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Spatial Matrices of Urban Expansion in Lafia, North-Central Nigeria

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Abstract

Rapid urbanisation in African cities has caused considerable problems by hindering their ability to meet infrastructure and service needs, resulting in rising land-use consumption. This study examines how land use/land cover change in Lafia, a city in North-central Nigeria, has impacted the city's boundaries between 1999 and 2019 and includes a projection using GIS simulation of land use/ land cover to 2029. This study used remote sensing techniques, statistical models, and spatiotemporal analysis of geographical measurements. This study involved spatial analysis and projection of city growth from 1999 to 2029 in Lafia using GIS. This analysis focuses on the changes in built-up areas, vegetal cover, bare land, and water bodies using land-use/landcover data. The results indicated significant urban expansion and its impact on the city's spatial patterns. The Urban Expansion Differentiation Index (UEDI) and Urban Expansion Intensity Index (UEII)were used to assess urban sprawl and socioeconomic patterns such as population density and density gradient. High residential and employment densities, varied land uses, continuous development, and multimodal transportation are all important for sustainable urban growth. The study indicates a direct relationship between population growth and urban expansion, as seen in Lafia. Furthermore, the findings suggest that cities grow beyond their typical boundaries, resulting in peri-urban expansion, as shown in the Alakio districts of the Lafia Metropolis. The study findings have important implications for urban growth policy and land use/land cover change. They will contribute to a better understanding of the effects of urban growth on the spatial matrix and morphology of cities, assisting city planners in recognizing these effects. Furthermore, the study adds evidence to the continuing debate about urban expansion, liveability, and spatial sustainability in African cities. The thorough examination of land use/land cover change in Lafia sheds light on the spatial dynamics of urbanisation and its implications for sustainable urban development.

Keywords: Spatial Metrics, Urbanisation, GIS, Urban Expansion, Remote Sensing, Latfia.

1. Introduction

Urbanisation is a complex process that has brought about significant changes in various aspects of society, including cultural, sociological, economic, ecological, and environmental domains (Long *et al*., 2014; Li *et al*., 2022; Şenik & Uzun, 2022; Lopez, 2021). The growing desire for a prosperous economy in developing countries has driven population growth and economic expansion in urban centres, resulting in changes to land use/land cover (LULC) (Li *et al*., 2009; Telfah *et al*., 2023). With more than half of the global population estimated to live in urban areas by 2050 (United Nations, 2010; Huang *et al*., 2019), understanding the dynamics of LULC and urban growth has become crucial for assessing the long-term ecological implications of urbanisation (Bhatta, 2009; Geymen & Baz, 2008; Hardin *et al*., 2007; Long *et al*., 2009; Maktav & Erbek, 2005; Weber & Puissant, 2003). However, the interplay between urban growth and socioeconomic processes requires further investigation (Hatab *et al*., 2019).

The city has long been the focus of scholarly interest across various disciplines, serving as a central element in understanding social organization and change (Domanski *et al*., 2020). Scholars have examined cities from different perspectives, including moral, historical, ecological, economic, and political viewpoints (Gössling, 2020; Estoque *et al*., 2020; Feng *et al*., 2021). Sociologists consider the city as a distinct human community, representing a shift from dispersed to concentrated population distribution and leading to changes in settlement patterns and social life (McKnight *et al*., 2019). Urbanisation is seen as a global phenomenon, representing an advanced stage of human evolution (Tian *et al*., 2022).

As urbanisation progresses globally, city landscapes undergo significant transformations, challenging conventional notions of urban and non-urban areas (Brenner & Schmid, 2014; 2015; Chen *et al*., 2016; Stanley *et al*., 2016; Chen & Yu, 2017). Biodiversity loss and homogenization are becoming widespread due to urbanisation, with different impacts observable in developed and developing countries (Liu *et al*., 2020; Sidemo-Holm *et al*., 2022). However, most studies on urban sprawl have focused on developed countries, leaving a knowledge gap regarding urbanisation in developing countries, including its impact on native and invasive biota (Fontes & Milano, 2002; Whitmore *et al*., 2002; Spanier & Zviely, 2022).

Reliable and recent land use/land cover (LULC) information is critical for urban planning and land resource management (Das *et al.*, 2022). Remote sensing and geographic information systems (GIS) have facilitated the acquisition and integration of LULC data, enabling the monitoring and analysis of urban environments (Zaman-ul-Haq *et al.*, 2022). Change detection algorithms, such as image differencing, have been employed to detect and map LULC changes over time (Asokan & Anitha, 2019). These advances in research have made it possible to study the spatial patterns and consequences of land use change, providing insights valuable to decision-making and policy implementation (Fasona & Omojola, 2005).

As in many other developing countries, urbanisation in Nigeria has been driven by the grow of population and economical condition (Li *et al*., 2009). As urban population growth continues, it is important to study the patterns and dynamics of land use/land cover change to manage the urban environment more effectively and address the associated challenges. Understanding the drivers and consequences of urban expansion can help policymakers and planners make informed decisions to promote sustainable development.

Urbanisation is a significant milestone in human evolution, with urbanized societies reaching unprecedented sizes and densities (Hussain & Imitiyas, 2016). This phenomenon has attracted scholars from various disciplines due to the complex nature of urbanisation and its profound impact on society (asghar Pilehvar, 2021; Liu et al., 2021; Qian & An, 2021; Cobbinah, 2023). Previous studies have highlighted the significance of modeling land use/land cover and urban growth while considering the long-term ecological effects of urbanisation (Bhatta, 2009; Geymen & Baz, 2008; Hardin *et al*., 2007; Long *et al*., 2009; Maktav & Erbek, 2005; Weber & Puissant, 2003; Patra *et al*, 2018). However, there is still a need to bridge the gap between urban growth and socioeconomic processes to understand the interplay between urbanisation and its environmental consequences (Irwin & Geoghegan, 2001).

