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Evaluation of Land Cover Dynamics and Landscape Fragmentation in Ijebu Ode, Nigeria

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Abstract

Landscape fragmentation has been found to be a major consequence of urbanization and land use/cover (LULC) changes. Thus, this study analyzed the spatiotemporal land use/land cover changes in Ijebu Ode, Nigeria, between 1986 and 2021. This is with a view to assessing the pattern of landscape fragmentation in the study area. The study used data obtained through a Global Positioning System (GPS) receiver and satellite imagery (Landsat 5 MSS/TM, 1986; Landsat 7 ETM+, 2000 and 2014; and Landsat 8 OLI/TIR, 2021). The data were analyzed using spatial landscape metrics. Results indicated that Ijebu Ode has witnessed a dramatic increase in built-up areas between 1986 and 2000 by 11.03%, 2000 to 2014 (65.24%), and 2014 to 2021 by 131.25%. Expansion of the built-up area was aided by reductions in bare land (1986 to 2000, 15.78%; 2014 to 2021, 98.27%), and the cultivated area by 47.74% between 1986 and 2014. Landscape metrics were estimated over the four epochs of the study. The results revealed that most of the metrics suggest similar trends over the entire period of study. However, the Largest Patch Index (LPI), Landscape Shape Index (LSI) and Normalized Landscape Shape Index (NLSI) were useful in capturing the spatio-temporal variations in landscape transformation. Also, Class Area (CA) was useful to show the degree of land cover change. The study concluded that the location of spatial structures influenced the landscape patterns and urbanization processes in the study area. Hence, the study recommended regular monitoring of the expansion of the built-up area to check for imminent urban sprawl in the study area.

Keywords: *land use, landscape fragmentation, spatial metrics, landscape pattern, Ijebu Ode.*
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I. INTRODUCTION

Land use and land cover change (LULCC) is a continuous process which has both spatiotemporal connotations with great environmental implications. As a result, it becomes imperative to study the nature of changes in land use and land cover patterns across time and space [1]. However, in modern times, most of the conventional approaches for analyzing and evaluating spatial data appear rather inadequate for complex multi-factorial ecological studies. Thus, for a thorough examination and in-depth analysis of such studies, more advanced techniques are usually required. A popular approach of studying the LULCC is the adoption of Remote Sensing (RS) and Geographic Information Systems (GIS) tools [2-6]. In this regard, remotely sensed data are accessed to track the spatiotemporal dynamics of both accessible and inaccessible data on pixel basis. In geospatial studies, RS and GIS tools are used for thorough analysis, monitoring and managing of different types of land use and land cover (LULC) and their changing characters [7-10].

Studies have shown that GIS techniques can be used assess and predict future statuses of the LULCC dynamics. For instance, Cellular Automata (CA)–Markov has been adopted to assess the temporal and spatial LULC dynamics of the past and to predict the future [11-14]. Also, Leta, et al. [15] adopted Land Change Modeler (LCM) to achieve the same purpose. Furthermore, Mishra, et al. [16] employed the use of three hybrid models: stochastic Markov chain (ST-MC), cellular automata-Markov chain (CA-MC), and multi-layer perceptron-Markov chain (MLP-MC) to predict future LULC scenario used approach to quantify past, current and model the future changes of LULC. Wang, et al. [17] reviewed the possibilities of adopting traditional cellular automata to assess the current status, challenges and prospects of LULCC modelling.

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Landscape metrics, otherwise referred to as spatial metrics, is a very useful tool for quantifying and assessing the distribution, pattern and structure of land use and land cover [18-20]. The focus of landscape metrics is usually on three major characteristics of landscape: structure, function and change [20]. Different types of landscape metrics have been identified and applied to quantify and assess landscape fragmentation, both at level and class levels [14, 21-26]. Urban landscape fragmentation is usually the consequence of changes in landscape structure [18, 19, 27]. These changes are by-products of decreasing heterogeneity of landscape compositions and profound landscape fragmentation [28-34].

