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Spatial pattern of urban growth using remote sensing and landscape metrics

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Abstract: The growth of cities, occurring in uneven and unplanned patterns, affects land use and land cover and it changes the spatial distribution of urban residents. This study seeks to critically understand the pattern of urban growth in Ibadan metropolis, Nigeria by applying heuristic techniques. This study utilized Landsat 5 TM, 7 ETM+ and 8 OLI-TIRS satellite imageries of 1986, 2000 and 2013 respectively of Ibadan. These were integrated into a GIS environment using post-classification change detection approach and employing selected Landscape Metrics (TA, NP, MPS, TE, ED, AWMPFD) to analyze the pattern of urban growth in the area. The built up area in Ibadan has grown from 13302ha in 1986 to 45868ha in 2013 at an average growth rate of 2 and 12% per annum during 1986-2000 and 2000-2013 study periods respectively. Landscape metrics analysis reveal fragmented process of development along the fringes of Ibadan throughout the study periods with substantial increase of urban patches occurring during the second period of urbanization (2000-2013). The core of the city underwent compact growth by infilling of open spaces and through edge expansion over time. Remote sensing and landscape metrics proved valuable for the description of processes in the study.

Keywords: Urban growth, Urban Pattern, Landscape metrics, Urban patches, Fragmentation

1. Introduction

Urban growth is widely viewed as an essential driver of environmental and social problems. It causes the loss of informal open space and the fragmentation of wildlife habitats. Appropriate and exact evaluations of future urban development situations and related ecological effects are crucial for urban planning, approach choice, and natural resource administration. Since modern transformation toward the end of eighteenth century, world urban population has expanded exponentially with rapid speed. In 1830, urban population was about 1 billion and it expanded to 7 billion in 2011. In addition, urban population expanded more rapidly compared with rural population. Urban population increased from 14 percent in 1900 to 50.5 percent in 2010. By 2030, more than 60 percent of population are expected to be urban population (Wu et al., 2010).

Describing and understanding the dynamic patterns of urban growth is basic, given that urbanization continues to be one of the major global environmental changes in the nearest future. As a result of urbanization, the physical processes of urban land use changes are under study and investigation (Seto and Fragkias, 2005). Urban growth process significantly affects the land use patterns, influencing utilitarian parts of the landscape (Frohn and Hao, 2006; Akintunde et al., 2016). Spatial pattern of development on urban zones are changing impressively. Urban regions are expanding in rural zones and urban sprawl is taking place. In view of consistent change in structure and urban growth pattern, these zones have been in constant focal point of scientists (Seto and Fragkias, 2005).

While geographers and economic experts are creating geometric models that depict and clarify the morphology of urban communities for over a century (Herold et al., 2005), numerous components of urban spatial configuration have proven elusive. Availability of temporal remotely detected information procured through space-borne sensors helps distinguishing the urban landscape progression in connection to urban growth (Chen et al., 2000; Epstein et al. 2002; Lo and Yang 2002; Ji et al., 2001; Yeh and Li 2001; Sudhira et al., 2003; Ramachandra et al., 2012). This guides in describing the spatio-temporal patterns of urban growth process and development (Zerah, 2008). More current research that merges satellite/GIS data with landscape metrics is equipped for examining land cover fragmentation, diversity and richness, and compactness within and across urban areas. Computation of metrics and displaying based on multi-temporal spatial data gives a premise for predicting urbanization processes.

This information supports policy making for an effective urban planning with natural resources conservation. Further temporal dynamics information with spatial metrics gives insights to the urbanization pattern (i.e., property, complexity and size of the urban zone), which enables the sustainable regional development (Hill et al., 2004; DeFries, 2008; Bhatta, 2009).

2. Description of the study area

Ibadan is located in the South Western part of Oyo State, Nigeria (Figure 1). Ibadan metropolitan area is located at latitudes 7°14’15’’N to 7°36’34’’N and longitudes 3°42’00’’E to 4°06’56’’E. It is located about 145 km north-east of Lagos, the federal capital of Nigeria with a population of 2,550,593 according to 2006 census results, including 11 local government areas. As the dominant urban center in Oyo State, its administrative and commercial functions transcend beyond the city boundaries. Ibadan metropolis covers a total land area of 3,123km² with 586 persons per km² as the overall population density of which the main city covers a land area 463.33 km².