In Nigeria and other African countries, the pace of urban population growth has been remarkable, with urbanisation levels projected to increase significantly in the coming decades (zu Selhausen, 2022). The urban agglomerations in these regions strive for high levels of integration and face numerous environmental and ecological issues associated with overpopulation (Fang, 2014). Understanding the factors influencing urbanisation and their environmental impacts is crucial for promoting sustainable urban development.

Research on urbanisation and its effects on ecology and the environment has primarily focused on factors influencing individual strategies in urban areas, such as land conservation, land-use change, human demands, vegetation coverage, and the urban landscape (Delphin *et al*., 2016). However, there is a limited understanding of the interplay between urbanisation and the ecological environment at multiple time and space scales and how these dynamics affect the synergy between urban growth and environmental processes. Rapid urbanisation in African cities has put an enormous strain on these cities' ability to support their residents' infrastructure and service needs. It has accelerated the rate at which man uses space for activities alien to the natural world. Land use/land cover change has become a significant problem in many of these cities because of this scenario. This paper, therefore, examines land use and landcover change in Lafia North-Central Nigeria between 1999 and 2019 and shows how the spatial changes have affected the city limits and the human impact on the environment.

The spatial analysis of land use/land cover change in Lafia can reveal patterns and trends in urban expansion, conversion of agricultural land, encroachment on natural areas, and other changes. These findings can provide valuable insights for urban planners, policymakers, and stakeholders involved in sustainable development efforts. Understanding the dynamics of land use/land cover change can help decision-makers identify areas of concern, plan for infrastructure development, protect valuable ecosystems, and manage resources effectively

2. Research Methods

The study methodology involves utilizing remote sensing techniques (RS) and conducting spatiotemporal analysis of spatial metrics. It also applies statistical models. Images of built-up areas extracted from classified government images of the Nigerian landscape serve as input data for analysis undertaken using FRAGSTATS 4.2, a software tool developed by McGarigal *et al.* (2012). Remote sensing techniques gather data from satellite images, accurately identifying and extracting images of built-up areas. These images are then analyzed using FRAGSTATS 4.2 to assess the spatial characteristics of the urban environment. Additionally, statistical regression models are employed to quantify the relationships between urban growth and socioeconomic patterns.

2.1. Study area

Urbanisation in Nigeria has been transformed over the last thirty years due to changes events on a national and international scale. From 1999 to 2019, all of the major cities in Nigeria experienced a continuous influx of people searching for increased income. Many of these cities experienced unplanned urban growth and urbanisation due to this mass migration of people from rural areas. According to a UN (2015) report, Nigeria's annual urban population growth rate at the midpoint of this study was 4.84%, and the national growth rate was 3.2% (NPC, 2011). The year 1999 was chosen as the start-date for this study because it coincides roughly with the advent of civilian political rule in Nigeria.

2.2. Analysis of Land Cover Change

Figure 1 provides an overview of the methodology employed to obtain land cover change information using remote sensing (RS) data. The image classification process is conducted by utilising three specific indices: SAVI, MNDWI and UI, that is stand for Soil-Adjusted Vegetation Index, Modified Normalized Difference Water Index, and Urban Index, respectively. These indices play a crucial role in differentiating and categorizing land cover types. By applying these indices, the researcher can make accurate visual interpretations of the RS data.

