Analysis of Lagos Landscape Change Using Spatial Metrics Method from 2007 and 2013

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ABSTRACT

This research provides a detailed overview of the spatial patterns and urban growth processes in Lagos City, Nigeria from 2007 to 2013. The significance of this analysis lies in its ability to enhance understanding of built-up areas' dynamics and to guide sustainable urban development planning. The study utilized remotely sensed satellite image data between 2007 and 2013 to assess eight spatial metrics, revealing changes in urban growth patterns. The findings indicate a significant reduction of approximately 1228.91km² (9.8%) in vegetation cover and a 17.95% decrease in water bodies over the six years. Conversely, the built-up area increased by 61.11%, covering 1735.665km² by 2013. This transformation was driven by extensive government-led infrastructure projects and widespread housing construction. As a result, the city of Lagos and its surrounding areas experienced a considerable shift from green and wetlands spaces to a predominantly built-up landscape, expanding the city's perimeters and transforming its suburbs into major built-up areas.

Keywords: Urban sustainable development, GIS, Landcover maps, spatial metrics, water body, Vegetation, Built-up area, Lagos

INTRODUCTION

Urbanization is a universal and important social and economic phenomenon taking place all around the world. Rapid urban growth affecting the physical dimensions of cities has continued to be one of the crucial issues of spatial change in the 21st century with no sign of slowing down. Our cities have therefore experienced spectacular expansion which generates a great concern for urban planners.

The present-day metropolitan Lagos developed from a narrow low-lying island situated on Latitude 6^0 27' North and Longitude 3^0 28' East along the West African coast.

The original settlement, Eko by name, on which Lagos grew was first inhabited by fishermen and farmers. This settlement was christened in 1492 as Lago de Kuramo by the Portuguese who used it only as a harbor in their attempts at finding a route to the Far East. *(Folami, 1982).*

In 2002, when the results from the Nigerian Census of 2000 became available, demographers revised their estimates of the population of Lagos down dramatically. The current thinking is that there were probably around 2.6 million people in Lagos in 1980 and around 8.7 million by the year 2000. With such vagaries and uncertainties, there is a clear need to investigate demography reports in view of the current population growth and urban transition.

The growth of urban population and the spread-out of built-up areas have great influence on natural landscape in Land-use change. Natural environments such as forest, grasslands and other land-cover are replaced over a period of time by human induced activities such as mechanized farming, industrial activities and built-up urbanization.

Although Lagos state is the smallest state in Nigeria, with an area of 3568.61Km² of which 757.55km² are wetlands, yet it has the highest population, which is over five per cent of the national estimate.

As at 2006, the population of Lagos State was 17.5 million, (based on the parallel count conducted by the state during the National Census with a growth rate of 3.2%, the State today has a population of over 21 million. This was corroborated by the recent immunization exercise carried out across the State, where 4.3million children were immunized. Children within the Immunization bracket is estimated at 20% of the entire population.

The UN estimates that at its present growth rate, Lagos state will be third largest mega city the world by Year 2015 after Tokyo in Japan and Bombay in India.

Of this population, Metropolitan Lagos, as at 2006 was an area covering 37% of the land area of Lagos State and is home to over 85% of the State population. The rate of population growth was about 600,000 per annum with a population density of about 4,193 persons per sq. km. In the built-up areas of Metropolitan Lagos, the average density is over 20,000 persons per square km.

In 2013, the statistics had changed to accommodate the rapid spread of urbanization to the suburbs, expanding the expanse of the Lagos metropolis while the average population density has reduced.

According to the CEISEN world population map, Lagos is classified among the world highest populated cities. The Current demographic trend analysis revealed that the State population growth rate of 8% has resulted in its capturing of 36.8% of Nigeria's urban population (World Bank, 1996) estimate at 49.8 million people of the national populations. The implication is that whereas country population growth is 4.5% and global 2%, Lagos population is growing almost ten times faster than New York and Los Angeles with grave implication for urban sustainability.

Lagos is undoubtedly the most notorious example of enormous urban growth in Nigeria and Sub-Saharan Africa, it is Nigeria's most important commercial center. The influx of migrants attracted by the booming prosperity has continued over the years making Lagos to be acknowledged as the largest city in sub-Saharan Africa.

Study Objectives

The objectives of this study are:

1. Classification of acquired Satellite Images of the study area.
2. Change Detection and Accuracy assessment of the classified images for the study period.
3. Statistical analysis of classified images using Spatial Metrics Analysis.

METHODOLOGY

The following procedures were followed for this study:

i. Data acquisition of Landsat satellite images.
ii. Geodatabase creation; including point, line, and polygon shape files are created for different features necessary in the analysis. Map creation, overlaying, and querying of map database. ArcGIS is used in the map and Geodatabase creation.

iii. Supervised Classification of Landsat images, change detection, and Accuracy assessment test using Erdas Imagine.
iv. Statistical analysis of classified images using spatial metrics. Fragstat v4.2 was used for the analysis based on selected metrics.

DATA COLLECTION

Different remote sensing and GIS data from various sources were used in this research. Two medium-resolution Landsat images of 2007 (ETM+) and 2013 (OLI) were used to detect urban land cover change patterns of the study area.