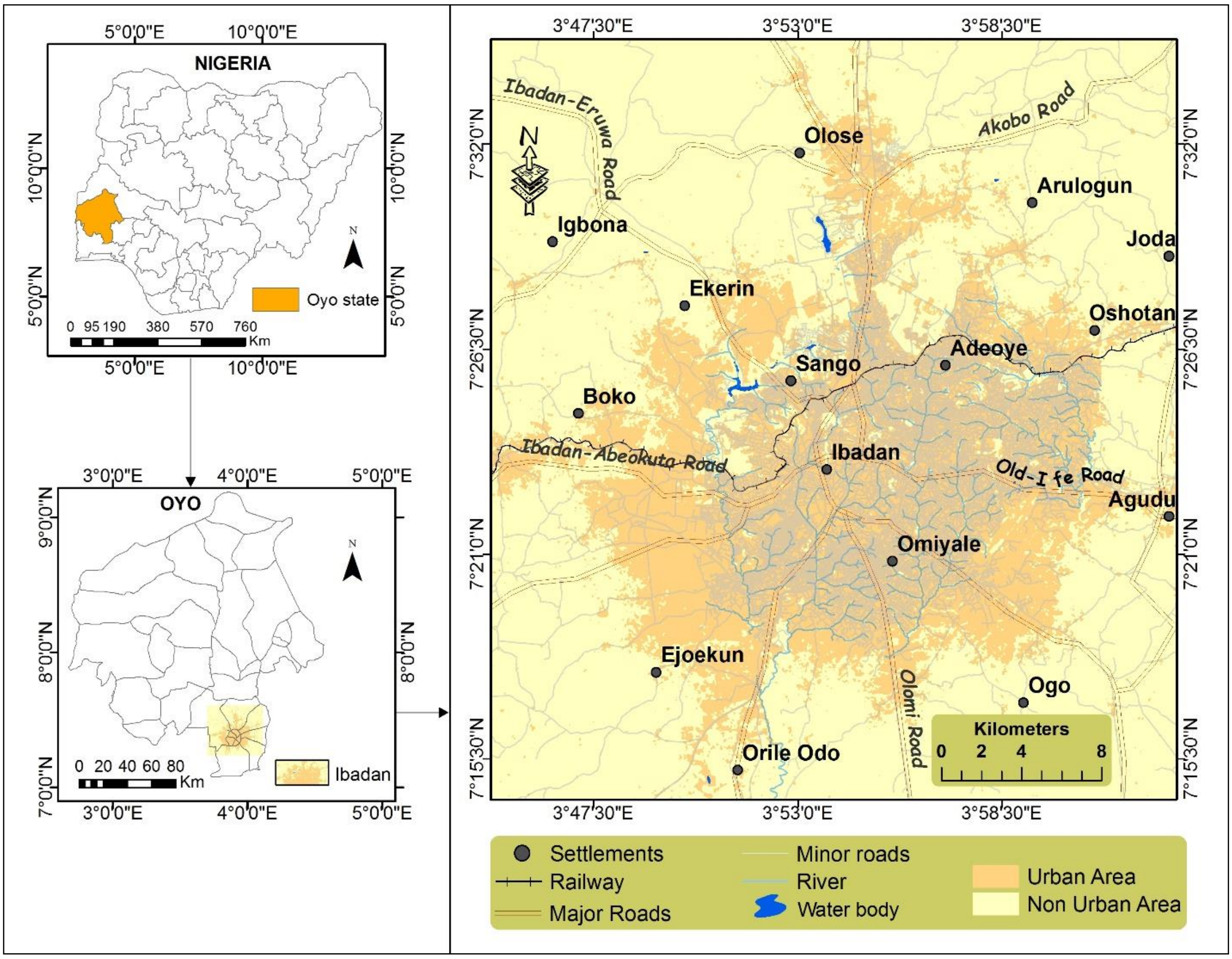

Figure 1: The Study Area.

Ibadan city is encountering unguided and uncontrolled expansion in all directions bringing about large scale urban growth and urban land use changes. Therefore, it is meaningful to extend landscape metrics application to fast developing urban communities. The current institutional structure of urban and regional planning framework (Master planning) cannot adequately address the issue of urban growth and its physical characteristics in Nigeria and Ibadan Metropolis in particular (Oyesiku, 2004; Alabi, 2008).

Therefore, this study will explore the spatio-temporal patterns of Ibadan's urban growth process and measure the hidden spatial configuration of the urban landscape. To achieve this task remote sensing and spatial metrics tools are employed. The combined use of these tools is believed to lead to new levels of understanding the urban development process which can assist city planners and policy makers to make informed decisions (Herold et al., 2005).

3. Methods and data analysis

3.1 Remote sensing image classification

The urban growth trends and patterns of Ibadan for a period of 27 years are analyzed using three multi-temporal medium resolution Landsat imageries (Table 1). All images are of the same spatial resolution, 30m.

Table 1. Data used and characteristics.