Ijebu Ode is the largest settlement inhabited by the Ijebus, in Southwest Nigeria. It has been the capital of the Ijebu kingdom since pre-colonial times. However, there is scanty of studies on Ijebu Ode. The only available study close to the topic at hand on the study area are the works of Bakare, et al. [35] who used remote sensing and GIS tools to analyze the spatio-temporal dynamics of wetland ecology. Another is the work of Onanuga, et al. [1] which analyzed the effects of urbanization on land and water resources in Ijebuland. The present study is focused on the analysis of landscape planning in the Study area. As such, the study used satellite imagery data to evaluate the nature and extent of urban land use change in Ijebu Ode, Nigeria between 1986 and 2021 and assessed the changes in landscape structure in the study area.

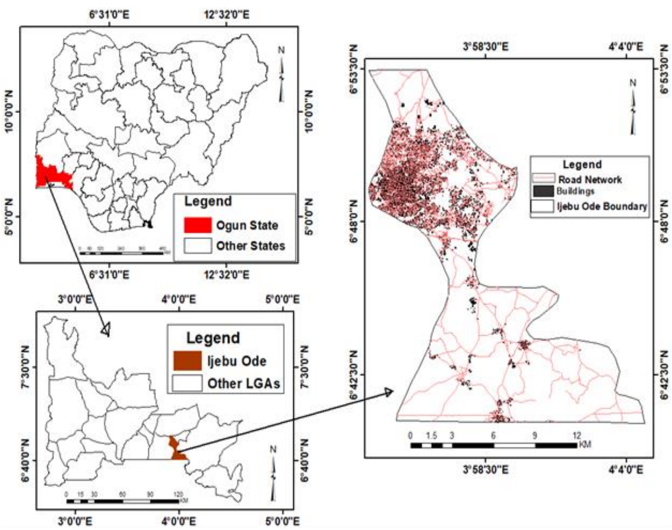

Fig. 1. Location of the study area

II. Study Area

This study was conducted in the ancient town of Ijebu Ode. It is one of the 20 Local Government Areas (LGA) that makeup Ogun State, Nigeria. The population of Ijebu Ode was 233,310 (National Population Commission, NPC, 2006). It covers an area of 190.543km² (Topographical map, Ijebu Ode Sheet 280 NE, 1963; Landsat 8 OLI/TIR, 2021). Ijebu Ode is located between latitudes 6º 28' N and 6º 49' N of the equator and longitude 3º 10' E and 3º 55' E of the Greenwich Meridian (Fig.1).

Ijebu Ode is the traditional and cultural headquarters of Ijebuland, the only kingdom that survived the political turbulent and anarchy that destroyed many Yoruba settlements during the inter-ethnic rivalries of the 18th and 19th centuries [36, 37]. The Ijebus are found in the south-central part of south western Nigeria. Whereas the largest part of Ijebu land is in Ogun State, modern Nigeria political division has placed three Ijebu-speaking Local Government Council Areas (Epe, Ibeju-Lekki and Ikorodu) under Lagos State [37, 38].

The study area has humid tropical climate with heavy annual rainfall, high temperature and relative humidity [39]. Like other parts of Nigeria, Ijebu Ode is characterized by wet and dry seasons. The annual rainfall is between 1575mm and 2340mm and the average annual temperature is 27.5°C [1, 40, 41]. The vegetation is tropical rain forest dotted in some parts by derived forest being altered by human activities [39, 42].

III. Materials and Methods

A. Data Sources and Acquisition

Data used for this study were extracted from Landsat 5 MSS/TM, 1986; Landsat 7 ETM+, 2000 and 2014; and Landsat 8 OLI/TIR, 2021 (Table I). Based on the availability of data, 1986 was selected as the base year of study; this was the first satellite imagery mission in Nigeria. However, to avoid omission and/or duplication of results, and to ensure adequate representation of data, 2000 and 2014 were selected at 14-year interval from the base year. The last study epoch, 2021, was selected as the current year. The imageries selected for the study were taken during the dry season when the weather was clear. The Landsat imageries were used to assess the spatiotemporal trends in the physical growth and expansion of the study area. Landsat 8 (2021), complemented with ground truthing using handheld Global Position System (GPS) receiver, was used as control for other images. In addition, topographical map of Ijebu Ode (Ijebu Ode Sheet 280 NE, 1963) was used to identify and map-out the shape file for the study area.