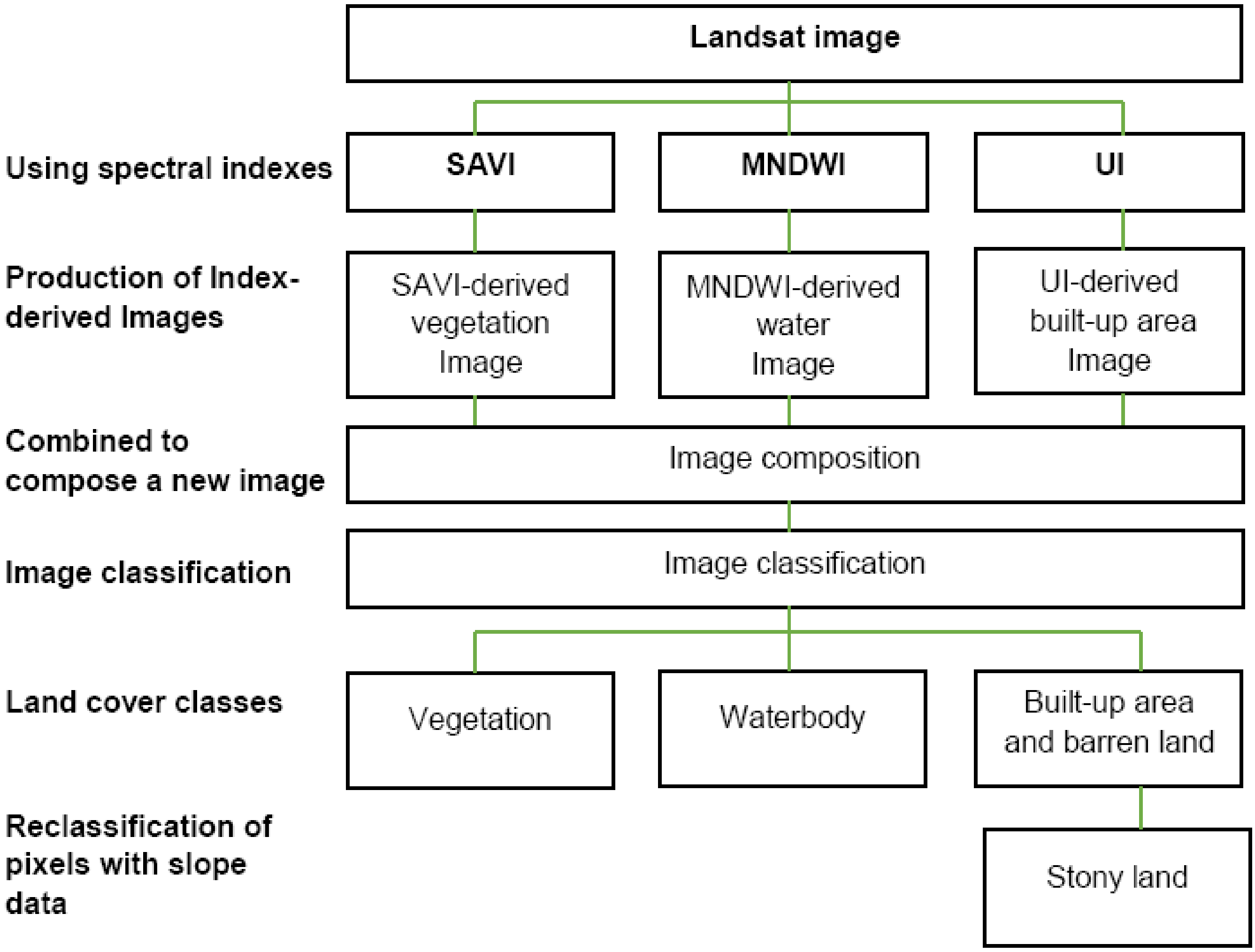

Figure 1. A classification scheme for land cover mapping (Yuan *et al.*, 2005).

2.2.1. Image classification

The Anderson classification system was developed for the United States but is widely used worldwide. The urban or built-up area is characterised by intensive land use where human activities have altered the landscape. Vegetable refers to all land used primarily to produce agricultural product and some of the structures associated with this production. Water body category refers to geographic areas that are covered by water. In the present study, we have introduced a new class of land that includes rock faces, rockslides, and cliffs (Table 1). These exposed land types have a significant vertical component and are often covered in moss and lichen.

Table 1. The Classification Scheme for Land Cover.

Land cover categories	Sub-categories
Built-up Area	Transportation, communications, utilities, industrial and commercial complexes, residential, commercial, service, and another type of built-up or mixed-use property
Vegetation	Ornamental horticulture regions, vineyards, nurseries, orchards, groves, and pastures, restricted feeding activities, more farmland, Evergreen forest, mixed forest, and deciduous forest
Waterbody	Lakes, Reservoirs, Bays, and Estuaries, as well as Streams and Canals
Bareland	Beaches, sandy areas away from beaches, mountaintop rock faces, rockslides, and cliffs

Source: Modified from Yuan *et al.*, (2005).

Due to the medium spatial resolution of the Landsat imagery, some land cover types may be contained inside a single pixel. Due to this, it may be challenging to distinguish one particular land cover class using spectral features from other classes (Ji and Jensen, 1999). For operational applications, land cover maps created from satellite images are typically insufficient.SAVI, UI, and MNDWI indexes were used to classify the land cover. The urban cover is divided into four broad categories: developed land, undeveloped land, vegetated land, and water body.

The reflection of red and near-infrared wavelengths might affect the values of the vegetation index where low vegetation and bare soil surfaces exist (Huete, 1988). SAVI makes use of the strong pigment absorption of red light, such as TM band 3, and NIR spectral range, such as TM band 4 that has high vegetation reflectance (Jensen, 2005; Li *et al.*, 2016). We used SAVI rather than Normalised Difference Index (NDVI), because of its greater capabilities for analyzing areas with minimal plant cover, such as urban areas, in order to highlight vegetation traits. SAVI can be used in areas with as little as 15% plant cover, but NDVI can only be used efficiently in areas with plant cover levels of at least 30% (Herold *et al.*, 2015). Equation 1 represents the Soil-Adjusted Vegetation Index (SAVI), where NIR is the Reflectance value of the band 4 (near-infrared) TM sensor. Red represents the band 3 (red) reflectance value on the TM sensor. L is a correction factor with a range of 0 for extremely high densities and 1 for extremely low densities. Given that the research region has an intermediate vegetation density, an enhanced vegetation image was generated using a value of 0.5. SAVI can distinguish between vegetation and built-up or arid land as its range expands.

$$SAVI = ((NIR - Red) / (NIR + Red + L)) \, x \, (1 + L) \quad (1)$$

Following the creation of vegetative images using SAVI, images of developed land were created using the Urban Index (UI) and Equation 2, where NIR and SWIR are the reflectance values of band 4 (near-infrared) and band 7, respectively, that were detected by the TM sensor.

$$UI = SWIR - NIR / SWIR + NIR \quad (2)$$

To help distinguish between populated areas and arid countryside, UI values from multi-temporal images were utilized. Urban characteristics are more distinguishable in the Urban Index (UI) compared to the Normalized Difference Built-up Index (NDBI). The most accurate identifications occur when utilizing band 7 rather than band 5 (Bouhennache *et al.*, 2015; Pratibha *et al.*, 2014). As a result, these UI values were employed instead of data from the Normalized Difference Built-up Index (NDBI). SAVI's wider coverage typically allows for the separation of vegetated area from urban or arid land.

MNDWI differentiate water from a background predominantly composed of built-up land areas. According to Xu (2007), MNDWI outperformed the Normalised Difference Water Index in terms of outcomes. Equation 3 (McFeeters,1996), describes the modified NDWI (MNDWI), where MIR represents a middle infrared band, for instance, TM band 5. Due to expanding water features and declining built-up land values, the contrast characteristic between water and the built-up area shown by the MNDWI will be relatively substantial in comparison to the study achievable with the NDWI (Hu, 2007).

$$MNDWI = Green - MIR / Green + MIR \quad (3)$$

A new dataset was made using these three images as the three bands after SAVI, MNDWI, and UI images were formed. Band correlation is greatly reduced when an image with seven multispectral bands is changed to one with three themes. Then, a new image was created by combining the three new bands. From the new images made comprised of the three thematically focused bands, land cover features were extracted using the supervised classification method. A maximum likelihood approach based on the signatures of training regions was used for the supervised classification process. As a result, there are four main types of urban land cover that may be distinguished: vegetation (high values of SAVI), water (high values of MNDWI), built-up regions (high values of UI), and bare land (low values of UI).

The study distinguishes between barren land with a significant vertical component and stony land (rock faces on mountains, rockslides). The researcher anticipated finding stony terrain in regions with slopes greater than 15 degrees. After reclassifying the research area, the stony land was located using slope data. The error matrix is most frequently used to evaluate the precision of land cover maps created from remote sensing data. On a class-by-class basis, the data were then compared to a reference image.

