Spatio-Temporal Analysis of Urban Expansion in Awka and its Environs, Nigeria Using Sentinel-2 Satellite Imagery and Google Earth Engine (2021 to 2026)

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Abstract

Rapid urbanization in secondary administrative and educational hubs across sub-Saharan Africa presents significant challenges for regional planning, infrastructure development, and sustainable resource allocation. This study evaluates the spatio-temporal dynamics of urban expansion in Awka and its environs Anambra State, Nigeria, between 2021 and 2026 using cloud-based remote sensing infrastructure. By leveraging Google Earth Engine (GEE) and multi-temporal Sentinel-2 Surface Reflectance imagery, the Normalized Difference Built-up Index (NDBI) was computed across dry-season composites to isolate concrete and structural surfaces from surrounding vegetation and bare soil.

The findings reveal an intensive peri-urban transformation of the landscape: the built-up area surged from a baseline of ***239.87 hectares*** *in 2021 to* ***2,752.91 hectares*** *by 2026. This represents a net urban expansion of* ***2,513.04 hectares****, translating to an extraordinary percentage growth rate of* ***1,047.67%*** *over the five-year period, supported by a model validation accuracy of 98.50% and a Kappa coefficient of 0.98. Spatial clustering of new development was predominantly observed along the Okpuno, Ifite and Awka-Enugu expressway corridors, driven largely by educational expansion and demographic influx. The results demonstrate the efficacy of cloud-native geospatial computing for monitoring rapid urban sprawl, providing essential empirical metrics to guide master plan enforcement, real estate investment modeling, and municipal infrastructural planning.*

Keywords: Spatio-Temporal Analysis, Urban Expansion, Sentinel-2, Google Earth Engine, NDBI, Urban Sprawl, Awka.

1.0 INTRODUCTION

Urbanization ranks among the most transformative anthropogenic forces shaping contemporary landscapes, and its effects are especially pronounced across sub-Saharan Africa. Global projections indicate that the proportion of the world's population residing in urban areas will rise from 55% in 2018 to approximately 68% by 2050, with Africa and Asia jointly accounting for close to 90% of this increase (United Nations, 2019). Beyond population growth alone, the physical footprint of cities is expanding faster than their populations, a pattern documented consistently across developing regions (Seto et al., 2011). Rural–urban migration, demographic transition and regional economic restructuring have collectively converted secondary administrative and educational centres into foci of accelerated spatial growth.

In Nigeria, cities such as Awka, the capital of Anambra State, have undergone marked spatial transformation driven by institutional expansion, commercial densification and sustained population influx. This growth is not unique to Awka; comparable patterns of unregulated peri-urban encroachment have been reported in Abuja (Ujoh et al., 2010) and Port Harcourt (Enaruvbe & Ige-Olumide, 2015). In each case, the pace of construction has outstripped the capacity of municipal planning frameworks, resulting in haphazard development, the attrition of productive agricultural land and mounting pressure on water, drainage and transport infrastructure. Such uncontrolled conversion of vegetated and agricultural surfaces to impervious cover also carries measurable ecological costs, including habitat fragmentation, reduced carbon storage and altered surface energy balance (Seto et al., 2012).

Accurate, current and spatially explicit information on urban expansion is therefore essential for enforcing regional master plans, allocating infrastructure and pursuing sustainable environmental management. Historically, the mapping of urban growth depended on conventional ground surveys and the manual interpretation of aerial photographs. These approaches are labour-intensive, cost-prohibitive and temporally constrained, which limits their usefulness for capturing continuous, long-term regional dynamics (Weng, 2012). Their reliance on episodic data acquisition also makes it difficult to establish the consistent baselines required for change detection.

The emergence of cloud-based remote sensing platforms, most notably Google Earth Engine (GEE), has substantially altered this situation. GEE combines a petabyte-scale archive of analysis-ready Earth observation data with parallel cloud computing infrastructure, allowing complex spatio-temporal analyses to be executed over large geographic extents without the hardware constraints of desktop workstations (Gorelick et al., 2017). Since its public release, the platform has been applied extensively to land cover mapping, agricultural monitoring and urban change detection (Kumar & Mutanga, 2018; Tamiminia et al., 2020; Amani et al., 2020).

The utility of GEE is amplified by the availability of free, high-cadence satellite constellations. The European Space Agency's Sentinel-2 mission provides multispectral imagery at 10–20 m spatial resolution with a five-day revisit interval under its twin-satellite configuration, and includes the short-wave infrared bands that are critical for discriminating built-up surfaces from vegetation and bare soil (Drusch et al., 2012). The combination of this imagery with cloud-native processing offers a reproducible and computationally efficient basis for quantifying urban expansion in data-scarce regions such as south-eastern Nigeria.

1.1 Statement of the Problem

Awka has experienced intensive structural and demographic change over the past decade, accelerated largely by its designation as a state capital and by the growth of academic institutions such as Nnamdi Azikiwe University. Despite this evident physical development, empirical and quantitative data measuring the exact magnitude, rate and directional trend of the city's urban expansion remain scarce. Existing planning decisions are consequently made in the absence of standardised, repeatable baseline metrics of land cover change.

