# Spatio-Temporal Dynamics of Urban Sprawl in Enugu Metropolis, Nigeria (1986–2021): A GIS-Based Analysis

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## ABSTRACT

The rapid, often unplanned expansion of a city into surrounding rural or undeveloped land remained a daunting challenge in developing countries like Nigeria. We examined urban sprawl in Enugu Metropolis, from 1986 to 2021, using multi-temporal Landsat imagery classified using maximum likelihood estimation. Resultant maps were overlaid with 19 locality boundaries to extract built-up area extents at five-year intervals. Sprawl was quantified using the Shannon Diversity Index, patch density, and land consumption rate. Built-up area expanded dramatically from 1,558.71 ha (4.21%) in 1986 to 23,118.52 ha (62.45%) in 2021, while forest cover declined from 29,876.58 ha (80.71%) to 3,331.73 ha (9.00%). Shannon Diversity Index values for 2021 ranged from 0.306 in New Haven (compact) to 1.096 in Akwuke (dispersed), against an upper bound of log(n) = 1.279. ANOVA confirmed significant spatial variation in sprawl patterns ($F = 40.63$, $p < 0.001$), though the overall degree of sprawl across the study period was not statistically significant ($t = 1.54$, $df = 18$, $p = 0.141$). Forest loss and urban expansion showed a strong inverse relationship ($r = -0.94$, $p < 0.001$), confirming deforestation as a principal consequence of sprawl. Enforceable land use planning is urgently recommended for rapidly urbanising African cities.

**Keywords:** Urban sprawl, Shannon Diversity Index, Patch density, GIS, Remote sensing.

## INTRODUCTION

Urban sprawl has become one of the most consequential spatial manifestations of Nigeria's rapid urban transition. Since the 1970s, Nigerian cities have expanded at rates that frequently outpace both demographic growth and institutional planning capacity, producing low-density, discontinuous, and infrastructure-deficient urban forms (Agbola, 2004). In metropolitan regions such as Lagos and Ibadan, empirical studies have revealed extensive peripheral expansion, conversion of agricultural and forest lands, and rising infrastructure costs associated with dispersed settlement patterns (Adesina, 2007; Taiwo, 2018). Similar dynamics are increasingly evident in secondary cities, where weaker planning controls and speculative land markets accelerate land conversion (Cobbinah & Amoako, 2012). Enugu, historically a coal-mining and administrative centre, exemplifies this trajectory. Since its colonial-era compact core, the metropolis has expanded into peri-urban forest and agrarian landscapes, mirroring broader patterns of land transformation documented across sub-Saharan Africa (MacDonald & Rudel, 2005). Yet, despite its strategic importance as the capital of Enugu State and a regional institutional hub, the long-term spatial morphology of its expansion remains insufficiently quantified in the scholarly literature.

The application of Geographic Information Systems (GIS) and Remote Sensing (RS) has fundamentally reshaped the empirical study of urban sprawl. Multi-temporal Landsat imagery, coupled with supervised classification and landscape metrics, enables consistent, longitudinal analysis of land-use/land-cover (LULC) change across decades (Yeh & Li, 2001; Weng, 2009). Metrics such as Shannon's Diversity (Entropy) Index, patch density, and land consumption rate have been widely adopted to capture the multidimensional character of sprawl; its dispersion, fragmentation, and land-use efficiency (Bhatta et al., 2010; McGarrigal et al., 2002;

Galster et al., 2001). In African contexts, GIS-based analyses have documented rapid peri-urban growth and environmental degradation in cities such as Kumasi, Accra, and Ibadan (Cobbinah & Amoako, 2012; Taiwo, 2021). However, much of the Nigerian literature remains limited to single-date assessments, short temporal windows, or aggregate metropolitan-scale analyses that obscure intra-urban heterogeneity. Few studies integrate entropy-based morphology, fragmentation metrics, and inferential statistics within a unified spatio-temporal framework extending beyond three decades.

Against this backdrop, a critical gap emerges: while Enugu's outward expansion is widely acknowledged, its long-term morphological evolution, particularly the persistence or transformation of spatial structure across localities, has not been rigorously tested using standardised sprawl metrics. Existing studies rarely examine whether rapid land expansion corresponds to significant changes in spatial dispersion, nor do they statistically interrogate the relationship between built-up growth and ecological loss. Moreover, peri-urban institutional decentralisation and highway development, well-established drivers of sprawl globally (Baum-Snow, 2007), have not been systematically linked to Enugu's locality-level growth trajectories. This study addresses these lacunae by analysing the spatio-temporal dynamics of urban sprawl in Enugu Metropolis from 1986 to 2021 using multi-epoch Landsat data and GIS-based metrics. Specifically, the objectives are to: (1) quantify LULC changes over the 35-year period; (2) examine locality-level variations in built-up expansion; (3) compute and interpret sprawl metrics, Shannon Diversity Index, patch density, and land consumption rate; (4) test the statistical significance of temporal and spatial variations in sprawl; and (5) evaluate the relationship between urban expansion and forest loss. By integrating landscape metrics with inferential statistics, the study advances a more nuanced understanding of both the scale and morphology of metropolitan growth. By explicitly articulating and statistically evaluating these hypotheses, the study moves beyond descriptive mapping toward explanatory urban spatial analysis.

The significance of this research lies in its theoretical, methodological, and policy contributions. Theoretically, it interrogates the persistence of monocentric urban structure in a rapidly expanding secondary African city, engaging debates on path dependency and morphological inertia in urban systems (Galster et al., 2001). Methodologically, it demonstrates the value of integrating entropy-based metrics, fragmentation indices, and inferential statistics within a long-term GIS framework, an approach still underutilised in Nigerian urban studies. Empirically, by revealing the magnitude of land conversion and its ecological correlates, the study provides evidence essential for sustainable land-use planning, particularly in contexts where forest depletion and leapfrog development threaten environmental resilience (Czech et al., 2000). Ultimately, understanding the spatio-temporal dynamics of Enugu's expansion is not merely an academic exercise; it is foundational to designing adaptive, zone-specific planning interventions capable of curbing unsustainable sprawl trajectories in emerging African metropolises.