2.2.2. Land Cover Change Detection

As a method of change detection, post-classification was chosen to track changes in the various land cover types across time. The process produced a two-way cross matrix that contained information on "from-to" land cover conversion. For each time, a fresh themed map displaying the various combinations of land cover data was also created.

2.3. Land Cover Change Detection

2.3.1. Growth Ratio Analysis

Using the growth ratio index and GIS analytical methods, several studies have sought to determine and quantify the pace, volume, and intensity of urban expansion. The Landscape Expansion Index (LEI) (Liu, *et al*., 2009), the Urban Expansion Intensity Index (UEII) (Herold *et al*., 2015), and the Urban Expansion Differentiation Index (UEDI) are a few examples of regularly used measures. This study used a hybrid technique to measure urban growth. Figure 2 provides an illustration of the overall methods employed in this section of the study.

The first statistical index to determine the average annual urban expansion rate is called the Average Annual Urban Expansion Rate (AUER). According to (Acheampong *et al*., 2016), this indicator calculates the average annual growth rate of built-up land in the case study across the time period. The Annual Urban Expansion Rate is calculated using Equation 4, where AUERi is the Annual Urban Expansion Rate, ULAit2, and ULAit1, respectively, are the areas measured in i units at times t2 and t1, and t is the research period.

$$AUERi = \frac{[(ULAit2)^{1/\Delta t} - 1] \times 100}{[ULAit1]} \quad (4)$$

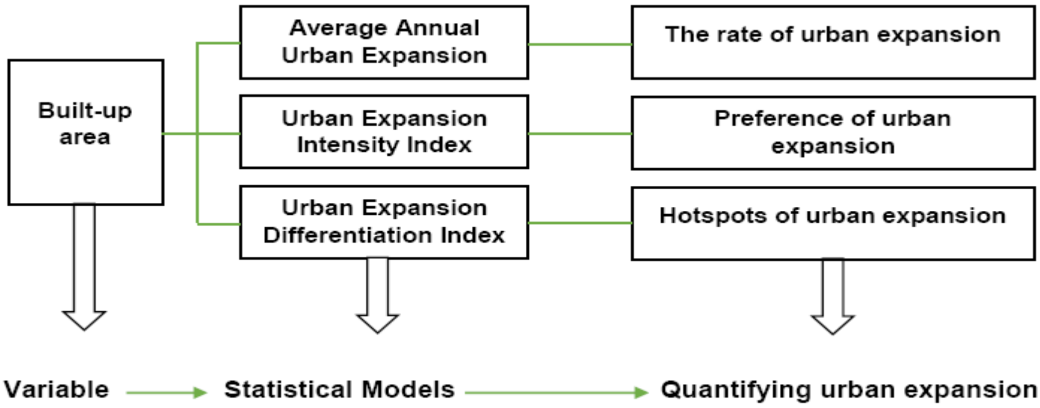

Figure 2. Growth Ratio Analysis.

In the current study, the Urban Expansion Intensity Index (UEII) was also used. The researcher can use the UEII to calculate the average annual proportion of newly increased built-up land within a spatial unit, standardised by that spatial unit's total area, as indicated in Equation 5 (Li *et al*., 2015; Herold *et al.*, 2015). where TLAi is the total area in i unit; ULAit2 and ULAit1 are the areas in i unit at times t2 and t1, respectively; UEIIi is the urban expansion intensity index in i unit; and t is the study period.

$$UEIIi = [ULAit2 - ULAit1] \times 100 \quad (5)$$

Urban expansion intensity is a crucial metric for assessing the spatial changes caused by urban expansion since it can be used to assess changes in the amount of urban area per unit of time. Urban expansion will differ in each zone during the expansion process due to the rule of urban driving variables and their spatial implications. The term "preference of urban growth" refers to this phenomena (Alsharif and Pradhan, 2013). The UEII was utilized in this study to statistically assess and analyze urban spatial expansion. The UEII was also utilized to determine a certain period's predilection for urban expansion. The UEII examines the intensity of urban cover changes through time and reflects the potentials of various urban expansion scenarios. To reveal the geographical evolution pattern of urban land development, the urban expansion intensity index (UEII) scores of the 21 concentric zones that make up the region are divided into five UEII zones. According to (Alsharif and Pradhan, 2013), slow development ranges from 0 to 0.28, low development ranges from 0.28 to 0.59, medium development ranges from 0.59 to 1.05, high development ranges from 1.05 to 1.92, and very high development ranges from >1.92.

Table 2. The Urban Expansion Intensity Index Range.

Range	Potentials of urban expansions
0 > UEII > 0.28	lower development
0.28 > UEII > 0.59	low-speed development
0.59 > UEII > 1.05	medium-speed development
1.05 > UEII > 1.92	high-speed development
UEII >1.92	very high-speed development

Source : Modified from Acheampong *et al*., (2016).

The Urban Expansion Differentiation Index (UEDI) also determines how much more urban space has been added to a unit relative to the overall area that has changed. The UEDI quantifies the differences between the urban land expansions of various spatial units, making such units comparable, in contrast to the UEII (Acheampong *et al*., 2016). As illustrated in Table 3. this metric is helpful in evaluating urban land expansion differentiation and locating urban expansion hotspots. The equation is given in Equation 6 (Li *et a*l., 2015), where ULAit1 and ULAit2 are the total areas in the i unit at times t2 and t1, respectively, and UEDIi is the urban expansion differentiation index in i units.

$$UEDIi = \frac{[ULAit2 \ - \ ULAit1] \ \times \ ULAt1 \ \times 100}{[ULAt2 \ - \ ULAt1] \ \times \ ULAit1} \tag{6}$$

UEDI can be categorized into three groups: if the differentiation index of the district is higher than one, it is classified as a fast-growing area within the entire study area; if it is lower than one, it is classified as a slow-growing area in the case study; and if it is equal to one, it is classified as a moderately growing area within the study area (Acheampong *et al.*, 2016).