B. Data Processing

Data acquired for this study were processed using digital image processing techniques. First, the grid referencing systems of the imageries were transformed to one reference system; World Geodetic Survey (WGS) 1984, Universal Transverse Mercator (UTM) Zone 31N. Then, image enhancement and filtering were performed to increase the graphic quality of the imageries, then the pixels were clearly identified. Following this, extraction, rectification and classification processes were performed [43-45].

TABLE I. Sources and Characteristics of Dataset

Data	Year	Resolution/ Scale	Path & Row / Sheet No.	Source	Bands used
Topographical map	1963	1:50,000	Sheet 280 NE	Dept. of Geography, Obafemi Awolowo University, Ile-Ife.	
Landsat 5 MSS/TM	Dec. 24, 1986	28.5m	Path 191, Row 55	https://earthexplorer.usgs.gov	5,3,2

Landsat 7 ETM+	Feb 6, 2000	28.5m	Path 191, Row 55	https://earthexplorer.usgs.gov	4,3,2
Landsat 7 ETM+	Jan 6, 2014	28.5m	Path 191, Row 55	https://earthexplorer.usgs.gov	4,3,2
Landsat 8 OLI/TIR	Jan. 20, 2021	28.5m	Path 191, Row 55	https://earthexplorer.usgs.gov	5,4,3
GPS Coordinate	2021	N/A	N/A	Ground Truthing	N/A

C. Analysis of Data

1) Land Use/Cover Classification

Image classification was performed using supervised maximum likelihood classification algorithm (Table II). False color composite consisting of green, red and NIR bands were generated to visualize the heterogeneous patches of the study area. Attribute information corresponding to these polygons were obtained from the field using handheld GPS receiver and GoogleEarth Map [43, 46].

TABLE II. LAND USE/COVER CLASSIFICATION

S/N	Classes	Sub-class
1.	Built-up Area	All areas containing buildings: residential, commercial, institutions, markets, transportation and industrial
2.	Vegetation	Forest, scrublands
3.	Bare Surface	Sandy areas, outcrop areas, open/exposed soils, landfill/dump sites and areas of active quarry
4.	Cultivated Land	Farmland/crop land, orchards, vineyards, nurseries, mixed forest and plantation

Accuracy assessment was conducted to establish links between features on the ground and the features on the satellite images and to ensure accurate interpretation of the satellite imageries [46, 47]. Accuracies of data extracted from Landsat imageries were validated using topographical map, Google Earth map and ground truthing. Topographical map of the study area was scanned and imported into ArcGIS software (ArcMap 10.8.1) where it was geo-referenced and analyzed to identify 35 reference points. Also, GoogleEarth map of the study area was downloaded and digitized to extract 65 reference points which were imported into ArcGIS as kml files (Table III). Furthermore, the accuracies of the remotely sensed data were validated, evaluated and confirmed through ground truthing and visual interpretation of satellite imageries. In this regard, GPS was used to take and record geographic coordinates of 80 control points in the study area (Table III). Using ArcMap 10.8.1 software, these points were converted from vector data to raster data and integrated with the images to produce a confusion matrix (Lyons [46, 48].

TABLE III. DISTRIBUTION OF VALIDATION POINTS (BY LULC)

S/N	LULC Class	No. of Points		
		Topographical Map	*GoogleEarth Map*	*Ground Points*
1.	Built-up	20	20	25
2.	Bare Land	0	10	10
3.	Vegetation	10	20	30
4.	Cultivated Land	5	15	15
	Total	**35**	**65**	**80**

Accuracies of the LULC classification were calculated using user's accuracy (UA), producer's accuracy (PA), overall accuracy (OA), and the kappa coefficient (Kc) in a confusion matrix [46-48]. In the calculations, the number of pixels correctly classified in a category was represented as nii; and the total number of pixels in the confusion matrix was denoted as N; the number of rows was r; nirow are the predicted classes; and the reference data are depicted as nicol (Equations 1- 4):

$$OA = 1/N \sum ri=1\ nii \quad (1)$$

$$PA = nii/\ nicol \quad (2)$$

$$UA = nii/\ nirow \quad (3)$$

$$KC = N \sum ri=1\ nii - N \sum ri=1\ nicol\ nirow/N^2 - \sum ri=1\ nicol\ nirow \quad (4)$$