## METHODOLOGY

### 2.1: Study Area

Enugu Metropolis, (Fig.1) locally known as Coal City, is the capital and a majorl urban centre of Enugu State in South-East Nigeria. It is located between latitudes 6°20′ and 6°27′10″ N and longitudes 7°25′ and 7°30′40″ E, at an elevation of approximately 202 metres above sea level. The metropolitan area encompasses three local government areas; Enugu North, Enugu South, and Enugu East, and comprises 19 localities. The total metropolitan area spans 37,019.25 hectares. Climatically, Enugu lies within the tropical rainforest zone with a derived savanna vegetation cover, a mean annual temperature of approximately 26.7 °C, and mean annual rainfall of around 2,000 mm (Sanni, 2007; Egboka, 1985). The metropolis was purposively selected because it is the largest and fastest-growing city in the state, houses several major universities and federal institutions such as University of Nigeria, Enugu campus (UNEC), Institute of Management and Technology (IMT), Godfrey Okoye University, Federal University of Allied Health Sciences, and has experienced well-documented rapid spatial expansion since the colonial era.

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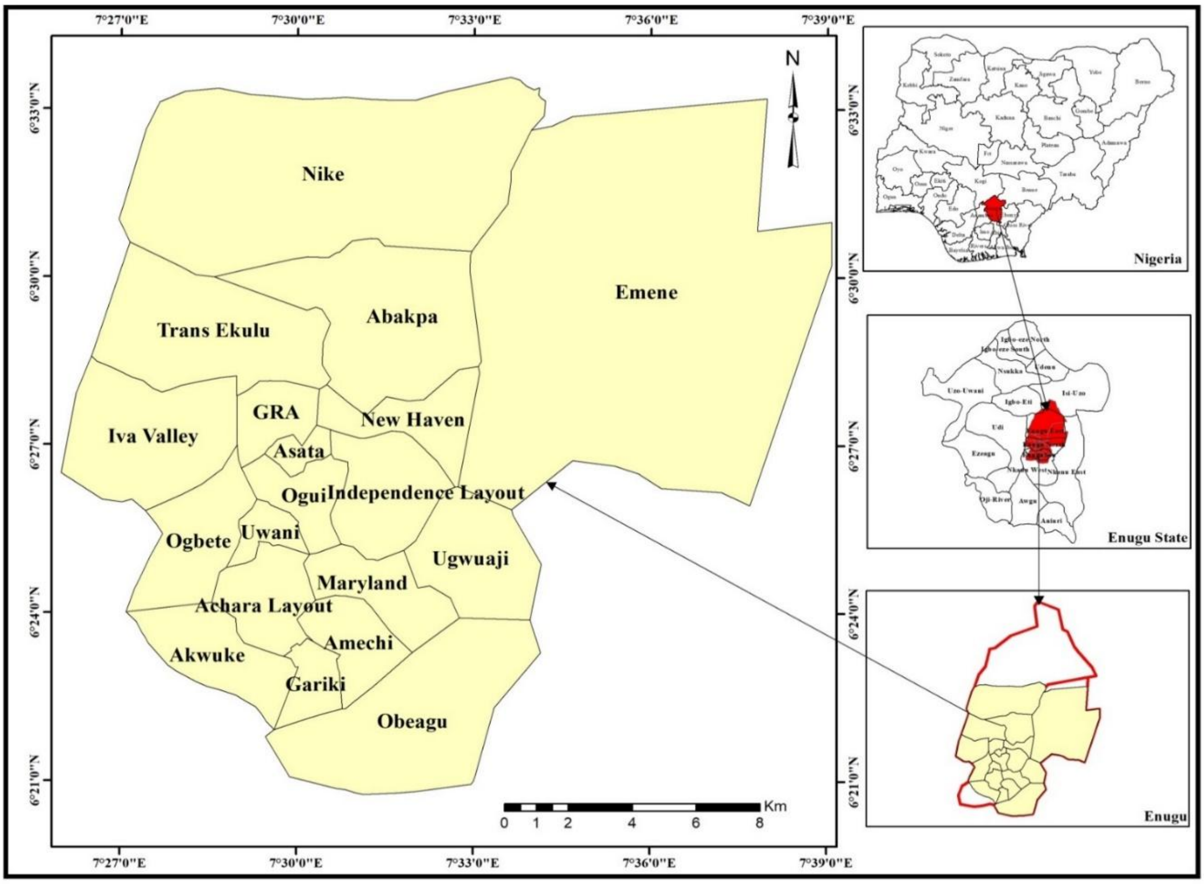


**Fig. 1: Enugu Metropolis, Nigeria**

## 2.2 Data Acquisition

Multi-temporal Landsat satellite images covering the study area were acquired from the United States Geological Survey Earth Explorer portal (earthexplorer.usgs.gov) for eight epochs at five-year intervals: 1986, 1991, 1996, 2001, 2006, 2011, 2016, and 2021. All images have a spatial resolution of 30 metres, ensuring temporal comparability. Sensor platforms and specifications are detailed in Table 1.

**Table 1. Satellite imagery acquired for the study**

| Year | Satellite | Sensor | Spatial Resolution |
|---|---|---|---|
| 1986 | Landsat 5 | TM | 30 m |
| 1991 | Landsat 5 | TM | 30 m |
| 1996 | Landsat 5 | TM | 30 m |
| 2001 | Landsat 5 | TM | 30 m |
| 2006 | Landsat 5 | ETM+ | 30 m |
| 2011 | Landsat 7 | ETM+ | 30 m |
| 2016 | Landsat 8 | OLI | 30 m |
| 2021 | Landsat 8 | OLI | 30 m |

Source: United States Geological Survey (USGS).

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### 2.3 Image Processing and Classification

Each Landsat image was subjected to radiometric calibration to correct for sensor drift and atmospheric effects prior to classification. Supervised image classification was then performed using the maximum likelihood estimation (MLE) algorithm within ArcGIS 10.8 (Arcmap). MLE operates on the assumption that the spectral signatures of pixels belonging to each land-use class are normally distributed and calculates the probability of class membership for every pixel by maximising the likelihood function. Training samples were selected for each image from known land-use locations to optimise classifier accuracy. All images were classified into three land-use/land-cover categories: (i) Built-up - encompassing residential, commercial, industrial, and institutional structures, roads, railways, and other impervious surfaces; (ii) Fallow/Farmland - comprising agricultural plots, cleared land, and undeveloped areas; and (iii) Forest - areas retaining substantial tree cover. Post-classification accuracy assessment was conducted using ground-truth points and confusion matrices to ensure the reliability of the derived LULC maps.