Table 3. The Urban Expansion Differentiation Index Range.

Range	Urban expansion differentiation
UEDI >1	Fast-growing area
UEDI = 1	Moderate growing area
UEDI <1	Slow growing area

Source : Modified from Acheampong *et al*., (2016).

2.3.2. Spatial Metrics for Quantifying Urban Spatial Patterns

The researcher has established three dimensions to comprehend the primary urban expansion patterns that led to the city's spatial patterns. Figure 3 illustrates the general process of this analysis. The researcher used Fragstats 4 to calculate numerous landscape metrics in order to sketch the urban spatial pattern (McGarigal *et al.*, 2012). Other land kinds were classed as non-urban land, and built-up land was defined as urban land. The spatial metrics utilized in the study, which utilised Equations 7 to 9 are described in Table 4.The UEDI is more accurate than other indices measuring general landscape aggregation since it is class-specific. It offers a quantitative foundation for connecting a class's spatial pattern to a particular process. Compactness To calculate how closely the urban footprint resembles a circle, in-dexes are used. The mean separation between each patch cell and the patch centroid is equal to the mean radius of the gyration index (Botequilha *et al*., 2006)

The Mean Euclidean Nearest Neighbour (ENN_MN) calculates the shortest straight-line distance from cell centres to determine the distance to the closest neighbouring patch of the same type (McGarigal and Marks, 1995). Without exception, the values for ENN are always greater than zero. As the distance to the closest neighbour gets less, ENN gets closer to zero. When using the neighbour patch rule, the cell size equals twice the cell size and constrains the minimum ENN. The top limit is limited by the size of the block, which represents the extent of the landscape for this study. If a patch has no neighbours, or if there are no patches in the same class, then ENN is undefined (McGarigal *et al.*, 2012).

Table 4. The characteristics of applied spatial indexes.

$AI = \frac{[gii](100)}{[max-gii)}$ (7)	Using the single-count method, gii is the quantity of like adjacencies (joins) between pixels of patch type (class) i. Using the single-count method, max gii is the greatest number of similar adjacencies (joins) between pixels of patch type (class) i.
Unit: Percent	.
Range	0≤AI≤100, With respect to any Pi, AI is equal to 0 when the focal patch type is maximally deaggregated; it rises as the focal patch type is aggregated more and more, reaching a maximum of 100 when the patch type is maximally combined into a single, compact patch.
$\text{MGYRATE} = \sum_{r=1}^{z} \left(\frac{hijr}{z}\right)$ (8)	based on cell-centre to cell-centre distance, hijr = distance (m) between cell ijr [placed within patch ij] and the centroid of patch ij (the average location); Z = the quantity of cells in patch ij
Unit: Meters	
Range	When the patch consists of a single cell, GYRATE 0, GYRATE = 0, and GYRATE increases without restriction as the patch gets larger. When the patch completely covers the terrain, GYRATE is at its most valuable. Using the edge-to-edge distance between patches that is calculated from cell centre to cell centre, hij is the distance (in meters) from patch ij to the closest adjoining patch of the same kind (class).
$ENNMN = \frac{\sum_{j=1}^{n} hij}{ni}$ (9)	ENN > 0 without restriction. As the distance to the closest neighbour gets less, ENN gets closer to 0. When the 8-neighbor patch rule is applied, the cell size equals twice that size, and when the 4-neighbor rule is applied, it equals the distance between diagonal neighbours. The upper limit is constrained by the size of the landscape. If a patch has no neighbours, or other patches of the same class, ENN is undefined and reported as "N/A" in the "basename" patch file.
Unit: Meters	
Range	

2.3.3. Exploring the effects of urban expansion on spatial patterns

Changes in the values of spatial measurements were utilized as dependent variables to analyze how urban expansion affected the spatiotemporal patterns of Lafia. To understand the effects of urban expansion on the city's spatial patterns, the growth ratio index results (UEII and UEDI) were used as independent variables, and the changes in the values of the spatial metrics (AI, GYRATE_MN, and ENN_MN) were used as dependent variables.

One of the many geographical regression methods that is being used more and more in geography and other related fields is geographic weighted regression (GWR). By applying a regression equation to each feature of the data set, GWR generates a local model of a variable (Fotheringham *et al*., 2002). GWR generates spatial data that express the spatial differences in the interactions among variables, in contrast to conventional regression, which produces a single regression equation to summarize global relationships among the explanatory and dependant variables. The maps created with these data are crucial for analyzing and understanding spatial relationships. Equation 10 can be used to represent the GWR equation (Fotheringham *et al*., 2002). In this equation, yî represents the estimated value of the dependent variable for observation i, 0 represents the intercept, k represents the parameter estimate for variable k, x ik represents the value of the kth variable for i, i represents the error term, and (uivi) represents the observation's coordinate position.

$$y\hat{i} = \beta 0\,(uivi) + \Sigma\, \beta k\,(uivi)\, x\, ik + \varepsilon i \quad (10)$$

The idea is that observations close together affect one another's parameter estimates more than observations farther apart. Each observation's weight is based on a distance decay function that is centred on observation i. When dealing with areal data, the separation between observations is determined by the spacing between the centroids of the polygons. The bandwidth setting, which determines the distance at which the weight rapidly approaches zero, modifies the distance decay function, which can take on several shapes. The analyst has two options for optimizing: manually selecting the bandwidth or using an algorithm that reduces the cross-validation score (CV). Alternately, the Akaike Information Criteria (AIC) score (Equation 11) can be minimized to determine the bandwidth (Nakaya *et al.*, 2005).

$$AICt = 2nloge(\hat{\sigma}) + nloge(2\pi) + \frac{n\{n + tr(S)\}}{\{n - 2 - tr(S)\}} \quad (11)$$

The AIC technique has the benefit that models focused on various observations may have varying degrees of freedom. Additionally, the user has the option of selecting a constant bandwidth that applies to all observations or a variable bandwidth that enlarges in sparse observations and contracts in dense ones. Therefore, the AICt approach was applied in this work for the GWR model.