These images were compiled from the United States Geological Survey (USGS) website using the Landsat Look and the Glovis image downloaders with geometric and radiometric corrections. To avoid the impact of seasonal variation, images were selected from the same season (i.e. between November and February) in such a way that the cloud cover will not exceed 10% and the sensors are at a spatial resolution of 30m.

For ground data acquisition, the AutoCAD boundary map of Lagos as well as other demographic data sources were collected from both Lagos State online resource and the office of the State's Surveyor General. The Digital Elevation Model (DEM) used to analyze the driving forces of urban growth is downloaded from the SRTM- USGS centre.

Figure 1: Landsat image of Lagos in 2007 is captured with Enhanced Thematic Mapper plus

Figure 2: Landsat image of Lagos in 2013 captured with Operational Land Imager OLI sensor

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Supervised Image Classification

Image classification is the art and science of recognizing meaningful patterns in data by spatially and spectrally enhancing an image. The supervised Maximum Likelihood Image classification is used with Erdas Imagine tools for analyzing input data, creating training samples and signature files for the classification.

The images are clipped to reflect only the parts of Lagos city necessary for this study, that is, the most densely populated areas of Lagos state including the border towns that over the time has become part of the city.

The classification process used breaks down into two parts: training and classifying.

Pattern recognition is performed both by physical observation and using a computer system. Statistics are derived from the spectral characteristics of all pixels in the images. The pixels are then sorted based on mathematical criteria.

Based on the Created training signature, the computer system is then instructed to identify pixels with similar characteristics.

The result of image training is a set of signatures that defines a training sample or cluster. Each signature corresponds to a class, and is used with a decision rule to assign the pixels in the image file to a class.

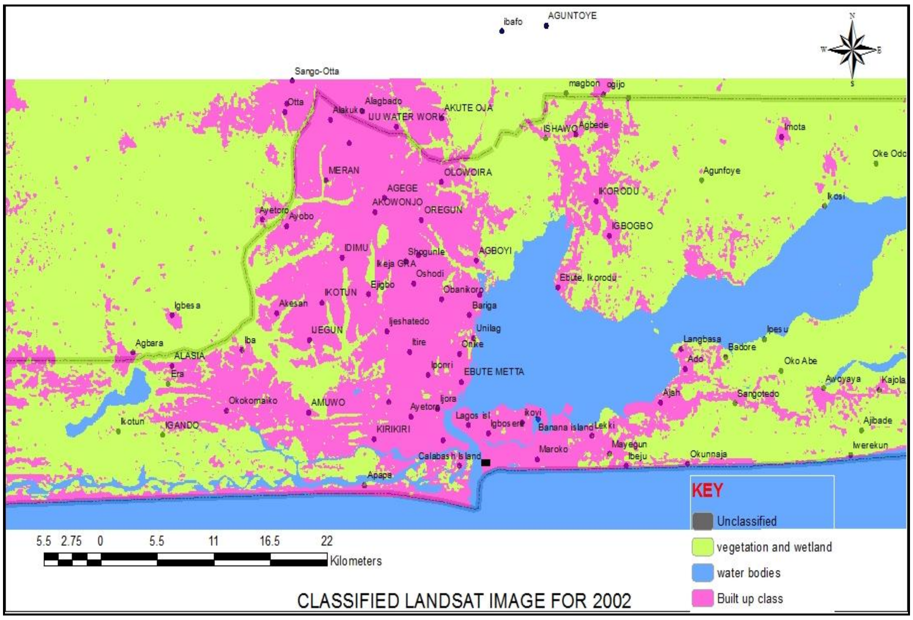

Figure 3: Classified LandSat Image for 2007 2007

Training samples is closely controlled using Erdas imagine. In this process, pixels that represent patterns or land cover features are selected, training samples are created from areas of interests (AOI) for the desired growth patterns. Accordingly training samples are created for only three land cover AOIs. Under Signature editor window, training samples are taken from each of the features to represent only water bodies, vegetation and built-up areas to form three signature classes;

- **The built-up area-** consist of continuous and discontinuous urban fabric, residential, industrial and commercial units, road/railway networks and other associated lands, airports, parking lots, dump sites, construction sites, sport and leisure facilities, etc.
- **Vegetation class** - includes Wetland, crop (agriculture) land, parks, grasslands, forests, woodland shrubs, green spaces, wetlands, bare soil and others.
- **Water body-** consists of the part of the Atlantic Ocean, Lagos Lagoon, lakes, artificial ponds, swamps, swimming pools and others.

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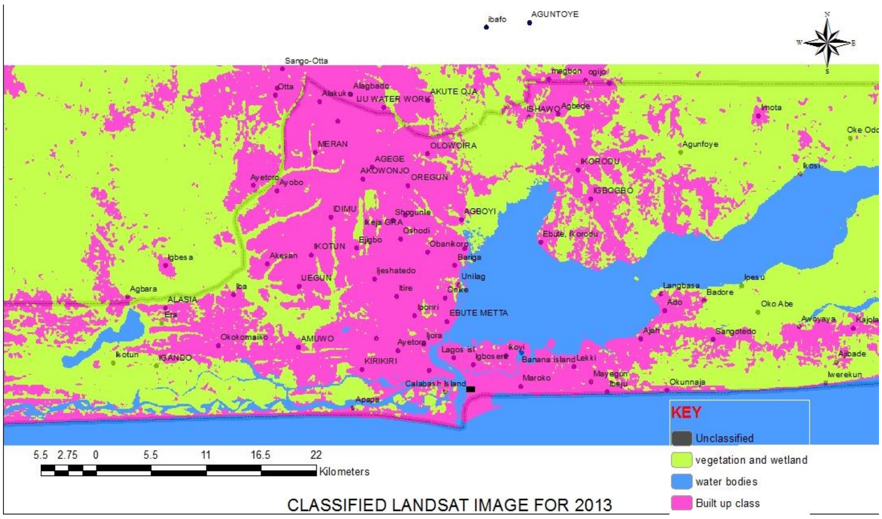