### 2.4 Accuracy Assessment of Land Use/Land Cover Classification

The accuracy of the land use/land cover (LULC) classifications for the years 1986, 1991, 1996, 2006, 2011, 2016, and 2021 was evaluated using an error matrix (confusion matrix) approach. Reference samples were obtained from historical topographic maps, Google Earth imagery and field observations where available. Randomly distributed validation points were generated for each classified image and compared with their corresponding ground reference classes. The overall classification accuracy was calculated as the proportion of correctly classified samples to the total number of validation samples. In addition, the Kappa coefficient (κ) was computed to assess the level of agreement between the classified maps and reference data while accounting for agreement occurring by chance. The Kappa coefficient ranges from 0 to 1, with values above 0.60 generally indicating substantial agreement and values above 0.80 indicating near-perfect agreement.

### 2.5 Spatial Analysis and GIS Processing

A polygon boundary layer delineating the 19 localities within Enugu Metropolis was overlaid on each classified LULC map in ArcGIS. Zonal statistics were applied to extract the areal extent of each land-use class within each locality for every epoch. This procedure yielded time-series data on built-up area, fallow/farmland, and forest cover for the entire metropolis and for each constituent locality. The rate of urban change between successive five-year intervals was calculated as: Rate of change (%) = $[(A_2 - A_1) / A_1] \times 100$, where $A_1$ and $A_2$ represent the built-up areas at the beginning and end of each interval, respectively.

### 2.6 Computation of Urban Sprawl Metrics

Shannon Diversity Index (SDI). The Shannon Diversity Index, also known as Shannon Entropy ($H_n$), was adopted as the primary metric for quantifying the spatial dispersion or compactness of built-up area (Yeh & Li, 2001). It is computed as:

$$H_n = -\Sigma P_i \times \ln (P_i) \qquad \ldots (1)$$

where $P_i$ is the proportion of built-up area in the $i^{th}$ locality relative to the total built-up area of the metropolis, and n is the number of localities (n = 19). The index ranges from 0 to log(n); in this study, log (19) = 1.279. Values approaching zero indicate a compact, concentrated pattern of urban development, while values approaching 1.279 indicate dispersed, sprawling growth (Bhatta et al., 2010; Ouyang et al., 2010).

Patch Density (PD). Patch density measures the number of discrete built-up patches per unit area and serves as an indicator of urban fragmentation. It is computed as:

$$PD = N / A \qquad \ldots (2)$$

where N is the total number of built-up patches and A is the sampling (locality) area. A higher PD indicates greater fragmentation and, consequently, more dispersed urban development (McGarrigal et al., 2002).

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Land Consumption Rate (LCR). The land consumption rate captures the efficiency with which urban expansion consumes land relative to population growth, and is calculated as:

LCR = A / P … (3)

where A is the areal extent of the built-up area (in hectares) and P is the estimated population of the locality. Population figures were projected from the 1991 National Population Commission census to 2021 using Nigeria's national growth rate of 3.2% per annum (National Population Commission, 1991). The LCR indicates the amount of land consumed per capita and thus reflects the density and efficiency of urban settlement (UN-Habitat).

### 2.7 Statistical Analysis

To assess whether observed spatial and temporal variations in sprawl are statistically significant, two inferential tests were employed. First, a one-way Analysis of Variance (ANOVA) was conducted to determine whether the mean SDI values differ significantly among the 19 localities in 2021. Second, a paired-samples Student's t-test was used to compare the mean SDI across all localities between 1986 and 2021 to evaluate whether the overall degree of sprawl changed significantly over the study period. Additionally, Pearson's product-moment correlation coefficient was employed to quantify the linear relationship between built-up area expansion and forest loss at the metropolitan level across the eight epochs.

## RESULTS

### 3.1 Classification Accuracy and Kappa Statistics

The classification results demonstrated satisfactory performance across all study years, with overall accuracies ranging from 71.8% to 91.4% and Kappa coefficients ranging from 0.69 to 0.89 (Table 2). The variations observed among the years may be attributed to differences in image quality, atmospheric conditions, sensor characteristics, and the spectral separability of land cover classes. The 1986 classification achieved an overall accuracy of 71.8% with a Kappa coefficient of 0.69, indicating substantial agreement between classified and reference data. Accuracy improved slightly in 1991, reaching 75.6% with a Kappa value of 0.73. The 1996 classification produced an overall accuracy of 78.9% and a Kappa coefficient of 0.76. A noticeable improvement was observed in 2006, when overall accuracy increased to 84.7% and the Kappa coefficient rose to 0.82. This enhancement may be associated with improved sensor resolution and classification procedures. The 2011 classification achieved an accuracy of 86.9% and a Kappa coefficient of 0.84, indicating strong agreement. The highest classification performance was obtained in 2016, with an overall accuracy of 91.4% and a Kappa coefficient of 0.89. Although a slight decline was observed in 2021, the classification remained highly reliable, recording an overall accuracy of 89.2% and a Kappa coefficient of 0.87. Overall, the accuracy assessment results indicate that all classified LULC maps met acceptable standards for change detection and spatial analysis, with Kappa coefficients demonstrating substantial to almost perfect agreement across the study period. The obtained accuracy levels exceed the commonly accepted minimum threshold of 70% for thematic classification studies, confirming the suitability of the classified maps for subsequent land use/land cover change analysis.