The regression model with a lower AICt score is thought to be more accurate in reflecting reality. (Griffith, 2008).

3. Results and Discussion

3.1. Spatial Analysis and Projection of City Growth from 1999 to 2029

The city of Lafia in Nasarawa state is the capitals of one of the states in the last set of states created by the military government of General Sani Abacha in 1996. The city's spatial extent was analyzed regarding four important features: built-up areas, vegetal cover, bare ground, and water bodies. Analysis shows that in 1999, 9.8% of the city's total land area was built-up and 11.3% covered by vegetation. There is no record of a water body estimate for the city in 1999 as there was no data on water bodies.

The 2009 analysis of the land-use/landcover of Lafia is presented in Table 6. The analysis indicated that the built-up land in the city increased to 20.6% in 2009, while vegetal cover was estimated at 20.2%, and bare ground at 59.2%. The spread of the brown patch on the map representing built-up areas was estimated at 4,724.8 ha in 2019. The bare ground in the city, which included all spaces that have not been altered, stood at 6,267.2 ha. By 2029, the percentage of Multiparas in the City of Lafia is projected to reach 49.5%, vegetal cover is expected to shrink to just 7.0%, and bare ground is projected to reach 43.5%. The simulation of the increase in land consumed is presented in Figure 3.

Analysis indicates the spatial changes in hectares of land gained and lost by the various identified land uses within the period under review. Over time, the vegetation cover and bare ground continue encroaching upon by the built-up areas in Lafia. The total land area of Lafia has been measured at 11,854 ha. Between 1999 and 2009, no water body was registered for Lafia. Table 5 shows that the built-up land area doubled between 1999 and 2009. l has the past. By contrast, the spatial extent of the city of Manchester has been reduced from 9359.9 ha in 1999 to 7017.9 ha in 2009, a decrease of 2342 ha, a 19.7% change in the spatial extent.

Table 5. Lafia Land use change Between 1999 And 2009.

Land cover	1999	2009	Δ	1999%	2009%	Δ %
Built-up	1159.9	2444.8	1284.9	9.8	20.6	10.8
Vegetation	1334.6	2391.7	1057.1	11.3	20.2	8.9
Bare ground	9359.9	7017.9	-2342	79.0	59.2	-19.7
Water bodies						0.0
Total	11854.40	11854.40	0	100.0	100	

Other aspects of the analysis of spatial changes in the city between 2009 and 2019 are presented in Table 6. Lafia has experienced a change in the percentage of the city classed as a built-up area during these ten years. The analysis also shows that bare ground declined from 7017.9 ha in 2009 to 6267.21 ha in 2019.

Table 6. Lafia Land use change Between 2009 And 2019.

Land cover	2009	2019	Δ	2009%	2019%	Δ %
Built-up	2444.8	4724.8	2280	20.6	39.9	19.3
Vegetation	2391.7	862.39	-1529.31	20.2	7.3	-12.9
Bare ground	7017.9	6267.21	-750.69	59.2	52.9	-6.3
Water bodies						0.0
Total	11854.4	11854.4	0	100.0	100.0	

3.2. Effects of Urban Expansion on Spatial Patterns

The Urban Expansion Differentiation Index (UEDI) and the Urban Expansion Intensity Index (UEII) are two spatial indexes utilized to quantify urban expansion, specifically representing sprawl ratio indexes. These indexes themselves can function as independent variables to explore the correlation between urban expansion and spatial patterns. In addition, the values of the spatial metrics can be employed as dependent variables.

To investigate the relationship between these variables, this study adopted geographically weighted regression (GWR) as an effective model. The GWR model generated Adjusted R^2 and AICt values for various periods, which are presented in Table 7. The coefficient varied noticeably across the different cities. The spatial change coefficient expresses that the relationships between spatial metrics and the UEII values vary spatially across the cities. At the same time, it can be observed that the trend of coefficients for each spatial pattern do not change considerably over the two decades examined in the study. The relationship between UEII and AI differ for various land uses over the course of the study period. The onset of trends has significant positive correlations. This indicates that the intensification of expansion may intensify the aggregation process. The GWR analysis indicates that the spatial pattern of the selected cities could be identified to a considerable degree by the expansion of intensification. The higher UEII values resulted in a decrease in the aggregation process and an increase in land fragmentation in the peri-urban areas of the three cities.

Table 7. Results of GWR analysis, 1999-20109.

City	Period	Spatial Metrics	Adjusted R^2		AICt	
			UEII	UEDI	UEII	UEDI
		AI	0.51	0.49	170.2	134.0
Lafia	1999-2009	GYRATE_MN	0.84	0.12	187.2	157.9
		ENN_MN	0.57	0.43	262.3	242.7
		AI	0.66	0.34	187.1	122.9
Lafia	2010-2019	GYRATE_MN	0.82	0.18	198.2	157.8
		ENN_MN	0.80	0.20	269.4	236.6