Data	Source	Year	Purpose
Landsat 5 TM	USGS	1986	Land cover and Land use analysis
Landsat 7 ETM+	USGS	2000	Land cover and Land use analysis
Landsat 8 OLI	USGS	2013	Land cover and Land use analysis
Topography Map [Scale (1:50000)]	OSGOF	1963	Generate boundary and Base layer maps
High resolution image	Google Earth	2014	Visual interpretation

Images used are acquired geometrically corrected and geo-referenced. Supervised maximum likelihood classification algorithm was applied in ENVI 5.1 software environment to run image classification due to its popularity and wide acceptance in classifying remote sensing images. Accordingly, the images were classified in to different land cover classes which finally ended up generating three different year land cover maps of the study area. Pixels with maximum likelihood are categorized into the matching class as shown in figure 2.

The land cover maps are composed of two major land cover classes namely; built up and non-built up. The built up consist of commercial, residential, road and impervious features, residential, industrial and commercial units, road and railway networks, parking lots, sport and leisure facilities, etc. while the non-built up includes cropland (agriculture land), parks, grasslands, forests, green spaces, bare soil and others.

3.2 Accuracy assessment

In remote sensing land cover mapping, classification accuracy is the most important aspect to assess the reliability of the final output maps. In this study, Accuracy Assessment is done through comparison of Kappa coefficients (Congalton *et al*., 1983). For this purpose, a confusion matrix was calculated. Accuracy assessment and Kappa coefficient are common measurements used in various publications to demonstrate the effectiveness of the classifications (Congalton, 1991; Lillesand and Kiefer, 2005). The main purpose of assessment is to assure classification quality and user confidence on the product (Foody, 2002). In the present study, accuracy was assessed after several classes were merged and classified to come out with three classes of interest.

3.3 Change detection

The method used in this analysis is the post classification comparison technique in which GIS overlay of the independently produced classified images in ArcGIS 10.5 (Alphan *et al.,* 2009). The subsequent land cover maps are then visually compared and change areas are simply those areas which are not classified the same at different times. This method is the most straightforward and intuitive change detection method. Following this method, maps are produced to show the built up class between each subsequent years, i.e. 1986-2000 and 2000-2013 (Yang and Lo, 2002). In combination with class area landscape metrics, these make it possible to quantify the spatial extent and rate of urban growth over time.

3.4 Measuring urban growth pattern using landscape metrics

Spatio-temporal patterns of Ibadan's growth were analyzed using landscape metrics for the time period 1986-2013. Landscape metrics are powerful tools to quantitatively describe and compare multi-date thematic maps. Metrics are computed only for the built up class in the study. The outputs for the selected metrics presented in tables are generated for the whole study area and calculated in Patch Analyst v5.0 and Fragstsats 4. These metrics were picked based on their intuitiveness, ease interpretation and their ability to describe the composition and configuration of urban landscape pattern. Nevertheless, the analysis is conducted including areas outside Ibadan, but only focusing on built up land cover class. Landscape metrics describe four dimensions: relative size, absolute size, spatial distribution of patches and complexity of urban form. Landscape metrics employed in this study are given below (Mcgarigal and Marks, 1995).

1) *Total (Class) Area (TA):* Total area measures how much of the landscape comprises of a particular type of patch.

$$TA = \sum_{j=1}^{n} a_{ij} \left(\frac{1}{10000}\right) \quad (1)$$

a_{ij} = area (m²) of patch ij.

2) *Number of Patches (NP):* NP is a measure of isolated urban areas in the landscape. During epochs of rapid urban nuclei development, NP is expected to increase but may experience decrease if urban areas expand and merge into continuous urban fabric (Seto and Fragkias, 2005).

$$NP = N \quad (2)$$

N = total number of patches in the landscape.

3) *Mean patch size:* MPS measures the number of urban patches per the size of each urban area which increases or decreases over time. (Seto and Fragkias, 2005).

$$MPS = \frac{A}{N_{patch}}(10000) \quad (3)$$

A = area (m²) of all patches of the corresponding patch.
N = total number of patches in the landscape.

4) *Total Edge:* TE sums up the lengths (in meters) of all edge segments that contain the similar patch type.

$$TE = E \quad (4)$$

E = total length (m) of edge in landscape.

5) *Edge Density (ED):* ED is computed by dividing the total length of the urban boundary to the total landscape area. ED has direct relationship with NP.

$$ED = \frac{E}{A}(10000) \quad (5)$$

E = total length (m) of edge in landscape.
A = total landscape area (m²).