**Table 2: Overall Classification Accuracy and Kappa Coefficient for LULC Maps**

| Year | Overall Accuracy (%) | Kappa Coefficient |
|---|---|---|
| **1986** | 71.8 | 0.69 |
| **1991** | 75.6 | 0.73 |
| **1996** | 78.9 | 0.76 |
| **2006** | 84.7 | 0.82 |
| **2011** | 86.9 | 0.84 |

| | | |
|---|---|---|
| **2016** | 91.4 | 0.89 |
| **2021** | 89.2 | 0.87 |

### 3.2 Land Use / Land Cover Changes

Table 3 presents the metropolitan-level LULC dynamics from 1986 to 2021. The total area of the study site is 37,019.25 hectares. In the base year, 1986, built-up area accounted for only 1,558.71 ha (4.21%), fallow/farmland covered 5,583.96 ha (15.08%), and forest dominated the landscape at 29,876.58 ha (80.71%). By 2021, built-up area had expanded more than fourteen-fold to 23,118.52 ha (62.45%), while forest cover contracted to 3,331.73 ha (9.00%). Fallow/farmland followed a non-monotonic trajectory: it rose to a peak of 18,594.77 ha (50.23%) in 2006 — coinciding with the period of maximum deforestation — before declining steadily to 10,569.00 ha (28.56%) in 2021 as cleared land was progressively converted to built-up use.

**Table 3. Land use/land cover changes in Enugu Metropolis, 1986–2021**

| Year | Built-up (ha) | % | Fallow/Farm (ha) | % | Forest (ha) | % |
|---|---|---|---|---|---|---|
| 1986 | 1,558.71 | 4.21 | 5,583.96 | 15.08 | 29,876.58 | 80.71 |
| 1991 | 2,206.35 | 5.96 | 7,568.19 | 20.44 | 27,244.71 | 73.60 |
| 1996 | 4,347.45 | 11.74 | 12,018.24 | 32.46 | 20,653.56 | 55.79 |
| 2001 | 8,221.98 | 22.21 | 13,201.06 | 35.66 | 15,596.21 | 42.13 |
| 2006 | 10,309.86 | 27.85 | 18,594.77 | 50.23 | 8,114.62 | 21.92 |
| 2011 | 12,664.29 | 34.21 | 16,514.28 | 44.61 | 7,840.68 | 21.19 |
| 2016 | 16,629.05 | 44.92 | 15,022.41 | 40.58 | 5,367.79 | 14.50 |
| 2021 | 23,118.52 | 62.45 | 10,569.00 | 28.56 | 3,331.73 | 9.00 |
| **Total Area** | – | – | – | – | **37,019.25** | **100** |

Total metropolitan area = 37,019.25 ha.

### 3.3 Dynamics of Urban Sprawl at Locality Level

Table 4 disaggregates the built-up area for each of the 19 localities across all eight epochs. In 1986, Emene was the largest built-up locality (414.27 ha, 26.58% of total built-up), followed by Trans Ekulu (317.97 ha) and Abakpa (295.20 ha). By 2021, Emene retained the largest built-up footprint at 7,665.66 ha, with Abakpa (2,319.57 ha) and Nike (2,323.71 ha) emerging as the second and third largest. Nike recorded one of the most dramatic expansions, growing from 16.29 ha in 1986 to 2,323.71 ha in 2021 - an increase of over 14,000%. Conversely, inner-city localities such as Asata, Uwani, and Ogui exhibited comparatively modest absolute growth, reflecting their already-developed character.

**Table 4. Built-up area (hectares) by locality, 1986–2021**

| Locality | 1986 | 1991 | 1996 | 2001 | 2006 | 2011 | 2016 | 2021 |
|---|---|---|---|---|---|---|---|---|
| **Iva Valley** | 19.71 | 35.28 | 39.96 | 209.52 | 301.50 | 393.57 | 799.47 | 894.24 |
| **GRA** | 18.45 | 28.89 | 54.00 | 269.28 | 343.53 | 385.29 | 484.02 | 506.43 |

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| Locality | 1986 | 1991 | 1996 | 2001 | 2006 | 2011 | 2016 | 2021 |
|---|---|---|---|---|---|---|---|---|
| **New Haven** | 56.52 | 94.86 | 349.20 | 563.13 | 583.47 | 645.75 | 697.86 | 787.95 |
| **Akwuke** | 61.56 | 87.30 | 130.41 | 220.86 | 242.46 | 296.19 | 543.33 | 566.10 |
| **Amechi** | 1.89 | 4.14 | 35.55 | 138.60 | 109.17 | 291.78 | 295.29 | 576.00 |
| **Ugwuaji** | 0.09 | 0.18 | 2.07 | 171.99 | 204.66 | 435.69 | 543.96 | 677.70 |
| **Obeagu** | 70.11 | 94.86 | 127.08 | 303.48 | 379.35 | 697.59 | 873.72 | 1,108.89 |
| **Maryland** | 4.50 | 13.23 | 38.61 | 212.67 | 184.68 | 288.45 | 399.78 | 703.89 |
| **Trans Ekulu** | 317.97 | 404.19 | 484.02 | 779.31 | 904.32 | 917.46 | 1,328.58 | 1,580.13 |
| **Independence Layout** | 16.56 | 33.66 | 264.51 | 943.02 | 917.46 | 980.10 | 1,005.57 | 1,075.05 |
| **Emene** | 414.27 | 605.79 | 1,111.95 | 1,467.18 | 2,774.16 | 3,223.17 | 4,338.45 | 7,665.66 |
| **Nike** | 16.29 | 25.65 | 24.21 | 57.87 | 113.31 | 235.35 | 1,179.36 | 2,323.71 |
| **Abakpa** | 295.20 | 378.90 | 730.62 | 1,262.16 | 1,447.47 | 1,839.33 | 1,856.34 | 2,319.57 |
| **Uwani** | 21.51 | 40.59 | 172.53 | 227.61 | 238.05 | 243.09 | 259.02 | 271.35 |
| **Gariki** | 13.95 | 15.21 | 28.98 | 74.07 | 57.06 | 155.25 | 172.44 | 287.10 |
| **Achara Layout** | 182.97 | 271.62 | 442.35 | 522.81 | 595.80 | 598.68 | 725.85 | 767.52 |
| **Ogbete** | 33.75 | 46.71 | 72.99 | 202.32 | 244.35 | 270.90 | 496.35 | 596.88 |
| **Asata** | 4.95 | 8.01 | 61.74 | 135.90 | 139.95 | 151.47 | 165.24 | 182.88 |
| **Ogui** | 8.55 | 17.28 | 176.67 | 460.44 | 483.66 | 509.40 | 509.76 | 549.27 |