Figure 4: Classified Landsat Image for 2013

Accuracy Assessment Test

Accuracy assessment is the most important aspect of land cover and spatial growth study when using remote sensing. It is a general term for comparing the classified image to geographical data that are assumed to be true in order to determine the accuracy of the classification process. This is because the accuracy and reliability of the final map work is dependent on the classification accuracy.

Ground truth data collection

This vital aspect involves the following steps:

i. Random Sampling of Ground True Points: In the project, 300 Ground True Points are randomly sampled. The coordinate values of these points were obtained from various sources including Lagos state Survey data, previous survey data, and current fieldwork which entail the acquisition of the coordinates of the sample points from the field.
ii. Reference Pixels: Instead of ground truthing every pixel of a classified image, a set of reference pixels is used. These are points on the classified image where actual data (ground truth) is known.
iii. Selection of Reference Pixels: The reference pixels are carefully and randomly selected to avoid bias. This randomness ensures that the same pixels used in training samples are not used in testing the classification, reducing potential bias.
iv. Distribution Methods for Selecting Pixels: Erdas Imagine offers three types of distributions for selecting random pixels:
v. Random: No specific rules are applied.
vi. Stratified Random: The number of points is stratified according to the distribution of thematic layer classes.
vii. Equalized Random: Each class has an equal number of random points.
viii. Accuracy Assessment Cell Array: An array is created to compare the classified image with the reference data. This cell array lists class values for the pixels in the classified image and the corresponding reference pixels.
ix. Presentation of Results: The results of the accuracy assessment are presented after all analysis was completed (*Tables 1, 2, and Figure 5*).

The primary goal of this process is to determine the accuracy of the classification by comparing the classified data with the actual ground truth data.

It has been shown that more than 250 reference pixels are needed to estimate the mean accuracy of a class to within plus or minus five percent (Congalton, R. 1991).

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An Accuracy Assessment Cell Array is created to compare the classified image with reference data. This cell array is simply a list of class values for the pixels in the classified image file and the class values for the corresponding reference pixels.

Table 1: Accuracy assessment totals for 2007

Class Name	**Reference total**	**Classified total**	**Number Correct**	**Producer Accuracy**	**User Accuracy**
Unclassified	**0**	**0**	**0**	**-**	**-**
Water Bodies	**25**	**25**	**25**	100.00%	100.00%
Vegetation	59	74	59	100.00%	79.73%
Built up area	36	21	21	58.33%	100.00%
Totals	**120**	**120**	**105**		

Overall Classification Accuracy = 87.50%

Overall, Kappa Statistics = 0.7920

Classification Accuracy Assessment Report for Landsat 2013

Table 2: Accuracy assessment totals for 2013

Class Name	**Reference Totals**	**Classified Totals**	**Number Correct**	**Producer Accuracy**	**Users Accuracy**
Unclassified	3	4	3	-	-
Unclassified	**1**	**0**	**0**	**-**	**-**
Water bodies	15	14	14	93.33%	100.00%
Vegetation	69	74	68	98.55%	91.89%
Built up area	31	28	28	90.32%	100.00%
Totals	120	120	113		

Overall Classification Accuracy = 94.17%

Overall, Kappa Statistics = 0.8976

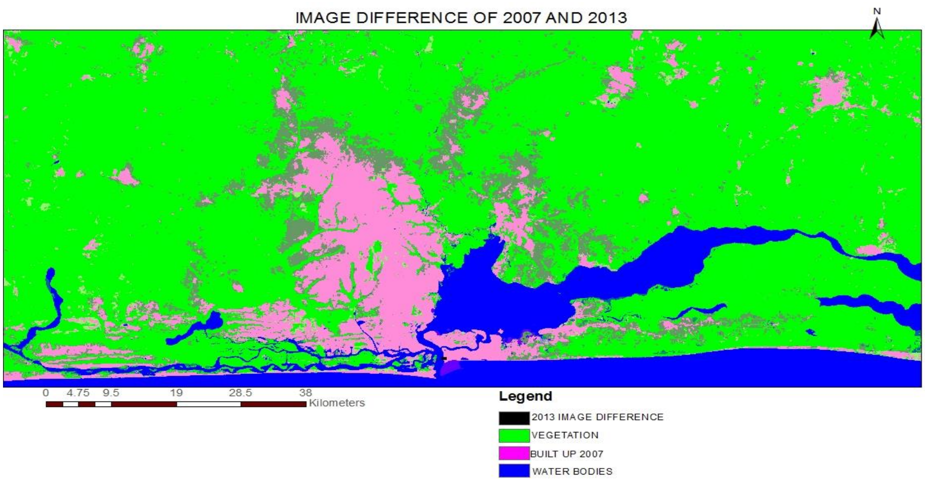

Figure 5: Image difference of 2007 and 2013

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Statistical Analysis of Landscape Change Using Spatial Metrics

Spatial metrics help quantify the dynamic patterns of ecological processes related to urbanization, which often lead to changes in the landscape patterns of urban regions. These changes can be detected using spatial metrics, which categorize complex landscape structures into simpler and identifiable patterns. The results of the classified images are used as input data in FRAGSTATS 4.1 for statistical analysis of the changing patterns and processes of urban landscape change.