2) Landscape Structure and Fragmentation

Landscape fragmentation was estimated to quantify and determine the pattern of land use intensity in the study area [49, 50]. This was accomplished using landscape metrics analytical techniques in Fragstat 4.2.1 software. This study adopted the three spatial metrics analyst tools of patch, class and landscape metrics that were usually employed for assessment of the extent of fragmentation in land uses [22, 25, 51]. However, seven of the numerous spatial metric quantifiers were considered useful and germane to this study (Table IV).

TABLE IV. LANDSCAPE METRICS

METRIC	FORMULAR	DESCRIPTION	UNITS	RANGE
CLASS AREA (CA)	$CA = \sum_{j=1}^{n} a_{ij}(1/1000)$, A is the total landscape area (m²); aij is the area (m²) of patch ij.	SUM OF THE AREAS (HA) OF ALL URBAN PATCHES.	HECTARE (HA)	CA > 0, NO LIMIT
NO. OF PATCHES (NP)	$NP = n$	NUMBER OF URBAN PATCHES IN THE LANDSCAPE.	NONE	NP ≥ 1, NO LIMIT
PATCH DENSITY (PD)	$PD = \frac{ni}{A}(10{,}000)\ (100)$ $PD = \frac{ni}{A}(10{,}000)\ (100)$ $nini$ = NUMBER OF PATCHES IN THE LANDSCAPE OF PATCH I; A = TOTAL LANDSCAPE AREA (M²)	NUMBER OF PATCHES DIVIDED BY THE TOTAL LANDSCAPE AREA	NUMBER PER 100	PD ≥ 1, NO LIMIT

LARGEST PATCH INDEX (LPI)	$LPI = \frac{\max_{i=1\ to\ n}(a_i)}{A} X\ 100$ $a_i a_i$ = AREA (M^2) OF PATCH I; A = TOTAL LANDSCAPE AREA	AREA (M^2) OF THE LARGEST PATCH OF THE CORRESPONDING PATCH TYPE DIVIDED BY TOTAL AREA OF THE URBAN LAND TYPE (M^2), MULTIPLIED BY 100.	PERCENT	0 < LPI ≤ 100
LANDSCAPE SHAPE INDEX (LSI)	$LSI = \frac{.25 \sum_{k=1}^{m} é_{ik}}{\sqrt{A}}$ É = TOTAL LENGTH (M) OF EDGE IN LANDSCAPE; ÉIK = TOTAL LENGTH (M) OF EDGE IN LANDSCAPE BETWEEN PATCH TYPES I AND K; N = TOTAL LANDSCAPE AREA (M^2)	IT IS THE TOTAL PERIMETER OF AN AREA. LSI=1, WHEN IT IS COMPACTED (FOR RASTER DATA). LSI CALCULATES REGARDLESS OF WHETHER THEY REPRESENT TRUE EDGE.	NONE	LSI>1, NO LIMIT
EDGE DENSITY (ED)	$ED = \frac{E}{A}\ (10{,}000) ED = \frac{E}{A}\ (10{,}000)$ E = TOTAL LENGTH (M) OF EDGE IN LANDSCAPE; A = TOTAL LANDSCAPE AREA (M^2)	SUM OF LENGTH (M) OF ALL EDGE SEGMENTS IN THE URBAN PATCH TYPE, DIVIDED BY TOTAL LANDSCAPE AREA (HA).	METERS PER HA	ED ≥ 0, NO LIMIT
NORMALIZED LANDSCAPE SHAPE INDEX (NLSI)	$NLSI = \frac{\sum_{i=1}^{i=N} \frac{P_i}{S_i}}{N}$ $P_i P_i$ IS THE PERIMETER OF PATCH I; $S_i S_i$ IS AREA OF PATCH I; N IS TOTAL NUMBER OF PATCHES	NLSI EQUAL TO ZERO WHEN IT IS EXTREMELY COMPACTED OR SQUARE, IT RISES WHEN A PATCH TYPE IS GRADUALLY DISAGGREGATED AND IT IS ONE WHEN THE PATCH IS GREATLY DISAGGREGATED.		0≤NLSI<1

