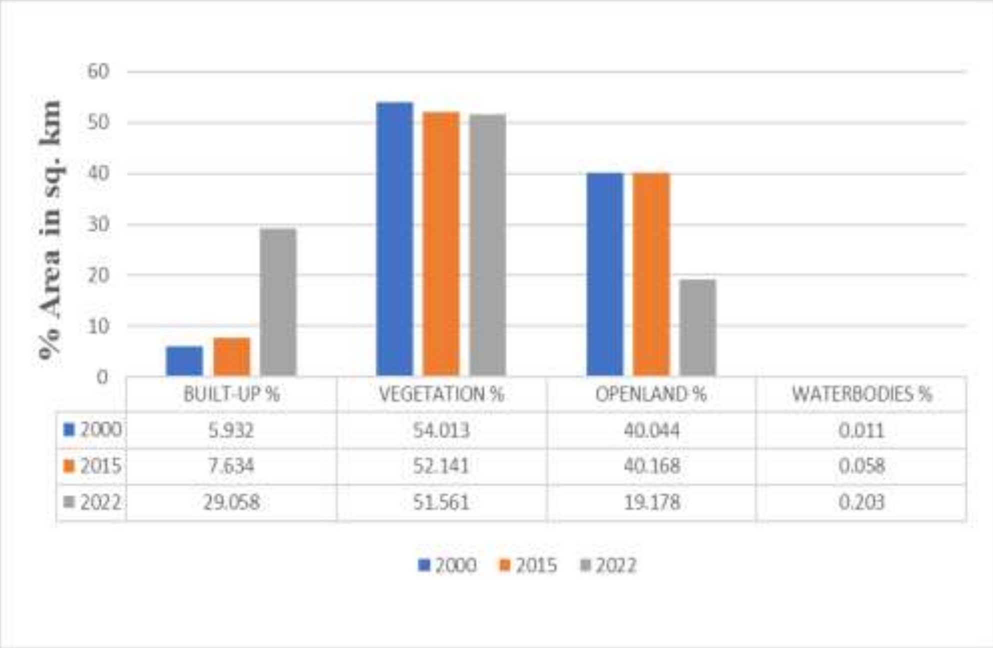

Figure 3: Land use/cover change pattern and percentage change

Source: Author's Work (2022)

Table 7: Class Area change and change trend

Land Cover/Use Categories	2000 – 2015 Area(Km^2)	2015 – 2022 Area(Km^2)	2000 - 2022 Area(Km^2)
Vegetation	-2.535	-8.17	-10.705
Built-up	7.424	93.547	100.971
Open land	0.544	-91.647	-91.103
Water bodies	0.202	0.635	0.837

Source: Author's Work (2022)

The built-up class represents an urbanized area that provided an indicator of an urban expansion. From the analysis of the classified maps, it is evident that the LGA has expanded tremendously from 25.90km^2 in 2000 to 33.33km^2 in 2015, and 126.86km^2 in 2022 at a rate of 28.68%, 280.62%, and 389.81%, respectively (Tables 3 and 7).Since the basic aim of the creation of the Isuikwuato Local Government Area council is to get an infrastructural allocation, ecological funds, and other socio-economic development from the federal government through the state to help the community dwellers, thus the area is in the transition from rural to urban status, so it is witnessing many development activities. In the last two decades, the area has witnessed a significantly rapid expansion in all directions. This may be attributable to the massive growth in industrialization, an influx of higher institutions of learning, and consequently booming economic activities all of which are population pull factors. Along with these developments, there is always an inclination towards the construction of new pavements, highways, roads, and other structures to ensure access to common amenities. An increase in population brings about an increase in the demand for goods and services. This in turn puts pressure on environmental resources and invariably threatens urban sustainability.

Nevertheless, the growth recorded has resulted in a significant loss in open land and vegetation and an increase in urban-related hazards. In recent history also, the area has experienced sustained flooding events with great impacts on the socio-economic lives of the inhabitants.