6) *Area weighted mean patch fractal dimension (AWMPFD):* AWMPFD metric describes the degree to which the shape of an urban area is irregular or complex. Values range between 1 and 2 with values closer to 1 indicating areas with relatively simple shapes such as squares or circles. Values that approach 2 represent irregular and complex shapes.

$$AWMPFD = \sum_{i=1}^{m} \sum_{j=1}^{n} \left(\frac{2In(.25_{ij})}{Ina_{ij}}\right)\left(\frac{a_{ij}}{A}\right) \quad (6)$$

aij = area (m²) of patch ij.
A = total landscape area (m²)

4. Results and discussion

4.1 Accuracy assessment

The overall accuracy of classified images was found to be greater than 85%. This is considered to be a good result for analysis performed using remote sensing images (Herold et al., 2005). Tables 2 and 3 below present the accuracy of classified images used.

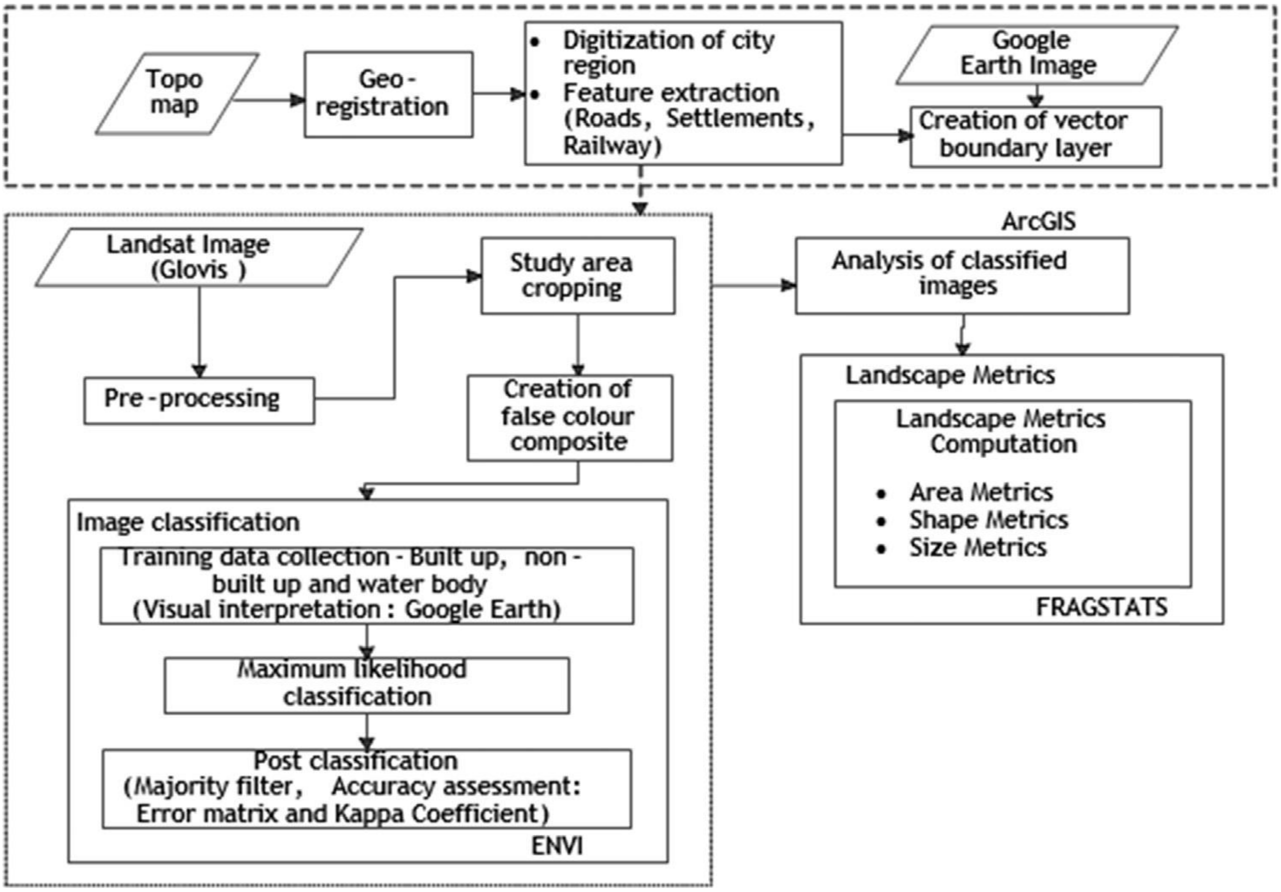

Figure 2: General Methodology workflow

Table 2. Error matrix of classified images (1986-2013)