Sources: [21, 29, 44, 52]

IV. RESULTS

A. *Results of Accuracy Assessment*

Table 5 indicates that the highest overall classification accuracy was achieved for the year 2021 image (88.27%) followed by that of 1986 (84.47%), 2014 (81.25%) and 2000 (79.22%). While the lowest UA was recorded for cultivated land in 2000 (70.35%), the highest was in 2021 (100%). The highest accuracy for the built-up class was recorded in 2000 (89.53%), the lowest was in 2014 (76.71%). Also, the PA results revealed that while bare land has the lowest classification accuracies, built-up recorded the best accuracy performance among the LULC classes (Table V).

The dynamic nature of the accuracies for cultivated land can be attributed to mixed pixel response, encroachment of forest canopies over some farmlands and error in image acquisition (time and season). Also, the validation of built-up was affected by the reflective capacities of some roofing materials. Furthermore, the oscillating performance of vegetation may be due to incapability of classifier to separate natural vegetation from some cultivated plants such as orchards and horticulture. Generally, for all the classes, accuracies of >70% was obtained for both UA and PA (Table V). This suggests that all the collected validation samples also belonged in the same class as the selected training sites [46, 47].

TABLE V. CONFUSION MATRIX FOR LAND USE/LAND COVER CLASSIFICATIONS

LULC Year	LULC classes	Classification Accuracy (%)	
		User's Accuracy	Producer's Accuracy
1986	Built-up	80.31	99.74
	Bare Land	94.62	78.06
	Vegetation	77.18	79.74
	Cultivated Land	85.71	89.43
	Overall Accuracy	84.47	
	Kappa coefficient (Kc)	0.7911	
2000	Built-up	89.53	100
	Bare Land	100	71.67
	Vegetation	91.71	80.02
	Cultivated Land	70.35	76.78
	Overall Accuracy	79.22	
	Kappa coefficient (Kc)	0.708	
2014	Built-up	76.71	98.44
	Bare Land	87.56	77.81
	Vegetation	89.19	88.11
	Cultivated Land	87.09	79.14
	Overall Accuracy	81.25	
	Kappa coefficient (Kc)	0.750	
2021	Built-up	80.23	90.70
	Bare Land	91.52	70.18
	Vegetation	100	100
	Cultivated Land	100	75.24
	Overall Accuracy	88.27	
	Kappa coefficient (Kc)	0.850	

B. *Land use/ Land cover Classification (1986 to 2021)*

Four classes of LULC were identified in the study area over four epochs (1986, 2000, 2014 and 2021). The classes are built-up, bare land, cultivated land and vegetation (Table 6). In 1986, while cultivated land was the largest proportion of land use

(68.97%), built-up was the lowest (4.76%). In 2014, there was a significant increase in the proportion of bare land from 8.42% in 2000 to 17.93% due to intense human activities that led to clearing of land for the provision of urban infrastructure such as expansion and dualization of roads, educational, sports and recreation and health facilities. However, by 2021, most of these projects have been completed and, thus, loss of bare land to the built-up.