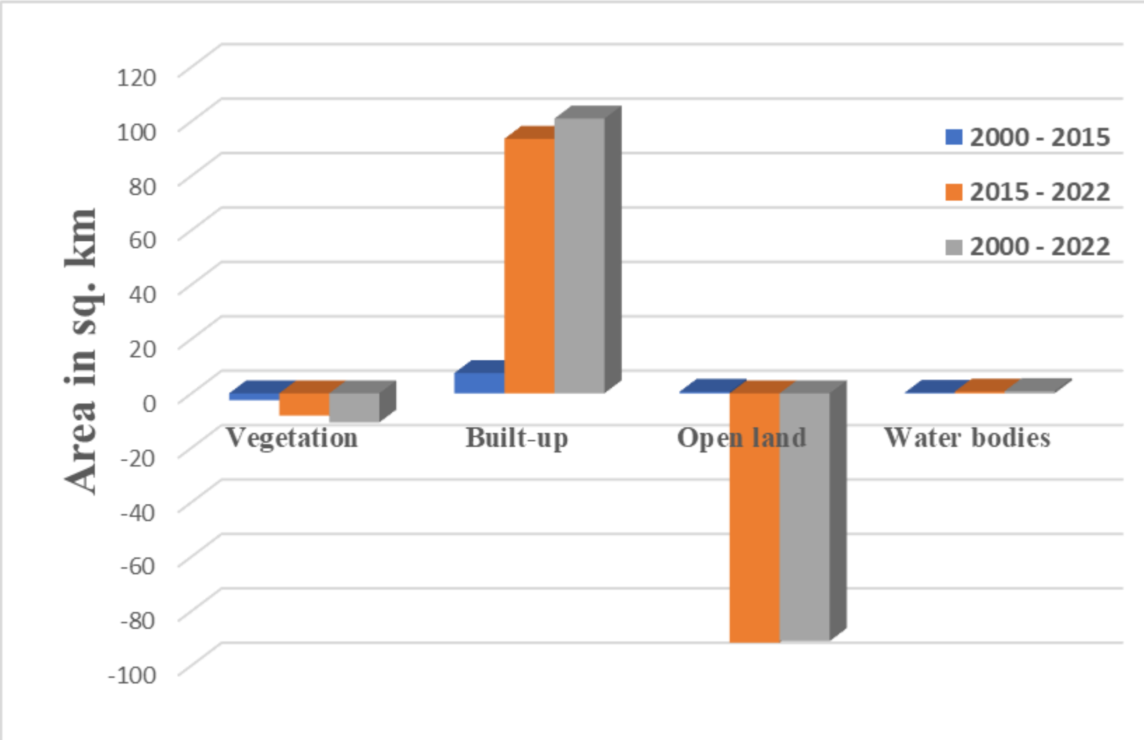

Figure 4: Histogram of the Land use changes from 2000 – 2022
Source: Author's Work (2022

The change detection map in Fig.5 depicts rapid expansion of urbanized area within Isuikwuato Local Government Area evident over time. The map revealed that urban expansion intensity is higher towards the west and south of the area. These areas are places of increasing development pressure and urban expansion. Expansion of the already existing urban fabrics through rapid construction sites of residential units, commercial and industrial units and road networks and pavements port and leisure facilities and other impervious surfaces all combined together leads to continuous expansion of built-up surfaces in the different corners of the LGAs.