1986				
Class	Builtup	Non Builtup	Waterbody	Row Total
Builtup	**2772**	0	0	2772
Non Builtup	0	**6186**	1	6187
Waterbody	0	0	**87**	87
Column Total	2772	6186	88	9046
2000				
Class	Builtup	Non Builtup	Waterbody	Row Total
Builtup	**2771**	0	0	2771
Non Builtup	1	**5985**	11	5997
Waterbody	0	201	**77**	278
Column Total	2772	6186	88	9046
2013				
Class	Builtup	Non Builtup	Waterbody	Row Total
Builtup	**13904**	20	1	13925
Non Builtup	0	**9445**	0	9445
Waterbody	0	0	**386**	386
Column Total	13904	9465	387	23756

4.2 Image classification

The classification of the multi-temporal satellite images into built up, non-built up and water body for the three different time periods of 1986, 2000, and 2013 (Figure 3a, b and c) shows a highly simplified and abstracted depiction of the study area.

The maps show a clear increase in the pattern of urban expansion extending from the city core to the adjoining non-built up areas along the major transportation corridors. Figure 3d shows the spatial and temporal pattern of urban growth in the study area experiencing rapid expansion along the fringes of the built up areas. Post classification composition of images classified revealed the pattern of urban growth of the city in different directions, specially, the open spaces experiencing infilling amid already built up regions and the dynamics of expansion of the urban regions in the study area. However, it is imperative to assist the findings with statistical evidences as it is useful to describe the spatial extent and different urban growth patterns that have been occurring in the study area. This will help understand how the city is changing over time and to compare the various growth patterns taking place quantitatively in different time epochs.

4.3 Spatio-temporal analysis of urban growth pattern using landscape metrics

The highest rate of urban growth is observed during the second period of urbanization (2000-2013) with an increase in the built up area of more than six times (160%) within 13 years (Table 4).

Table 3. Accuracy assessment of classified images (1986-2013)

Land Use Class	Reference Total	Classified Total	Number Correct	Number Wrong	Producer's Accuracy (%)	User's Accuracy (%)
1986						
Builtup	2772	2772	2772	0	100	99.85
Non Builtup	6187	6186	6186	0	99.79	100
Waterbody	87	88	87	1	99.74	100
Total	9046	9046	9045	1		
2000						
Builtup	2771	2772	2771	1	99.96	100
Non Builtup	5997	6186	5985	201	96.75	99.8
Waterbody	278	88	77	11	87.5	27.7
Total	9046	9046	8833	213		
2013						
Builtup	13925	13904	13904	0	100	98.85
Non Builtup	9445	9465	9445	20	99.79	100
Waterbody	386	387	386	1	99.74	100
Total	23756	23756	23735	21		

1986: Overall accuracy = 99.988, Kappa coefficient = 0.999 ***2000***: Overall accuracy = 97.645, Kappa coefficient = 0.948 ***2013***: Overall accuracy = 99.911, Kappa coefficient = 0.998