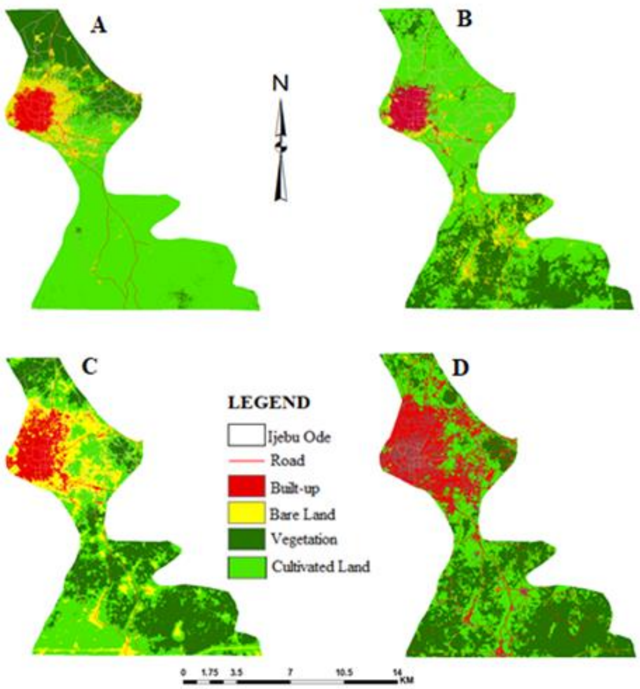

Fig. 2. Urban land Use Development of Ijebu Ode, A 1986, B 2000, C 2014, D 2021.

It was observed that there was an increase in the proportion of cultivated land from 34.12% in 2014 to 40.09% in 2021. This was due to the cultivation of some parts of the cleared surfaces in 2021 (Fig. 2, Table V). Also, there was persistent increase in the area occupied by vegetation throughout the study epochs (1986 to 2021). At the initial stage, this could be attributed to gradual shift from agriculture to some other secondary/tertiary occupations thereby resulting in the cultivated areas been overgrown by weeds. Later, in 2014, Ogun State Government launched tree planting policy which further increased the area covered by vegetation. In sum, the built-up area was found to change at a growth rate of 11.03% between 1986 and 2000, 65.24% between 2000 and 2014, and 131.25% between 2014 and 2021 (Table VI). However, cultivated land lost much of its area to vegetation and built-up between 1986 and 2014 (Fig. 3). This encroachment of the built-up into the cultivated land could be attributed to the need for more land to accommodate urban facilities necessary to cater for the fast expanding population and availability of other more lucrative sources of income rather than farming. Ramachandra and Aithal [52] corroborated by Richards [45] commented that this trend represents a situation of land use invasion and succession.

TABLE VI. LAND USE /LAND COVER STATISTICS BETWEEN 1986 AND 2021

LULC	1986		2000		Change Rate	2014		Change Rate	2021		Change Rate
	Area (km²)	%	Area (km²)	%	%	Area (km²)	%	%	Area (km²)	%	%
Built-Up	9.073	4.76	10.074	5.29	11.03	16.646	8.74	65.24	38.494	20.20	131.25
Bare Land	19.046	9.10	16.041	8.42	-15.78	34.173	17.93	113.04	0.588	0.31	-98.27
Vegetation	32.535	17.07	56.983	29.91	75.14	65.006	39.21	14.08	75.078	39.40	15.49
Cultivated Land	129.889	68.97	107.445	56.38	-17.28	74.718	34.12	-30.46	76.383	40.09	2.23
Total	**190.543**	**100**	**190.543**	**100**		**190.543**	**100**		**190.54**	**100**	

Sources: Landsat 5 TM 1986; ETM+ 2000, OLI 2014 and 2021

C. Land Use Fragmentation in the Study Area

Results of landscape analysis showed that the total built-up area (CA) increased from 90,732m² in 1986 to 100,736m² in 2000 and 160,058m² in 2014. In 2021, the CA of the of built-up was more than doubled upon that of 2014 by 384,941 (Table VII). This is an indication of more rapid urbanization in the study area during 2014-2021 compared to the previous periods.

TABLE VII. SPATIAL METRICS OF LAND USE/LAND COVER AT THE CLASS LEVEL

Metrics Year	LULC	CA	NP	PD	LPI	LSI	ED	NLSI
1986	Built-up	90732	271	1.4221	9.9797	14.1441	15.1313	0.0782
	Bare Land	190461	1156	6.0662	14.7854	39.3368	59.1628	0.1612
	Vegetation	325348	1008	5.2896	16.1122	40.5159	60.0438	0.1688
	Cultivated Land	1298886	1548	8.1233	5.8353	61.66	103.748	0.2239
2000	Built-up	100736	482	2.5293	11.6159	18.0274	18.6616	0.1048
	Bare Land	160409	642	3.3690	10.5004	30.0144	39.810	0.1400
	Vegetation	569831	602	3.1590	6.2027	31.0697	53.2789	0.1108
	Cultivated Land	1074453	964	5.0587	14.1671	47.3197	76.3802	0.1818
2014	Built-up	160058	509	2.6710	12.5955	18.6585	21.6633	0.0964
	Bare Land	341732	1639	8.6008	21.0744	53.9717	77.9471	0.2326