Selection of Metrics and Definition of Spatial Domain

Spatial pattern metrics are commonly used to quantify various aspects of landscapes. However, some metrics may be redundant as they fail to capture different qualities of spatial patterns. Given the rapid evolution of quantitative metrics, it is unlikely that a single set of metrics can fully describe a landscape. Therefore, the choice of metrics depends on the specific problem being investigated and the characteristics of the landscape.

For our study, we have selected a group of nine metrics based on a thorough review of the literature and the potential of each metric to accurately describe urban patterns. One of the most crucial considerations in spatial metrics is defining the spatial domain of the study, as this directly impacts the spatial metrics. When evaluating intra-urban landscape structures, it is valuable to divide the urban environment into relatively homogeneous spatial units, which will serve as the spatial domains for metric analysis. The spatial domain refers to the geographic extent under examination and its subdivisions. In some cases, the study area's extent determines the spatial domain. For our work, we have adopted a region-based approach for calculating metrics. The selected metrics include:

1. Class area -CA
2. Number of Patches -NP
3. Patch Density -PD
4. Edge Density -ED
5. Largest Patch Index -LPI
6. Shannon’s Diversity Index -SHDI
7. Contagion Index -CONTAG
8. Contiguity Index –CONTIG
9. Patch Richness –PR

Class Area (CA) The concept of class area (TA) is a fundamental and easy-to-understand metric used in spatial metrics computation to describe urban growth patterns. Total area, sometimes referred to as total area (TA), represents the overall area occupied by a specific land cover class in hectares. In the context of this study, CA or TA pertains to the complete area occupied by either built-up or non-built-up areas.

$$\mathrm{CA} = \sum_{j=1}^{n} a_{ij} \qquad \text{Eq. 1}$$

- CA approaches 0 as the patch type or land cover type becomes increasingly rare in the landscape.
- CA = TA when the entire landscape consists of a single patch or a single land cover type.
- CA equals the sum of the areas of all patches of the corresponding patch type. The class area (CA) metrics simply describe the growth of urban areas in terms of area or size. (McGarigal & Marks., 1995, p. 86)

Number of Patches (NP) The term "patch" refers to the extent of disconnected urban areas or separate class units within a landscape. As urban nuclei rapidly develop, the number of patches is anticipated to rise due to the formation of new fragmented urban areas around the nuclei. However, it's important to note that this measure, like other richness measures, may yield misleading outcomes as it doesn't take into account the actual

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area covered by each class. Even if a particular class covers the smallest possible area, it is still counted in this measure.

$$NP = n \text{ when } 0 < n < \infty \qquad \text{Eqn. 2}$$

NP = 1 when the landscape contains only 1 patch.

- NP being high when urban expansion is proportional to an increase in subdivided urban areas or when the landscape gets more fragmented and heterogeneous. (McGarigal et al., 2002)

Patch Density (PD) The patch density (PD) is a measure of landscape fragmentation and the spatial distribution of land cover patches within a specific area, such as per square kilometre. An increase in the number of small patches without a significant increase in the total landscape area will result in a higher PD, indicating a more diverse and fragmented urban development. Conversely, an increase in the total landscape area without a significant change in the number of urban patches will result in a lower patch density, suggesting the development of a continuous urban surface due to the merging of smaller urban patches.

A patch represents an area, which is covered by a single land cover class. The patch density (PD) expresses the number of patches within the entire reference unit on a per-area basis. It is measured in *Number per unit area* and calculated as:

$$PD = \frac{N}{A} \qquad \text{Eqn. 3}$$

$$0 < PD < \infty$$

- Description: PD equals the number of patches in the landscape divided by the total landscape area, multiplied by 10,000 and 100 (to convert to 100 hectares) (McGarigal & Marks., 1995, p. 88).
- The index is a reflection of the extent to which the landscape is fragmented. This index is important for the assessment of landscape structures, enabling comparisons of units with different sizes.

Edge Density (ED) The Edge Density (ED) is an important measure of urban expansion, indicating the total length of urban patch boundaries relative to the total landscape area. Essentially, it reflects the level of land cover fragmentation. As the number of patches increases, the Edge Density also increases correspondingly. The index is calculated by dividing the total length of the borders between different patch types by the total area of the reference unit.

$$ED = \frac{E}{A} \qquad \text{Eqn. 4}$$

- ED equals the sum of the lengths (m) of all edge segments in the landscape, divided by the total landscape area (m^2), multiplied by 10,000 (to convert to hectares) (McGarigal & Marks., 1995, p. 89).