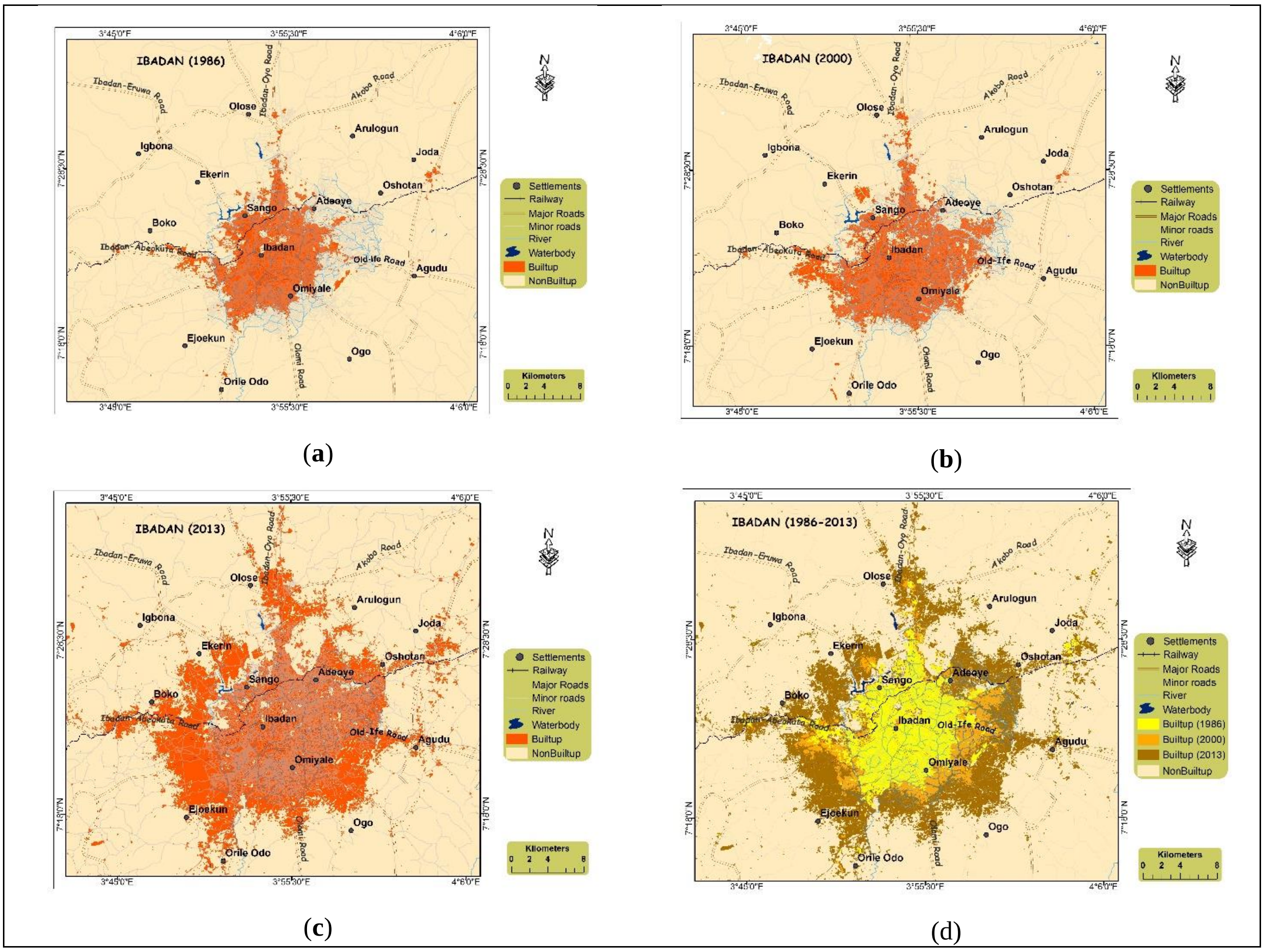

Figure 3: (a) Image classification, 1986; (b) Image classification, 2000; (c) Image classification, 2013; (d) Spatio-temporal growth map of the study area (1986-2013).

Table 4. Analysis of built up area expansion based on total area (TA) metrics.

Study period	Change (ha)	Change (%)	Time span	Growth rate/year	Average
1986-2000	4325	33	14	2	7
2000-2013	28241	160	13	12	

This is followed by 33% during the first period of urbanization (1986-2000). This indicates that more rapid urban growth took place in the study area during the period of 2000-2013 compared to the first period. As the statistics obtained from the area metrics computation confirms, the built up area increased at an average annual growth rate of 2 and 12% during the periods 1986-2000 and 2000-2013 respectively (Figure 4).

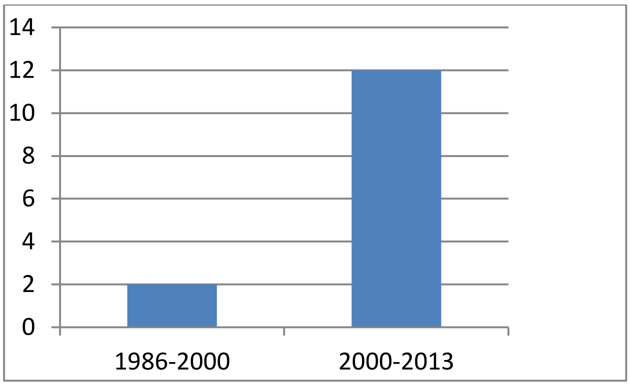

Figure 4: Built up area growth rate (%) per annum per study period

The results presented in Table 5 show that the total built-up area (TA) has grown from 13302ha in 1986 to 17627ha in 2000 and to 45868ha in 2013.

Table 5. Landscape metrics at the entire landscape.

Year	LUC	TA	NP	MPS	TE	ED	AWMPFD
1986	Builtup	13302	473	28	758400	4	1.38
2000	Builtup	17627	523	34	1122300	6	1.41
2013	Builtup	45868	2212	21	3078780	16	1.43

In terms of absolute change in (ha) of land cover the second period 2000 to 2013 (Figure 5) remains the highest witnessing the conversion of 28241ha of non-built up land to urban land. The first period of urbanization (1986-2000) experienced 4325ha of land changed to built up area. Totally 32566ha of non-built up land has been converted to built up land over the period 1986 to 2013.