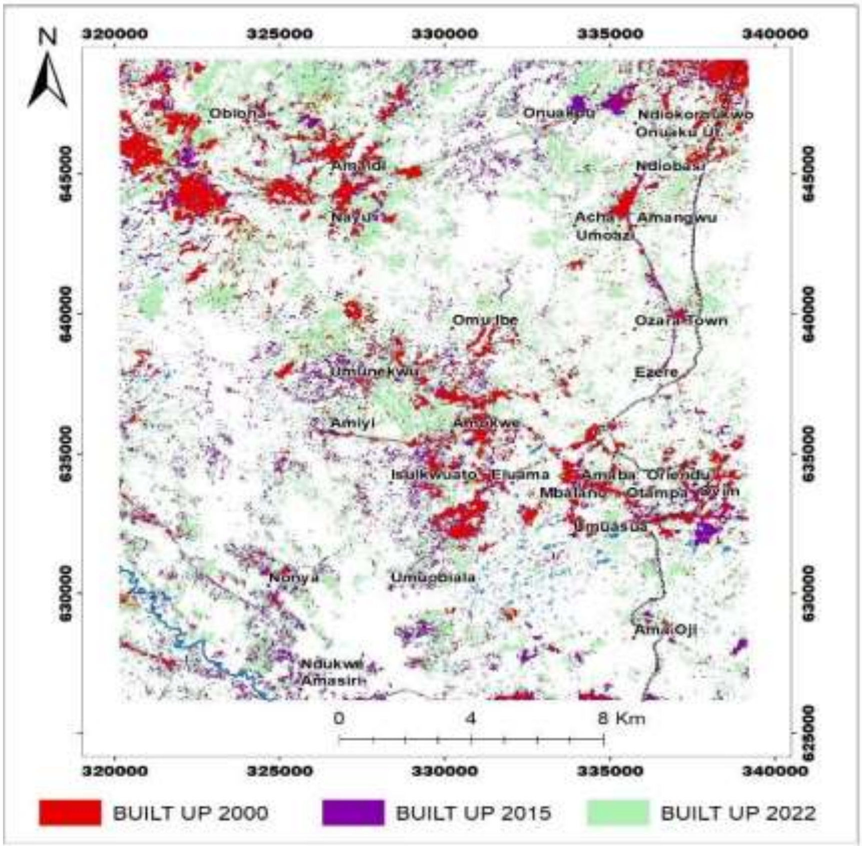

Figure 5: Post-classification overlay of the Land use changes from 2000 – 2022

5. CONCLUSION

The objectives of this study was to produce the land use/cover map and carry out change detection analysis vis-a vis determination of the trend, nature, and rate of land use and land cover change of the study area between 2000 to 2022 using multi-temporal Land sat datasets. The geospatial techniques provide accurate, cost-effective, and spatial dynamics of the land cover from 2000 to 2022. It is inferred from our investigation that changes have been taking place in the study area particularly during the recent two decades. It is revealed that the changes and expansion observed occurred in all directions, which has equally led to the loss of much of the agricultural and open lands. The inference made out of the finding is that uncontrolled urban growth has had negative implications as witnessed in the recent decade when the city has been facing incidents of frequent flooding and there have been cases of burst pipe, which have had severe effects on the local economy and environment. The methodology employed in this study, along with ground-truthing and field inventory will be useful in understanding the land use development, future planning, and proper management. The approach can also be used to assess and estimate future population pressure on the land demands for various developmental activities for any area of interest. In addition, these notable relevant findings can also be considered as a strategic guide to land-cover planning, and help local authorities (policymakers, urban planner, natural resources managers, and land-cover management organizations) better understand a complex land-cover system and develop the improved land-cover management that can better balance urban expansion and ecological environment conservation.

6. RECOMMENDATION

To alleviate the dramatic land use/land cover change and adverse environmental impacts of urban expansion and increasing built-up surfaces, the current growth pattern needs to be managed through effective land use planning and management. A review of existing Master Plans for the major centers and the preparation of an integrated regional Master Plan for the state as a whole are essential. The state must also review the existing Town Planning Laws and Regulations per the Nigerian Urban and Regional Law (Decree 88 of 1992). This would be useful to protect the fertile agricultural land in the region and further reduce environmental degradation. With the area becoming even more urban in the future, there is a need to focus on the urban population, as this is a key factor in the country meeting its overall economic and development goals. In addition, the Government should as a matter of urgency embark on Land use/Land cover mapping in the entire region in order to facilitate accurate base map producing of Abia State. The region should therefore pursue the management of increasing population and the elimination of insecurity alongside with protection of the environment and natural resources to achieve sustainable development. Finally, the Surveyors Council of Nigeria (SURCON) and The Nigerian Institution of Surveyors (NIS) as a professional body of surveying profession should do a collaborative work with the institution in order to carry out more research on urban land use dynamics.

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