Largest Patch Index (LPI) The patch dominance index (PDI) is a relative measure that can be used to compare different regions with varying spatial extents. It quantifies the extent to which urban landscapes are fragmented into smaller discrete patches versus having a dominant core. The PDI is calculated by dividing the area (m2) of the largest patch of the corresponding patch type by the total landscape area (m2) and multiplying by 100 to convert it to a percentage (McGarigal & Marks, 1995, p. 87). An increase in the PDI indicates that urban areas are becoming more aggregated and integrated with the urban cores.

$$LPI = \frac{\max_{j=1} a_{ij}}{A} * 100 \ \%. \qquad \text{Eqn.5}$$

$$0 < LPI \leqq 100$$

- LPI = 100 when the entire landscape consists of a single patch.

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Shannon's Diversity Index (SHDI) is the quantitative measure of the variety and relative abundance of the patch types represented on the landscape. The composition of the pattern is typically quantified with diversity indices.

$$SHDI = \sum_{i=1}^{m} (P_i^{\circ}) \ln P_i \qquad \text{Eqn. 6}$$

$$0 \leq SHDI \leq 1$$

- SHDI = 1 when the landscape contains only one patch (i.e. proportional abundances are the same) and approaches 0 as the distribution of area among the different patch types becomes increasingly uneven.
- SHDI equals the sum, across all patch types, of the proportional abundance of each patch type multiplied by that proportion (McGarigal & Marks., 1995, p. 118).

Contagion (Contag) Index The concept of contagion measures the likelihood of nearby pixels belonging to the same class and illustrates how closely landscapes are clustered or dispersed (O'Neill et al., 1988). In simpler terms, contagion quantifies adjacency. Landscapes with high contagion values comprise large, connected patches. Conversely, a low contagion index indicates the presence of numerous small or fragmented patches in the landscape.

$$CONTAG = \left[1 + \frac{\sum_{i=1}^{m} \sum_{k=1}^{m} \left\{ (P_i) \left[\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}} \right] \right\} * \left\{ \ln(P_i) \left[\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}} \right] \right\}}{2 \ln(m)} \right] * 100\% \qquad \text{Eqn. 7}$$

Where 0 < CONTAG < 100

- In other words, it is the observed contagion over the maximum possible contagion for the given number of patch types (McGarigal & Marks., 1995, p. 121).
- CONTAG approaches 0 when the distribution of adjacencies among unique patch types becomes increasingly uneven. CONTAG = 100 when all patch types are equally adjacent to all other patch types.

Contiguity Index (Contig) The quantification involves convolving a 3x3 pixel template with a binary digital image. In this image, the pixels within the area of interest are assigned a value of 1, while the background pixels are given a value of zero. The contiguity value for a pixel in the output image is obtained by summing the products of each template value and the corresponding input image pixel value within the nine-cell neighborhood. As a result, larger contiguous patches lead to higher contiguity index values.

$$0 \leqq CONTIG \leqq 1$$

- CONTIG equals the average contiguity value for the cells in a patch (i.e., a sum of the cell values divided by the total number of pixels in the patch) minus 1, divided by the sum of the template values minus 1.
- CONTIG equals 0 for a one-pixel patch and increases to a limit of 1 as patch contiguity, or connectedness, increases.

Spatial Metrics Analysis Using Fragstat

When using Fragstat v4 software to calculate and analyze equations 3.1 to 3.7 mentioned above, it is important to recognize three distinct levels of analysis for categorical map patterns (or patch mosaics). These levels represent different perspectives on landscape pattern analysis and have significant implications for the selection and interpretation of individual landscape metrics as well as the form of the results. The three levels are:

1. Focal patch analysis
2. Local neighborhood structure or class analysis
3. Global landscape structure analysis

It is the responsibility of the investigator to determine the appropriate scope of analysis for the specific question at hand and then select suitable landscape metrics that align with this scope of analysis.

Table 3: Fragstat analysis result of TA, NP, PD, AND ED

	TA	NP	PD	ED
class2013	597.9945	7373	1232.955	462.6681
class2007	607.958	3314	545.1034	318.5056

The table above displays the fragstat analysis findings for TA, NP, PD, and ED, while

Figure 4: Provides a visual comparison of these metrics.