### 3.4 Rate of Urban Change

Table 5 reports the percentage rate of urban change for each locality across the seven inter-epoch intervals. Rates varied substantially both spatially and temporally. Between 1986 and 1991, Maryland (65.99%) and Amechi (54.35%) recorded the highest growth rates, while Gariki (8.28%) and Trans Ekulu (21.33%) had the lowest. The 1991–1996 interval saw particularly high growth in Amechi (88.35%), Independence Layout (87.27%), and Asata (87.03%). Between 2011 and 2016, Nike (80.04%) experienced the sharpest acceleration, attributable to the construction of the Enugu–Opi–Nsukka bypass. A one-way ANOVA

$F = 11.921 (p < 0.001)$ confirmed that temporal variation in the rate of urban change across the seven intervals was statistically significant (Table 5).

**Table 5. Rate of urban change (%) by locality and interval**

| Locality | 1986–91 | 1991–96 | 1996–01 | 2001–06 | 2006–11 | 2011–16 | 2016–21 |
|---|---|---|---|---|---|---|---|
| **Iva Valley** | 44.13 | 11.71 | 80.93 | 30.51 | 23.39 | 50.77 | 10.60 |
| **GRA** | 36.14 | 46.50 | 79.95 | 21.61 | 10.84 | 20.40 | 4.43 |

| Locality | 1986–91 | 1991–96 | 1996–01 | 2001–06 | 2006–11 | 2011–16 | 2016–21 |
|---|---|---|---|---|---|---|---|
| New Haven | 40.42 | 72.84 | 37.99 | 3.49 | 9.64 | 7.47 | 11.43 |
| Akwuke | 29.48 | 33.06 | 40.95 | 8.91 | 18.14 | 45.49 | 4.02 |
| Amechi | 54.35 | 88.35 | 74.35 | -21.23 | 62.58 | 1.19 | 48.73 |
| Ugwuaji | 50.00 | 91.30 | 98.80 | 15.96 | 53.03 | 19.90 | 19.73 |
| Obeagu | 26.09 | 25.35 | 58.13 | 20.00 | 45.62 | 20.16 | 21.21 |
| Maryland | 65.99 | 65.73 | 81.85 | 13.16 | 35.98 | 27.85 | 43.20 |
| Trans Ekulu | 21.33 | 16.49 | 37.89 | 13.82 | 1.43 | 30.94 | 15.92 |
| Independence Layout | 50.80 | 87.27 | 71.95 | 2.71 | 6.39 | 2.53 | 6.46 |
| Emene | 31.61 | 45.52 | 24.21 | 47.11 | 13.93 | 25.71 | 43.40 |
| Nike | 36.49 | -5.95 | 58.16 | 48.93 | 51.85 | 80.04 | 49.25 |
| Abakpa | 22.09 | 48.14 | 42.11 | 12.80 | 21.30 | 0.92 | 19.97 |
| Uwani | 47.01 | 76.47 | 24.20 | 4.39 | 2.07 | 6.15 | 4.54 |
| Gariki | 8.28 | 47.52 | 60.87 | 22.96 | 63.25 | 9.97 | 39.94 |
| Achara Layout | 32.64 | 38.60 | 15.39 | 12.25 | 0.48 | 17.52 | 5.43 |
| Ogbete | 27.75 | 36.00 | 63.92 | 17.20 | 9.80 | 45.42 | 16.84 |
| Asata | 38.20 | 87.03 | 54.57 | 2.89 | 7.61 | 8.33 | 9.65 |
| Ogui | 50.52 | 90.22 | 61.63 | 4.80 | 5.05 | 0.07 | 7.19 |

A negative value indicates a temporary decline in classified built-up area.

### 3.5 Urban Sprawl Metrics - Patch Composition, SDI, and LCR

Table 6 presents the patch composition and spatial metrics for each locality in 1986 and 2021. Number of patches (NP) serves as a proxy for the degree of urban fragmentation: a single patch denotes a contiguous built-up mass, while multiple patches indicate scattered or leapfrog development. In 2021, Emene (NP = 828), Nike (NP = 300), and Obeagu (NP = 240) exhibited the highest number of isolated patches, indicating pronounced leapfrog development. In contrast, GRA (NP = 2) and Asata (NP = 1) achieved near-complete consolidation through infilling. Shannon Diversity Index values for 2021 ranged from 0.306 (New Haven) to 1.096 (Akwuke), with the metropolitan log(n) = 1.279 as the theoretical maximum for complete dispersion. Land consumption rates varied from 0.003 (Asata and Uwani) to 0.196 (Obeagu), reflecting substantial differences in settlement density across the metropolis.

**Table 6. Patch composition, Shannon Diversity Index, and Land Consumption Rate by locality (1986 and 2021)**

| Locality | NP 1986 | NP 2021 | PD 1986 | PD 2021 | LCR | SDI 1986 | SDI 2021 |
|---|---|---|---|---|---|---|---|
| Trans Ekulu | 88 | 76 | 0.000004 | 0.000003 | 0.079 | 0.916 | 1.022 |