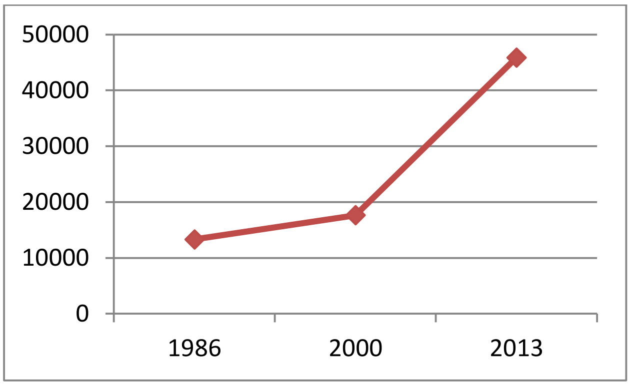

Figure 5: Total Built up area (TA)

The continuous rise of number of patches (NP) has led to and is revealed by the rapid urban growth process in the study area landscape throughout the study periods. In 1986 the NP in the region was 473 and gradually increased to 523 in 2000, and rapidly increased to 2212 in 2013 (Figure 6). This could be an indication of fragmented and heterogeneous process of urban growth taking place in the study area. During the 2000 to 2013 period, there was a significant change observed in NP. However, the peak occurred in 2013 indicating the continuing development of scattered and fragmented urban patches in the study area. This situation can be attributed to a development of small and irregular built up patches around the periphery of the city and in peri-urban regions. This could happen as the city expands outward in the form of scattered development, the gap between the peri-urban regions and the urban core will decrease by increasing the attractiveness of the peri-urban area for development.

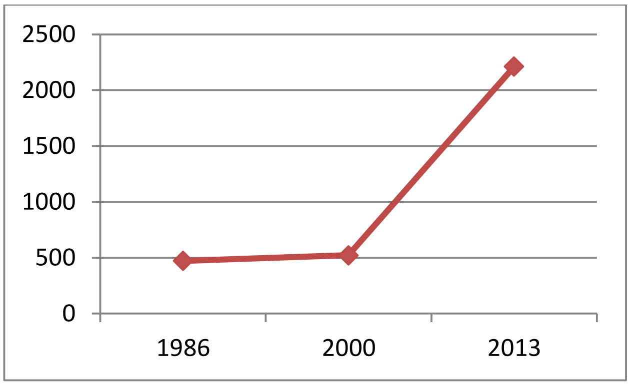

Figure 6: Number of Patches (NP)

Mean patch size (MPS) presents the relationship between urban patches land area and their number. The reduction in MPS shows that new patches have been developed. The increase in MPS shows the extension of existing urban patches. Figure 7 shows that the value of this metric increased during 1986-2000. Since 1986, it has decreasing trend. In 1986, the MPS was 28. With the joining of new patches, MPS extended to 34 in 2000. With the expansion of new patches, the MPS witnessed considerable reduction, 21 in 2013. The fluctuation is associated to the growth of central core and annexation of patches surrounding the central core until 2000. Since 2000, the urban areas experienced more developments of the new patches.

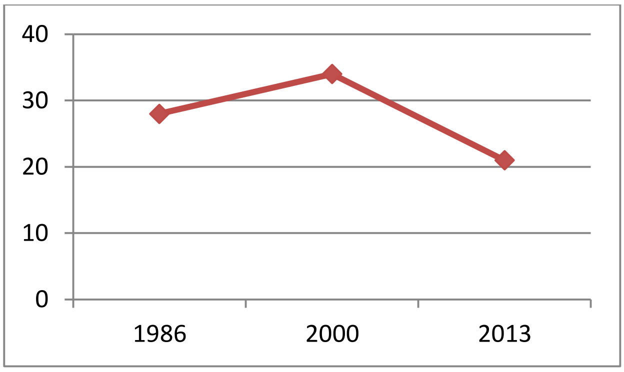

Figure 7: Mean Patch Size (MPS)

Total Edge (TE) considers true edges values greater than or equal to zero. Larger continuous patches indicate edges with larger values. Figure 8 indicates that during 1986 and 2000 the edges were smaller and hence there were discontinuous patches as the landscape was fragmented. In 2000 and 2013, larger edges indicated that the urban edges are ubiquitous and continuous.