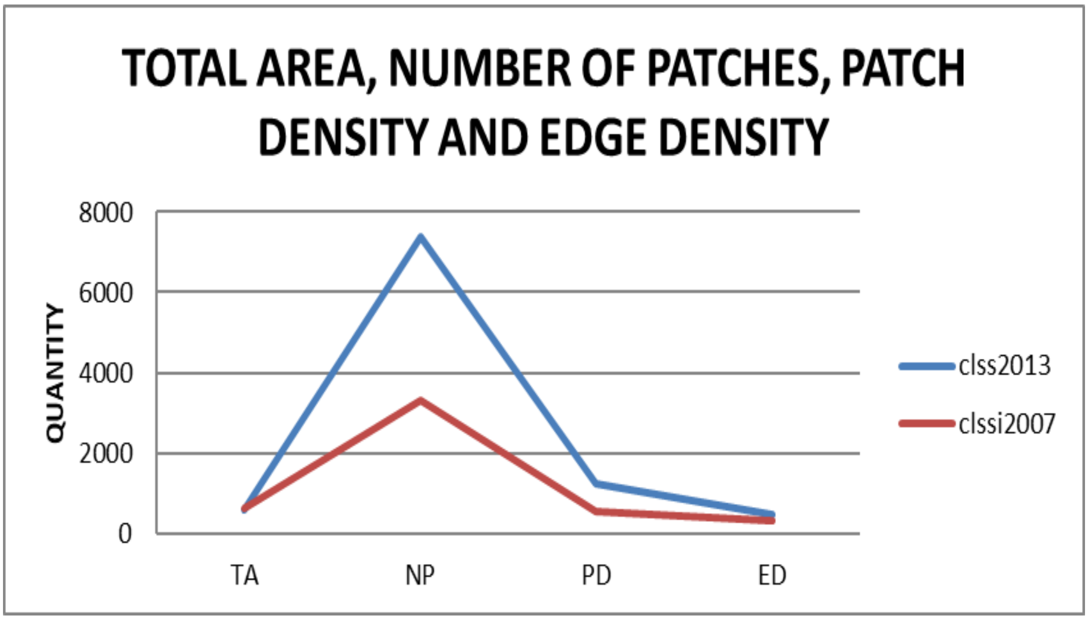

Figure 6 Graph comparing TA, NP, PD, AND ED for the years 2007 AND 2013

However, the negative slope in TA is notably more pronounced between 2007 and 2013. This is because our study scope is limited to the core population district. TE would show a positive slope if we considered all the state borders and the population spill areas of Lagos towards the north.

As depicted in Figure 6, the higher values of NP and PD in 2013 compared to 2007 are attributed to the mandatory horticultural practice in Lagos by the new government regime, as well as the extensive in-fill of roads and vertical constructions.

ED is slightly higher due to in-fill at the border area, and TE remains almost the same. However, the significant increase in Land Cover fragmentation in 2013 indicates continuous government involvement in major road constructions, opening up the remote areas and the suburbs, as well as the opening of canals, reclamation of wetland and shallow water areas, etc.

Vegetation Class Analysis

Land cover categorized as vegetation encompasses wetland vegetation, grasses, trees, forests, and farmlands. This classification pertains to all other types of land cover falling within this specific category.

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Table 4: Comparison of the metrics quantifying vegetation spread for 2007 and 2013

	CA	NP/100	PD	LPI	ED	CONTIG_CV
VEGETATION 2013	341.7139	31.83	532.2791	38.3333	443.9706	86.9581
VEGETATION 2007	378.9537	12.64	207.9091	42.0553	306.9357	80.219

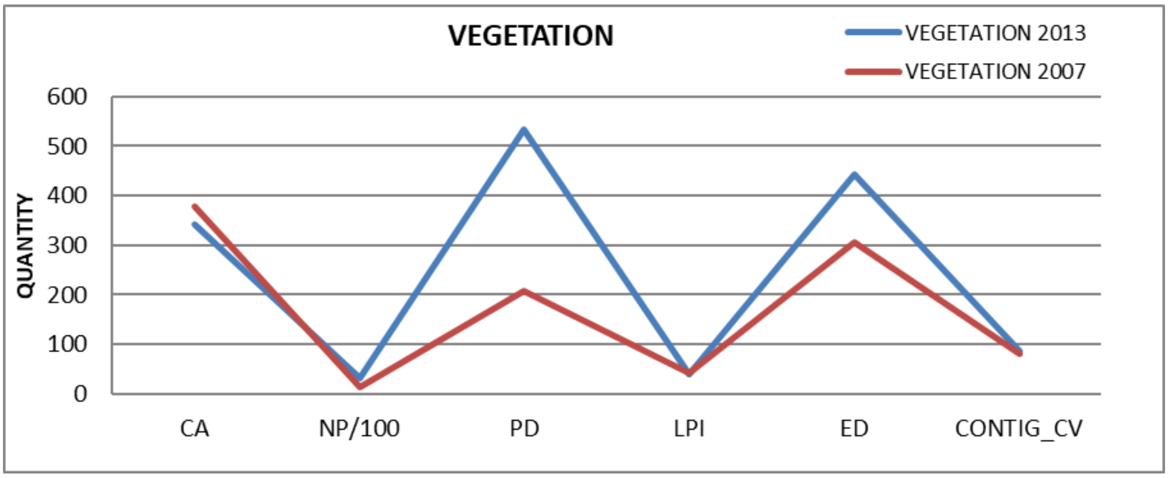

Figure 7: Vegetation class analysis using CA, NP, PD, LPI, AND ED

Water Body Class Analysis

The waterbody class includes the ocean, sea, lagoon, rivers, streams, canals, and every other land cover that falls into this category.