| Locality | NP 1986 | NP 2021 | PD 1986 | PD 2021 | LCR | SDI 1986 | SDI 2021 |
|---|---|---|---|---|---|---|---|
| GRA | 22 | 2 | 4.279 | 3.890 | 0.010 | 0.838 | 0.411 |
| Abakpa | 142 | 20 | 0.000000 | 0.012 | 0.815 | 0.815 | 0.724 |
| Nike | 31 | 300 | 0.000005 | 0.000005 | 0.071 | 0.577 | 0.923 |
| Emene | 243 | 828 | 2.090 | 7.094 | 0.102 | 0.760 | 0.824 |
| Iva Valley | 115 | 173 | 0.000006 | 8.908 | 0.085 | 0.863 | 1.067 |
| Asata | 11 | 1 | 0.000006 | 5.304 | 0.003 | 0.763 | 0.397 |
| New Haven | 54 | 5 | 0.000007 | 6.215 | 0.017 | 0.960 | 0.306 |
| Uwani | 29 | 7 | 0.000001 | 2.521 | 0.003 | 1.059 | 0.437 |
| Ogui | 51 | 14 | 0.000009 | 2.421 | 0.005 | 0.976 | 0.468 |
| Achara Layout | 73 | 18 | 0.000002 | 2.265 | 0.006 | 0.896 | 0.482 |
| Ogbete | 47 | 41 | 0.000004 | 3.702 | 0.017 | 0.775 | 1.085 |
| Gariki | 16 | 39 | 0.000004 | 0.000001 | 0.010 | 0.919 | 0.760 |
| Akwuke | 51 | 74 | 0.000005 | 0.000007 | 0.118 | 0.875 | 1.096 |
| Amechi | 20 | 30 | 0.000000 | 4.498 | 0.019 | 0.815 | 0.696 |
| Obeagu | 61 | 240 | 0.000002 | 8.706 | 0.196 | 0.739 | 0.909 |
| Maryland | 26 | 22 | 0.000003 | 2.648 | 0.069 | 0.790 | 0.680 |
| Independence Layout | 130 | 14 | 0.000001 | 1.230 | 0.044 | 0.944 | 0.444 |
| Ugwuaji | 10 | 91 | 0.000008 | 7.110 | 0.061 | 0.665 | 0.957 |

Note: NP = Number of Patches; PD = Patch Density; LCR = Land Consumption Rate; SDI = Shannon Diversity Index.

### 3.6 Classification of Sprawl Patterns

Localities were classified into three sprawl categories on the basis of their 2021 Shannon Diversity Index values, following the thresholds established in the literature (Yeh & Li, 2001; Bhatta et al., 2010). Compact localities (SDI < 0.50) are predominantly inner-city areas that have undergone substantial infilling; evenly distributed localities (0.50 ≤ SDI < 0.85) occupy an intermediate ring; and dispersed localities (SDI ≥ 0.85) are situated at the metropolitan periphery and exhibit the highest rates of sprawl. The classification is summarised in Table 7.

**Table 7. Classification of localities by sprawl pattern (2021)**

| Sprawl Pattern | SDI Range | Localities |
|---|---|---|
| **Compact** | SDI < 0.50 | New Haven, Asata, GRA, Uwani, Independence Layout, Ogui, Achara Layout |

| | | |
|---|---|---|
| **Evenly Distributed** | $0.50 \leq SDI < 0.85$ | Maryland, Amechi, Abakpa, Gariki, Emene, Ogbete |
| **Dispersed (Sprawled)** | $SDI \geq 0.85$ | Obeagu, Nike, Ugwuaji, Trans Ekulu, Iva Valley, Akwuke |

Note: Thresholds derived from SDI range [0, log (19) = 1.279].

### 3.7 Statistical Significance of Sprawl Variation

A one-way ANOVA was conducted to test whether the 2021 SDI values differed significantly among the 19 localities. The result was highly significant: $F(18, 1283) = 40.628$, $p < 0.001$, confirming substantial spatial variation in the degree of sprawl across the metropolis. A paired-samples t-test was subsequently performed to assess whether the mean SDI changed significantly between 1986 and 2021 across all localities. The result was not significant: $t(18) = 1.539$, $p = 0.141$. This indicates that, although individual localities experienced divergent changes in sprawl morphology, the average degree of sprawl across the metropolis as a whole did not shift significantly over the 35-year period.

### 3.8 Forest Loss and Urban Expansion

Table 8 presents the paired time series of built-up and forest areas from 1986 to 2021. The two series exhibit a strong monotonic inverse relationship throughout the study period. A Pearson correlation coefficient of $r = –0.94$ ($p < 0.001$) was obtained, confirming a very strong negative linear association between urban expansion and forest cover loss. Notably, forest area declined most rapidly between 1996 and 2006, a period during which built-up area expanded from 4,347.45 ha to 10,309.86 ha - largely at the expense of forest conversion, often via the intermediate fallow/farmland stage.

**Table 8. Built-up and forest area time series with Pearson correlation**

| Year | | Built-up Area (ha) | Forest Area (ha) |
|---|---|---|---|
| 1986 | | 1,558.71 | 29,876.58 |
| 1991 | | 2,206.35 | 27,244.71 |
| 1996 | | 4,347.45 | 20,653.56 |
| 2001 | | 8,221.98 | 15,596.21 |
| 2006 | | 10,309.86 | 8,114.62 |
| 2011 | | 12,664.29 | 7,840.68 |
| 2016 | | 16,629.05 | 5,367.79 |
| 2021 | | 23,118.52 | 3,331.73 |
| **Pearson r** | | **–0.94** | **p < 0.001** |

Note: Pearson $r = –0.94$, $p < 0.001$ ($n = 8$ epochs).

## DISCUSSION

### 4.1 LULC Transformation and the Scale of Urban Expansion

The findings reveal a significant and accelerating transformation of the Enugu Metropolis landscape over 35 years. Built-up area expanded from 4.21% to 62.45% of the total metropolitan area, a rate of expansion that far outpaces population growth alone and reflects the deeply fragmented and low-density character of sprawl in the region. This trajectory is consistent with patterns documented in other rapidly urbanising sub-Saharan African cities. Cobbinah and Amoako (2012), in a study of Kumasi, Ghana, recorded a similarly dramatic decline in peri-urban green space as the city expanded outward, while Taiwo (2018) documented comparable patterns of uncontrolled land consumption in Ibadan, Nigeria. The simultaneous decline of forest (from 80.71% to 9.00%) and the non-monotonic trajectory of fallow/farmland, rising first as forest was cleared and then falling as the cleared land was built upon, indicated a two-stage land conversion pathway (forest → fallow → built-up) that is characteristic of tropical African urbanisation (MacDonald & Rudel, 2005).