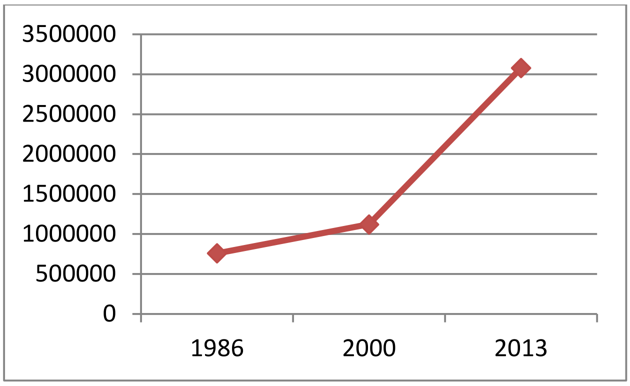

Figure 8: Total Edge (TE)

The result of this study revealed that the edge density (ED) increased from 4 in 1986 to 6 in 2000 and to 16 in 2013 (Figure 9). This shows that there has been significant urban growth with the emergence of various fragmented urban patches observed in the study landscape.

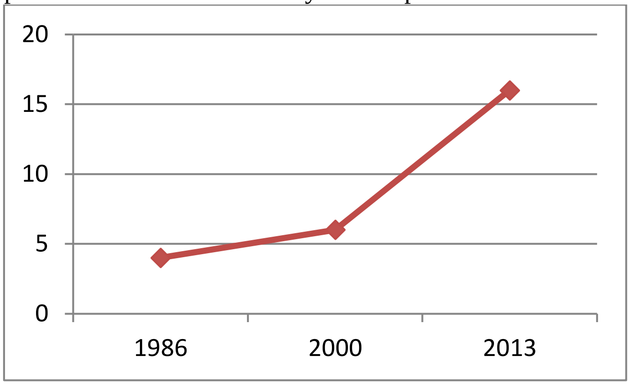

Figure 9: Edge Density (ED)

The area weighted mean patch fractal dimension (AWMPFD) with a consistent increasing trend observed in figure 10 shows the complexity and growing irregularity of urban patches due to fragmentation. This can be associated with the partial integration of existing individual patches and probably the formation of fewer new patches during both periods.

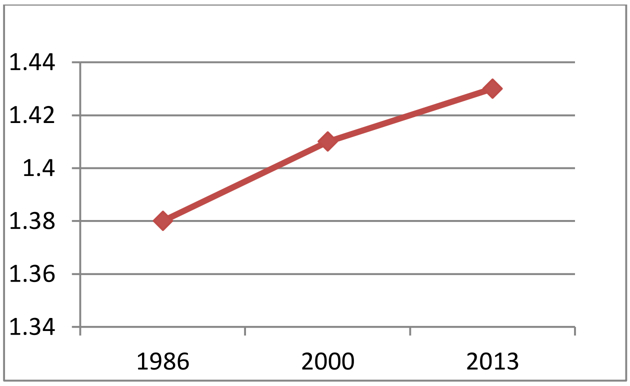

Figure 10: Area Weighted Mean Patch Fractal Dimension (AWMPFD)

5. Conclusions and recommendations

The study has made it possible to successfully capture the changing subtleties of the urban growth pattern at metropolitan (landscape) urban level. Ibadan metropolis experienced fragmented urban growth process, particularly, at the fringe areas with substantial built up increase while, the core of the city underwent relatively compact growth by infilling open spaces and through edge expansion over time. The built up area in the metropolis has grown from 13302ha in 1986 to 45868ha in 2013 at an average growth rate of 2 and 12% per annum during 1986-2000 and 2000-2013 study periods respectively. In total, 32566ha of non-built up has been converted to urban area.

Analyzing the spatial extent and rate of urban growth as well as identifying the growth directions alone does not give sufficient insight in to the patterns of urban growth processes, which are important to having a better understanding of the urban pattern. To bridge this gap, landscape metrics are used. Six metrics namely: total area (TA), number of patches (NP), mean patch size (MPS), total edge (TE), edge density (ED) and area weighted mean patch fractal dimension (AWMPFD) were utilized to evaluate the patterns of urban growth and processes experienced in Ibadan and its environs at landscape level. Based on the number of patches (NP), the built up area experienced fragmented growth process all through study periods with the second period of urbanization, 2000 to 2013 witnessing substantial increase of built up area (TA). The fluctuation in metric value of mean patch size (MPS) is linked to the enlargement of the central core and annexation of patches surrounding the central core until 2000. Since 2000, there is a clear increase in developments of the new urban patches. The area weighted mean patch fractal dimension (AWMPFD) showed increasing trend. This illustrates that the entire built up area will keep on getting more complex and thus, fragmented over time mainly at the fringe areas. Unorganized development that could be due to poor planning scheme could have played an inevitable part in the fragmented process of development of Ibadan metropolis.

Since the value of information extracted from landscape metrics is dependent on the quality of image classification, future studies could attempt to improve on the classification accuracy of the satellite images utilized in this study or perhaps use images from the same sensor, for instance all images from Landsat ETM+. This could help in solving the issues involved with image consistency.

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