Table 5: Comparison of the metrics quantifying water bodies spread for 2007 and 2013

	CA	NP/100	PD	LPI	ED	CONTIG_CV
WATER BODIES 2013	**113.8477**	**3.44**	**57.5256**	**17.6607**	**60.1745**	**82.4647**
WATER BODIES 2007	**138.7676**	**2.18**	**35.8577**	**22.5554**	**57.6898**	**76.9795**

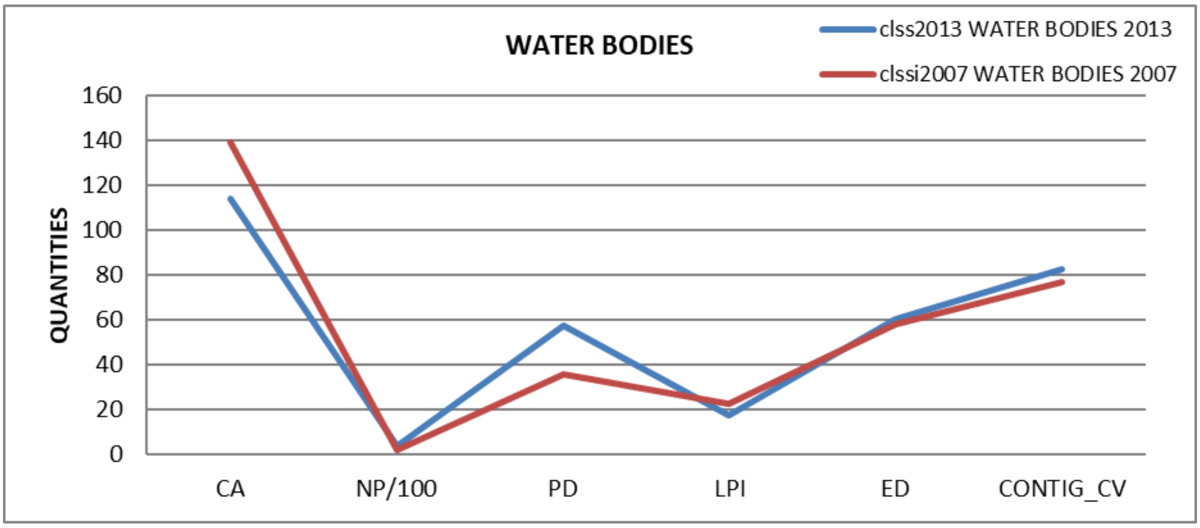

Figure 8: Water bodies class analysis using CA, NP, PD, LPI, AND ED

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Built-Up Class Analysis

Built-up class includes any artificial construction including houses, stadiums, roads, and many others in that category.

Table 6: Comparison of the metrics quantifying Built-up area for 2007 and 2013

	CA	NP/100	PD	LPI	ED	CONTIG_CV
BUILT UP 2013	138.6511	38.27	639.9724	11.3895	414.1944	75.3363
BUILT UP 2007	86.0552	18.24	300.0207	7.0886	260.8815	48.6151

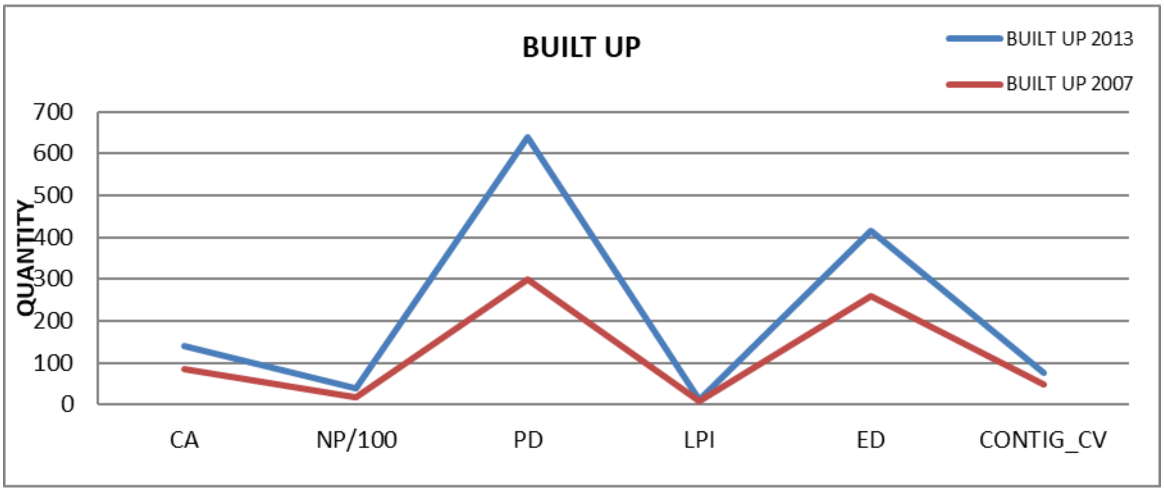

Figure 9: Chart Built-up class analysis using CA, NP, PD, LPI, AND ED

Table 7: Change in Class Area

	VEGETATION	BUILT UP	WATER BODIES
YEAR 2007	378.954	86.0552	138.8
YEAR 2013	341.714	138.651	113.8
CHANGE IN CLASS AREA	**-37.2398**	**52.5959**	**-24.9199**

In the image classification, a map factor of 1:33 was used. The actual true ground data are therefore given as follows:

(1) Reduction in vegetation cover between 2007 and 2013 is:

$$37.2398 \times 33 = 1228.91 \text{ Kmsq}$$

Percentage Change of a particular land cover is the ratio of change in the area of that land cover and the initial area size of the land cover within the time frame.

The percentage reduction in vegetation is 9.8%

(2) Reduction in water bodies between 2007 and 2013 is:

$$24.9199 \times 33 = 822.357 \text{ Kmsq}$$

The percentage reduction in water bodies is 17.95%

(3) Increase in Built up area between 2007 and 2013 is:

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52.5959 x 33 = 1735.665 Kmsq

The percentage increase in built-up area is 61.11%

The preceding analysis indicates a significant transformation of land cover in the city of Lagos and its surrounding areas over the past seven years. The once-green areas and wetlands have been increasingly replaced by extensive infrastructural development and residential constructions.