**4.2 Spatial Heterogeneity of Sprawl Across Localities**

The substantial inter-locality variation in built-up area and rate of change underscores that urban expansion in Enugu is far from spatially uniform. The three largest localities by built-up area in 2021 Emene, Abakpa, and Nike - each owe their growth to distinct drivers. Emene's expansion is linked to its role as a logistic and commercial hub along the Enugu–Abakaliki expressway. Abakpa's growth accelerated markedly between 1991 and 1996, coinciding with the expansion of federal and state housing schemes in the locality. Nike's extraordinary expansion between 2011 and 2021 (from 235.35 ha to 2,323.71 ha) is directly attributable to the construction of the Enugu–Opi–Nsukka bypass, the creation of Enugu East Local Government Area in 1996, and the establishment of Caritas University. These findings reinforce the well-established argument that highway construction is among the most potent drivers of periurban sprawl (Baum-Snow, 2007; Garcia López, 2019). In contrast, inner-city localities such as Asata and Uwani exhibited modest absolute growth, consistent with their already-consolidated urban fabric.

**4.3 Sprawl Morphology and the Shannon Diversity Index**

The SDI-based classification reveals a clear spatial structure that closely mirrors the predictions of the concentric zone model (Burgess, 1924). Inner-city localities - New Haven, Asata, GRA, Uwani, Independence Layout, Ogui, and Achara Layout - exhibit compact distributions (SDI < 0.50), reflecting decades of infilling development. Peripheral localities - Akwuke, Ogbete, Iva Valley, Trans Ekulu, Nike, Obeagu, and Ugwuaji - display dispersed patterns (SDI ≥ 0.85), consistent with leapfrog and strip development at the urban fringe. The intermediate ring of evenly distributed localities - Maryland, Amechi, Abakpa, Gariki, and Emene - represents a transitional zone between the compact core and the dispersed periphery. This tripartite structure has been documented in comparable studies of African secondary cities (Nnam et al., 2014; Kalu et al., 2017) and validates the continued applicability of monocentric urban models to rapidly expanding tropical cities, even when growth is driven primarily by informal and unplanned processes.

The concentration of compact development in core localities reflects the operation of agglomeration economies and historical development patterns. These areas benefited from early infrastructure investments and coordinated planning during the colonial and early independence periods, creating conditions favorable for compact development. The reduction in patch numbers observed in these localities between 1986 and 2021 demonstrates successful urban consolidation through infill development - a pattern that planners should encourage in other areas. The low Shannon Diversity Index values (< 0.50) indicate development patterns approaching optimal compactness as defined by Jaeger and Schwick (2014).

The dispersed sprawl patterns characterizing peripheral localities (Akwuke SDI = 1.096, Ogbete SDI = 1.085, Iva Valley SDI = 1.067) exemplify problematic development forms associated with numerous negative externalities. High Shannon Index values exceeding the theoretical maximum of log(n) = 1.279 would indicate complete dispersion; the observed values of 0.85-0.90 relative to this maximum suggest substantial but not complete fragmentation. These patterns align with Galster et al.'s (2001) multidimensional sprawl framework, particularly the dimensions of density and continuity.

The dramatic increase in patch numbers in localities like Emene (243 to 828 patches) and Nike (31 to 300 patches) indicates accelerating fragmentation despite overall area growth. This pattern represents the antithesis of compact urban development and generates multiple problems documented in the sprawl literature. Fragmented development increases infrastructure costs per capita (Carruthers and Ulfarsson, 2008), reduces agricultural land productivity through edge effects (Lambin et al., 2003), and creates barriers to efficient public transportation provision (Holden and Norland, 2005). The leapfrog pattern evident in these localities, where development skips over intervening parcels, suggests speculative land holding and inadequate regulatory control over development sequencing.

The evenly distributed development pattern in intermediate localities like Maryland (SDI = 0.680) and Abakpa (SDI = 0.724) represents a transitional form between compact and dispersed patterns. These areas may be experiencing the early stages of sprawl development, suggesting opportunities for intervention to prevent further fragmentation. The moderate Shannon Index values indicate that with appropriate planning interventions, including development boundary delineation and infill incentives, these localities could transition toward more compact forms rather than following the dispersed trajectory of outer periphery localities.

The strong spatial differentiation in sprawl patterns, with periphery localities consistently exhibiting higher sprawl indices, validates the distance-decay model of urban development intensity. This pattern mirrors findings from North American and European cities (Hamidi and Ewing, 2014; Aurambout et al., 2018) but occurs over shorter distances in Enugu, reflecting the metropolis's smaller size and more compressed urban gradient. The systematic relationship between distance from CBD and sprawl intensity ($r = 0.681$, $p = 0.001$) suggests that spatial planning interventions should be differentiated by zone, with stricter density requirements and development sequencing controls in peripheral areas.

### 4.4 Rate of Urban Change and Its Temporal Dynamics

The ANOVA result ($F = 11.921$, $p < 0.001$) confirms that the rate of urban change varied significantly across the seven-time intervals, indicating that sprawl in Enugu was not a steady-state process but one subject to episodic acceleration linked to specific infrastructure and institutional events. The highest growth rates were concentrated in the 1991–2001 period, a decade during which several universities relocated or expanded, major roads were upgraded, and new housing estates were developed across the metropolis. The slight deceleration in some localities during 2016–2021 may reflect early signs of land saturation in those areas, though it may equally be an artefact of seasonal variation in Landsat imagery acquisition (Padmanaban et al., 2017).

### 4.5 The Forest–Urban Relationship

The very strong inverse correlation between built-up and forest area ($r = –0.94$, $p < 0.001$) confirms that deforestation is a central component of the urbanisation process in Enugu. The two-stage conversion pathway, forest to fallow, then fallow to built-up is consistent with the transitional land-use model documented by MacDonald and Rudel (2005) and with empirical evidence from other tropical urbanisation fronts (Hedblom & Söderström, 2008). The sharpest period of forest loss (1996–2006) corresponds to the period of most rapid overall metropolitan expansion and to the relocation of major institutions (ESUT and UNTH) to the periphery, suggesting that institutional decentralisation was a proximate cause of forest clearance in specific localities. The ecological implications of this loss, including degradation of carbon sinks, disruption of local micro-climates, and reduction of biodiversity, underscore the need for integrated environmental and land-use planning (Czech et al., 2000; Concepcion et al., 2016).