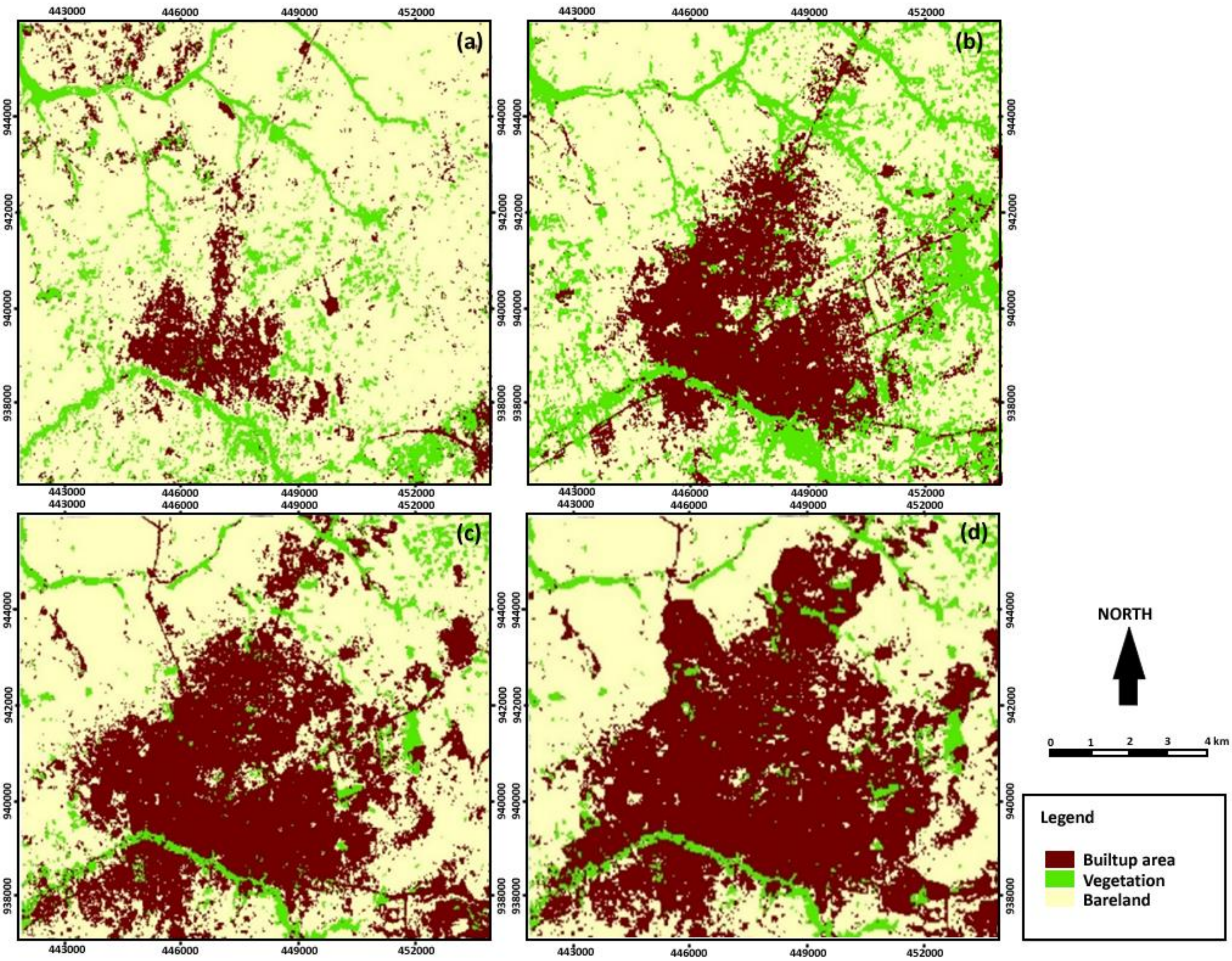

Figure 3. Spatial Extent of Lafia City. (a) Spatial extent in 1999; (b) spatial extent in 2009; (c) spatial extent in 2019, and (d) spatial extent 2029 based on simulation.

3.3. Socioeconomic Patterns

Another measurement of the extent and pace of urban sprawl is the prevalence and change of certain socioeconomic patterns in the city. The dimensions of these patterns are the density function, the density gradient, and the Gini coefficient.

3.3.1. Density functions

Density is a basic dimension of the city form widely used in form analysis. Population, employment, and size of built-up areas were measured for the selected cities in 1990, 2000, and 2010. Population plays two main roles in an economic system: supply (labour) and demand (the consumer). The population is more dense in built-up urban areas. Between 1999 and 2009, the built-up area in Lafia increased by 1,284.9Ha, whereas its population increased by about 122,089 people. Between 2009 and 2019, the built-up areas increased by 2280 ha, and the population increased by about 111,470 people.

Table 8. Annual Changes of Population and Urban Area in Lafia North Central, Nigeria.

Population				Built-up area (km^2)			
1999	**2009**	**2019**	**Annual change**	**1999**	**2009**	**2019**	**Annual change**
329,756	451,845	563,315	70.8	1,159.9	2,444.8	4,724.8	19.3

3.3.1. Density Gradient

Both linear and non-linear least square models were employed to fit the monocentric density function. The model with the highest overall *R*2 value was selected as the best model. As shown in Table 9, the negative exponential model provided the best fit in all 3 periods.

Table 9. Results of Regression Models to test Density Gradient.

City	Model	Year	Equation	R^2
		1999	Y= −0.5193x + 11762	0.1272
	Linear	2009	Y= −0.5267x + 10601	0.4497
		2019	Y= −0.513x + 12507	0.3372
		1999	Y= 13270e−8E −05x	0.451
	Exponential	2009	Y= 12432e−E −04x	0.4435
		2019	Y= 13835e−8E−07x	0.3002
Lafia		1999	Y= 163209x−0.464	0.3804
	Power	2009	Y= 372508x−0.558	0.3024
		20109	Y= 152759x−0.334	0.1678
		1999	Y= −2279ln(x) + 21948	0.2656
	Logarithmic	2009	Y= −2771ln(x) + 20034	0.3544
		2019	Y= −2824ln(x)+22008	0.1483

3.4. Distribution Pattern

Population data were obtained from the National Population and Housing Census of 2006 (NPC, 2011). Gini coefficient values show that population density is very high in these cities, where a Gini coefficient close to zero indicates that an area's population is evenly distributed (Table 10).

Table 10. Gini Index of Population in Lafia,Nigeria.

Gini Coefficient	1999	2009	2019	Mean
	0.45	0.84	0.90	0.73

The analysis presented above indicates that, as measured, urban sprawl must be stemmed by the city's compactness. The physical measurement of urban areas themselves is far more straightforward. The research focuses on a descriptive study of recommendations concerning compactness, enabled by measurements, rather than trying to determine the consequences and causes of compactness. The measure of compactness was reviewed using 10 criteria. Particular attention was paid to the population and job densities.

The total area of Lafia municipality was 11,854.4 Hectares in 2019 and the total population was 563,315. This translated to the calculated population density of 47.2. Population density leads to urban sprawl. Therefore, another measure, more representative of the compactness of the residential environment, can be calculated by only considering the surface of land occupied by the housing function. For Lafia, the built-up area accounts for 4,724.8Ha, and the population density is calculated as 119.2 inhabitants/Ha.