While the original Lagos metropolis experiences predominantly vertical expansion, its peripheries are continuously expanding, creating a nearly contiguous built-up area interspersed with narrow waterways and canals. The landscape is witnessing an ongoing shift from natural vegetation and water bodies to urban development, with the suburbs gradually transforming into substantial built-up areas.

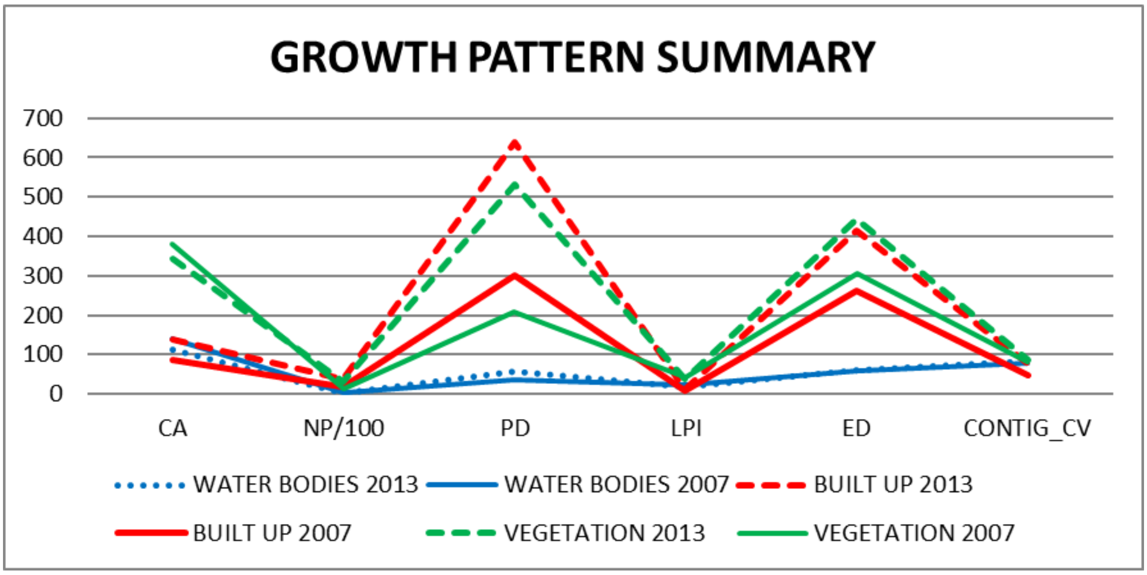

Figure 10 Chart showing the summary of the 3 classes, analyzing using CA, NP, PD, LPI, AND ED

Finally, table 7 and figure 10 present a clear picture of the changes, showing a decrease of 37.2sqkm in vegetation and wetland areas, a 24.9sqkm reduction in the overall size of water bodies, and a 52.6sqkm increase in built-up areas.

CONCLUSION

In recent years, urbanization has significantly changed the urban landscape of Lagos, with the city expanding from its central and sub-city centers into surrounding non-built-up areas in all directions. There is a need for considerable effort to enhance urban facilities to meet the growing demand. This paper provides insight into the urban growth patterns in Lagos metropolis using spatial metrics. The selected metrics measure different aspects of the landscape, such as configuration, fragmentation, area, and shape.

Evaluation of the metrics at the city level indicates that urbanization has substantially altered the landscape pattern of the study area, leading to significant land conversion and an increase in the size of Lagos. There has been a major fragmented development process in the built-up area, with substantial increases in built-up edges (TE) by 2007. The subsequent development in the central Lagos metropolis from 2013 is expected to be predominantly vertical.

The decreasing trend in the number of patches (NP) shows the merger of new patches with existing ones, particularly in the urban core, resulting in the formation of the largest patch. The increasing trends observed in patch density throughout the study periods reflect infill, vertical development, and edge expansion in major city centers or sub-city core areas across the borders of Lagos state. Despite the increasing trend in the largest urban core patch, the built-up area remains complex and fragmented, particularly in the fringe areas.

Poor planning and challenging topography, such as wetlands, contribute to unorganized development. The availability of waterways and alternative major transport systems will likely be significant drivers of future urban growth, with a continued focus on vertical developments.

In summary, a graphical analysis was conducted to assess the spatial extent, pace of urban growth, and growth direction of the Lagos metropolis.

RECOMMENDATIONS

For a more thorough understanding of the changing patterns and causal dynamics of urban landscapes in specific locations within the city, this research introduces a region-based analysis of spatial growth patterns for a more detailed examination. Additionally, a comprehensive analysis employing a greater number of spatial metrics would enhance our understanding of urban growth patterns, aiding in developmental planning and governmental decision-making.

Furthermore, logistic regression modeling using Change analysis software could be utilized to produce an output for evaluating the predictive power of a spatial growth model.

This evaluation can be achieved using the Percentage Correct Prediction (PCP) method, which measures the percentage of correctly predicted pixels from the sampled pixels in the model. A higher PCP indicates a stronger predictive power of the model.

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