	Vegetation	650058	1347	7.0685	17.5399	53.2747	93.3679	0.1886
	Cultivated Land	747181	994	5.2161	21.1178	27.0387	37.3484	0.1194
2021	Built-up	384941	764	4.0092	13.5049	36.1308	44.33367	0.1815
	Bare Land	58775	255	1.3381	8.4954	15.2733	14.9457	0.0928
	Vegetation	753832	1281	6.7222	26.6456	53.6498	90.1428	0.1987
	Cultivated Land	760779	749	3.9304	9.4963	34.8313	61.7020	0.1210

Sources: Landsat 5 TM 1986; ETM+ 2000, OLI 2014 and 2021

Table VII shows that cultivated land which was the major land use, consisted of the largest number of patches in 1986 and 2000 (NP = 1548 in 1986; 964 in 2000). Therefore, the level of fragmentation in the cultivated land could be attributed to its large area. In 2014, there was an important change in the sequence; whereas cultivated land which occupied 747,181m² consisted of 994 patches, bare land contained 1,639 patches on just 341,732m² area of land. The patch density of built-up increased from 1.4221 in 1986 through the years to 4.0092 in 2021 (Table VII). However, reduction of some of the patch density values was an indication that some patches are merging to form a homogeneous landscape. For instance, PD for bare land reduced from 6.0662 in 1986 to almost half in 2000 (PD = 3.3690). However, there were unstable values of PD for vegetation and cultivated land: both land covers reduced between 1986 and 2000, increased in 2014 and decreased again in 2021 (Table 7). Results of LPI indicated that in 1986, vegetation had the largest LPI followed by cultivated land. While bare land and cultivated land accounted for the highest index, vegetation was the highest in 2021 (Table VII).

V. Discussion

This study has explored the benefits of geospatial techniques to analyze the spatiotemporal land use/cover dynamics in Ijebu Ode, Nigeria over a period of 35 years (1986 to 2021) at four inter-temporal epochs. The results were used to assess the nature and pattern of landscape fragmentation in the study area. Using geospatial techniques in ArcGIS environment, the extracted data were subjected to rectification and classification processes. Results of the growth and pattern of land use development in Ijebu Ode between 1986 and 2021 indicated that there has been continuous increase in the growth of the built-up area which was a by-product of reduction in vegetation and cultivated land classes. By implication, this denotes the prevalence of urban expansion in the area as earlier reported in some earlier studies which noted the existence of inverse relationship between the built-up and other LULC such as vegetation [31, 32, 49, 53].

The consequence of uncoordinated urbanization process in the study area is landscape fragmentation. Metrics analysis of the landscape structure in Ijebu Ode indicated high fragmentation and less infilling development in the study area as indicated by the increases in the CP and NP of the built-up class. Therefore, the expansion of the built-up area can be explained as one of outward expansion. Changes in NP for bare land suggest that the land use class was more fragmented between 1986 and 2014 than in 2021. This is like some previous studies which established outward urban growth as a major consequence of high fragmentation of landscape within an urban environment [22, 27, 54].

Increase in patch density of the built-up can be attributed to increase in the demand for more houses, urban infrastructure and services. Consequently, new built-up areas were formed at the fringes that segmented the existing bare land, vegetation and cultivated lands in the latter epoch. However, there were reductions in the PD of some land use classes to indicate that some patches are merging to form a homogeneous landscape. For instance, bare land, vegetation and cultivated land reduced in 2000 and 2014. This is an indication of scattered cultivation in the area [27, 29, 55, 56].

Results of LPI, LSI, and NLSI were further proofs of urbanization in the area. These indices increased between 1986 and 2000, reduced in 2014 and rise again in 2021. This suggests alternating compact and dispersed development across the landscape. This further confirmed the nature of urbanization process in the area; dispersed in 1986 and 2000 as a result of scattered development, compacted in 2014 through infilling and became more dispersed in 2021 due to outward expansion. Studies have established that continuous increase of NLSI and LPI of land use/cover classes other than the built-up points to heterogeneity of landscape [50, 52].