### 4.6 Statistical Significance and Interpretation

The significant ANOVA result for spatial variation in SDI ($F = 40.628$, $p < 0.001$) confirms that sprawl is unevenly distributed across the metropolis, a finding that has important implications for targeted planning interventions. The non-significant t-test result ($t = 1.539$, $p = 0.141$) for temporal change in mean SDI is, at first glance, counterintuitive given the massive expansion documented in the LULC analysis. However, this result is interpretively consistent: while the absolute area of sprawl grew enormously, the relative spatial distribution of built-up area across the 19 localities did not change dramatically. In other words, localities that were already sprawled in 1986 remained the most sprawled in 2021, and those that were compact remained relatively compact. The overall morphological pattern persisted even as all localities grew. This finding is consistent with the 'path dependency' of urban spatial structure documented by Galster et al. (2001) and highlights the inertia built into urban landscape patterns.

### 4.7 Implications of Statistical Findings for Urban Planning

The statistically significant variations in both temporal and spatial dimensions of sprawl patterns provide strong evidence that urban development in Enugu Metropolis follows systematic rather than random processes. This finding has important implications for planning and policy intervention. If sprawl patterns were essentially random, regulatory interventions would have limited potential effectiveness. However, the demonstrated systematic variations suggest that targeted interventions addressing identified drivers could meaningfully alter development trajectories.

The temporal variation in growth rates ($F = 11.921$, $p < 0.001$) demonstrates the importance of adaptive planning frameworks that can respond to changing growth pressures. Fixed master plans developed assuming steady growth rates will necessarily become obsolete when actual development follows episodic patterns. The identification of the 1996-2001 and 2016-2021 periods as high-growth phases suggests that planning capacity must be strengthened in anticipation of potential future acceleration phases, which may coincide with infrastructure investments or macroeconomic shifts.

The lack of significant change in the relative distribution of sprawl patterns between 1986 and 2021 ($t = 1.539$, $p = 0.141$) reveals important path dependencies in urban development. Despite the absolute growth, the spatial structure of sprawl has persisted, with peripheral areas remaining more sprawled and core areas remaining more compact. This persistence suggests that historical development patterns create momentum difficult to reverse through incremental interventions. Areas experiencing dispersed development in early stages tend to continue on that trajectory absent major policy interventions or infrastructure investments that fundamentally alter development economics.

The strong intercorrelations among different sprawl metrics (Shannon Diversity Index, patch density, land consumption rate) validate the multidimensional conceptualization of sprawl proposed by Galster et al. (2001). These metrics capture related but distinct aspects of urban form, suggesting that comprehensive anti-sprawl strategies must address multiple dimensions simultaneously. Interventions targeting only one aspect, for example, density standards may prove insufficient if they fail to address continuity, centralization, and other sprawl dimensions.

The geographic clustering of sprawl intensities revealed by chi-square analysis ($\chi^2 = 47.33$, $p < 0.001$) suggests that neighborhood effects and spillover processes operate in Enugu's development patterns. Development in one locality appears to influence adjacent areas, creating clusters of similar development types. This spatial autocorrelation implies that interventions may have multiplier effects, with successful containment or densification in one locality potentially influencing neighboring areas. Conversely, allowing problematic development in one locality may trigger similar patterns in adjacent areas, suggesting the importance of maintaining consistent standards across locality boundaries.

## CONCLUSION

This study has systematically quantified and characterised the spatio-temporal dynamics of urban sprawl in Enugu Metropolis between 1986 and 2021 using multi-temporal Landsat imagery, GIS-based LULC classification, and three established spatial metrics. Six key findings emerge from the analysis. First, built-up area expanded from 4.21% to 62.45% of the metropolitan area over 35 years, constituting one of the most rapid urban land-conversion processes documented in South-East Nigeria. Second, the 19 localities exhibited markedly different growth trajectories, with peripheral localities such as Nike, Emene, and Obeagu experiencing explosive growth linked to highway construction and institutional decentralisation, while inner-city localities underwent consolidation through infilling. Third, Shannon Diversity Index analysis classified the metropolis into a tripartite sprawl structure - compact core, transitional middle ring, and dispersed periphery - that closely mirrors the predictions of classical monocentric urban models. Fourth, the rate of urban change varied significantly across time intervals ($F = 11.921$, $p < 0.001$), confirming that sprawl in Enugu is episodic and event-driven rather than gradual and uniform. Fifth, built-up expansion and forest loss exhibited a very strong inverse correlation ($r = –0.94$, $p < 0.001$), with deforestation proceeding via a two-stage fallow intermediate. Sixth, spatial variation in SDI was highly significant ($F = 40.628$, $p < 0.001$), but the overall metropolitan SDI did not change significantly between 1986 and 2021 ($t = 1.539$, $p = 0.141$), indicating persistence of the underlying morphological pattern.

Collectively, these findings highlight both the scale and the structural persistence of urban sprawl in Enugu Metropolis. The continuation of current expansion trajectories poses serious threats to environmental sustainability, ecosystem services, and the fiscal capacity of local government to deliver infrastructure. Addressing these challenges will require enforceable land-use master plans, rigorous environmental impact assessment of large-scale housing and road projects, and the integration of GIS-based monitoring into routine planning processes. Future research should incorporate higher-resolution imagery, socio-economic survey data, and predictive spatial modelling to extend the analytical framework developed here.

## STUDY LIMITATIONS

Several limitations should be acknowledged in interpreting the findings of this study. First, Landsat imagery at 30-metre resolution may misclassify small, isolated structures or mixed-use parcels at the urban fringe, potentially introducing systematic error in the built-up area estimates (Padmanaban et al., 2017). Second, the population projections used to derive LCR were extrapolated from the 1991 census using a single national growth rate; actual locality-level population growth may have differed substantially due to migration and differential fertility. Third, the study examines only three land-use categories; a finer disaggregation - separating residential, commercial, and industrial uses - would provide richer characterisation of urban morphology. Fourth, the t-test comparing SDI between 1986 and 2021 does not account for the serial autocorrelation inherent in repeated observations of the same localities, which may influence the type-II error probability. Finally, this study is limited to the spatial dimensions of sprawl and does not address socio-economic or environmental impact outcomes in depth.

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