3.5. Evaluation of the City's Characteristics

A compact city is much more than a dense urban environment. Other criteria, such as public transport, connectivity, open space, and continuity, come into play (Table 11). Ten such criteria have been chosen and estimated based on secondary data gathered and knowledge acquired during interviews conducted for this thesis. This section concisely evaluates some criteria necessary for the compact city's distinctive characteristics.

Table 11. Compact City Characteristics.

Measuring Criteria	Evaluation Criteria
High residential and employment densities	Both residential and employment densities are highest in and around the city centre. Population density remains averagely high until the limit of the built-up area. Employment density drops merely sharply
A mixture of land uses	Mix land uses in the city centre (retail, schools, restaurants, residential houses). Some residential areas on the peri-urban should be homogeneous (mainly residential housing- condominium), but always in the vicinity of public facilities or retail shops
The fine grain of land uses (proximity of varied uses and small relative size of a plot of land	Parcels of land should be smaller, especially in the traditional inner-city and old neighbourhoods. Parcel sizes tend to increase in the new residential areas built recently in peri-urban areas but remain much smaller than those usually found in other places
Contiguous development	Only a few vacant spaces should be left undeveloped. Space must be filled up in the future. No leapfrogging development should occur within the city boundaries.
Contained urban development, demarcated by legible limits	The limits of the city where the countryside begins should be sharply defined. Around the city itself, only a few roads should be sites for the ribbon development common in the past. Therefore, once one leaves the city, one should find oneself in a rural landscape of open fields. In the past, the land use regulations implemented through the Land Use Act and planning and building permits acted as the best tools to create limits around cities.
Multi-modal transportation	Everything must be done to limit the use of private cars in the inner city. This will reduce the problem of parking and encourage the use of public transport
A high degree of accessibility	All major public facilities (hospitals, schools, etc.) should be accessible by public transport for residents.
A high degree of street connectivity, including pavements.	The road network should be developed in a hierarchical order organised in main, secondary, and collector roads in such a way that the traffic in residential neighbourhoods remains as low as possible.
Low open space retention	Cities should be surrounded by green agricultural land. Increasing awareness of the need to conserve and create urban green spaces will improve the situation. This will help making space for water storage become a priority at the city level. Open recreational land and forest areas will come to be seen as an advantage for cities
Sufficient governmental fiscal capacity to finance urban facilities and infrastructure	The selected cities in North Central Nigeria, and Nigeria in general, should have different sources of revenue such as local tax of residents and firms, national subsidies, and the surplus money derived from their role in the land market.

Source : Authors Research, 2021

3.6. Discussion

Integrated spatial planning should be promoted to maintain urban growth: The key instrument to achieve systematic urbanisation that will not affect Land Use/Land Cover is spatial planning (Hersperger *et al*., 2018; Metternicht, 2018). Ronchi *et al.* (2020) noted that the primary role of spatial planning is the integration of various Land Use/Land Cover plans, strategic and urban infrastructure development priorities, and improvements in local governance. Such an effort is necessary to facilitate the rational use of land and water resources on a sustained basis in the long run.

Another implication is the increase of urban greenery and resulting environmental benefits because the vegetation is a natural mechanism used for cooling since it encourages evapotranspiration, and energy is dissipated more through latent heating rather than sensible heating (McPherson, 1994; Gunawardena *et al*., 2017). Vegetation is also a sink for CO2. Increased urban vegetation is expected to help in recharging of groundwater and soil conservation, although the type of vegetation also matters in this case (Petra *et al*., 2018).

The conservation of wetlands and water bodies is crucial: Retaining water in the urban landscape enhances evaporation (Kjelgren *et al*., 2000; Coutts *et al*., 2013; Koop & Leeuwen, 2017). Similarly, as vegetation and wetlands tend to absorb heat, ambient air temperatures are likely to decrease (Sarma *et al*., 2001; Blok *et al*., 2011; Petra *et al*., 2018). This will be especially noticeable in the case of daytime (maximum) temperatures. Hence, water-sensitive urban design is necessary to sustain a livable urban climate. Appropriate regulatory structures must be implemented to conserve and restore wetlands and water bodies.

More training and education programs should be run and publicity campaigns are also required: People should be made aware of how social, economic, and environmental changes have largely been caused by rapid, unplanned, and unsystematic urbanisation leading to the inefficient use of critical natural resources such as land and water. The state government, local bodies, and NGOs should initiate proper capacity-building and awareness programs to disseminate information about the adverse effects of rapid urbanisation on socioeconomic and environmental entities and systems (Petra *et al*., 2018; Olalekan *et al*., 2019).

4. Conclusion

The analysis of spatial changes in the city of Lafia from 1999 to 2019 reveals significant urban expansion and its impact on the city's spatial patterns. Built-up areas have experienced substantial growth, increasing from 9.8% in 1999 to 39.9% in 2019, indicating a rapid urbanisation trend. This expansion has resulted in the loss of vegetal cover and bare ground, indicating a decline in green spaces and an increase in land fragmentation. The Urban Expansion Differentiation Index (UEDI) and Urban Expansion Intensity Index (UEII) have been used to measure the urban sprawl, with the results showing a positive correlation between expansion intensity and land aggregation. Additionally, socioeconomic patterns, such as population density and density gradient, were examined to assess the impact of urban expansion. The size of the population and the land covered by built-up areas have both increased over the years, contributing to higher population density and the uneven distribution of shrinking resources. The evaluation of city characteristics indicates the importance of socioeconomic factors such as high residential and employment densities, mixed land uses, contiguous development, and multi-modal transportation in achieving a compact city. Additionally, the availability of open spaces, street connectivity, and sufficient fiscal capacity are essential considerations for sustainable urban development. Overall, the findings emphasize the need for effective urban planning strategies and policies to manage urban growth, preserve green spaces, and create liveable and sustainable cities in the face of rapid urbanisation.

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