It is obvious from the results that even small differences in land cover proportion can produce extremely different LPI values. Moreso, reduction of edges was found to coincide with reduced numbers of patches. Therefore, the NSLI becomes awfully difficult to interpret because its values were undistinguishable from landscapes exhibiting a vast continuum of class proportions. Although, LPI for built-up was also increasing proportionately during this period but not as high as some other classes. In like manner, as the built-up area in the region increased, the landscape shape started to be more regular from 2000 to 2014, which was evident with the decreasing value of the index at the levels of class and landscape metrics. LSI for built-up class increased for the city level between 2014 and 2021. Though the results of these indexes exhibit similar behavior, yet it must be stated that gradual increase in LPI of the built-up class was an indication of dominance of a class over other classes. This situation has been found to be characteristic of places where there was increase in the quantity of land used for buildings and other urban infrastructure [25, 29, 51, 55].

Despite the success achieved in this study, it was observed that using remotely sensed data to assess LULCC still require to be more advanced to allow for the integration of more exploratory variables. For instance, parallel success was not achieved in assessing the nature of dynamisms observed in the competition and transition among the LULC types in the study area. This was probably because of the multivarious physical and human drivers and activities influencing the observed changes in the land use/cover. In view of the foregoing, the study suggested inter-temporal monitoring and check on the land use development and territorial expansion of the area the built-up area. To accomplish this, stakeholders in the land use development and management such as town planners and local government authority should be thoroughly sensitized on the immense benefits of the utilization of Remote Sensing and Geographic Information System in decision-making and policy formulation to the study of land use/cover changes. Also, governments (at various levels) should identify urban infrastructure and services that are peculiar to certain area. Here, it is necessary for government to encourage public-private-partnership in the provision of sustainable infrastructural facilities in the disadvantaged areas to prevent lop-sidedness in their distribution and location. This will also mitigate the growth of haphazard and organic developments in the study area.

VI. Conclusion

Examination of land use and land cover of Ijebu Ode at temporal and spatial levels revealed the existence of spatial variation in the uses of the land. For instance, between 1986 and 2014, cultivated land occupied the largest proportion of land uses (68.97%) while the built-up area was the least (4.76%). In 2014, the built-up class rose to the third position. Detailed data relevant to land use and land cover studies are required for adequate planning and efficient implementation of land use policies. Though this can be used to meet the ever-increasing demand for basic urban facilities, yet, there should be a caution here to avoid land scarcity and the consequent urban sprawl. Also, since food is a foremost basic need of man, it is necessary to warn against incessant demands for human welfare facilities because it can result in severe environmental impacts and, consequently, unexpected fall in agricultural production.

Quantification of the landscape patterns and the consequent analysis of the interactions among various landscape indexes showed that the trend of growth in the study area was largely influenced by disorganized locational and distributional patterns of spatial structures. For instance, the indices increased between 1986 and 2000, reduced in 2014 and rise again in 2021. NLSI revealed that built-up patches increased from 1986 to 2000, reduced during 2000 to 2014, and increased between 2014 and 2021. On the contrary, the index for cultivated land increased between 1986 and 2014 but slightly increased from 0.1194 in 2014 to 0.1210 in 2021. The NSLI values fluctuate between minimum for built-up in 1986 (at 0.0782) and to a maximum of 0.2326 for bare land in 2014. On a general note, the NLSI values are greater than zero and less than 1 (NSLI >0<1).This suggests that the observed variance in inter-temporal spatial dimensions of land uses calls for spatial re-organization and re-structure of the study area. Hence, this study could provide substantial information to land use managers and administrators in Ijebu Ode. For instance, the class level metrics can be adopted for the re-organization of the built-up area, particularly, the clumsy and congested core area. Adequate knowledge of patch density, number of patches, percentage of landscape and largest patch index, can be employed for the description of the changes and configuration of the pattern of landscape in the study area.

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