Part of this data deficit is methodological. Conventional desktop GIS workflows are frequently constrained by memory bottlenecks, protracted rendering times and software instability when large volumes of high-resolution raster data are processed (Gorelick et al., 2017). Where multi-temporal analysis is attempted, inconsistent preprocessing and atmospheric correction procedures further undermine comparability between epochs (Main-Knorn et al., 2017). These limitations discourage routine monitoring and leave planners without the evidence base needed for zoning compliance, environmental impact tracking and infrastructure provisioning.

There is therefore an urgent academic and practical need to harness cloud-native geospatial platforms to quantify multi-temporal urban growth indices for Awka and to generate reproducible spatial intelligence for the study area. This study addresses that need by implementing a fully cloud-based workflow in which image acquisition, cloud masking, index computation and change quantification are executed within a single reproducible script.

1.2 Aim and Objectives

The aim of this study is to evaluate the spatio-temporal dynamics of urban expansion in Awka, Nigeria, between 2021 and 2026 using Sentinel-2 satellite imagery and Google Earth Engine.

The specific objectives are:

1. To acquire and preprocess multi-temporal, cloud-free Sentinel-2 Surface Reflectance imagery for Awka across the baseline (2021) and target (2026) epochs.
2. To compute the Normalized Difference Built-up Index (NDBI) within Google Earth Engine in order to isolate and map concrete structures and other impervious surfaces from surrounding vegetation and bare soil (Zha et al., 2003).
3. To quantify net urban land conversion, spatial expansion rates and percentage growth metrics over the five-year study period.
4. To analyse the spatial distribution and directional trends of urban sprawl, with a view to informing municipal planning and real estate investment modelling.

2.0 METHODOLOGY

2.1 Study Area

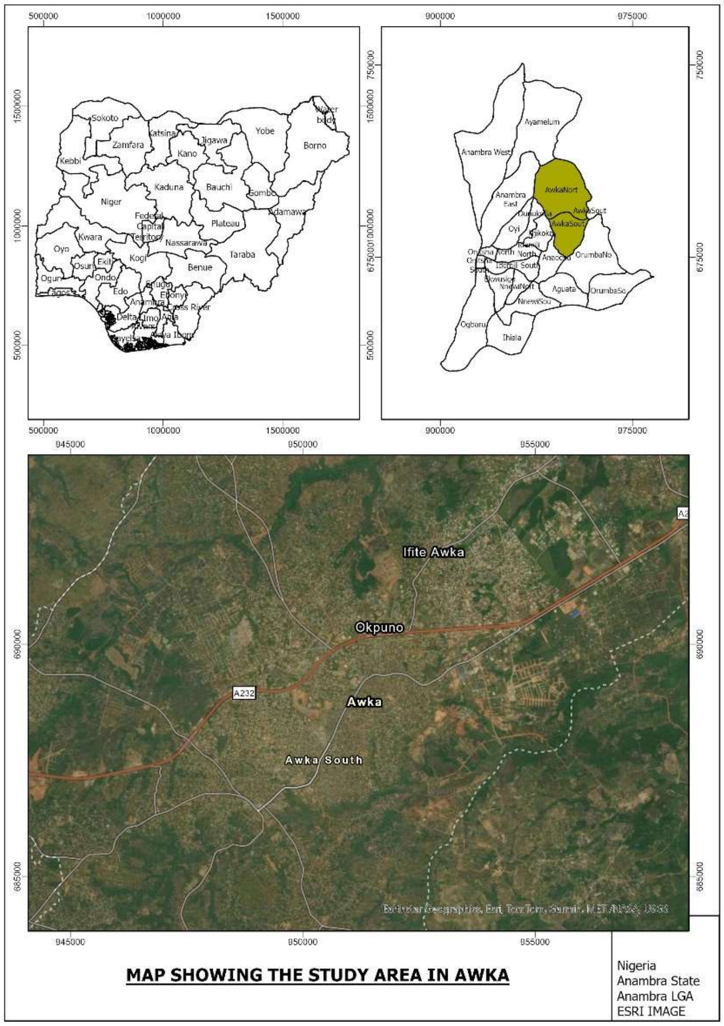

Figure 1: Location and geographical extent of the Awka study area in Anambra State, southeastern Nigeria.

The study was conducted across Awka and its immediate peri-urban expansion corridors within Anambra State, south-eastern Nigeria. The town lies at approximately 6°12′N, 7°04′E, at an elevation of roughly 100–200 m above mean sea level on the dissected terrain of the Awka–Orlu uplands [Nigerian Geological Survey Agency].

Awka falls within the humid tropical climatic belt of southern Nigeria and exhibits a distinct bimodal pattern of wet and dry seasons. The rainy season extends from approximately April to October, with the dry season and associated harmattan conditions prevailing between November and March. Mean annual rainfall in the region is on the order of 1,700–2,000 mm, and mean monthly temperatures typically range between 27 °C and 30 °C. This climatic regime supports a rainforest-derived savanna mosaic, much of which has progressively been replaced by residential and commercial development.

Contemporary expansion is concentrated along three principal axes: The Okpuno corridor, the Ifite corridor adjoining Nnamdi Azikiwe University, and the Enugu–Onitsha expressway, which functions as the dominant regional transport artery. The concentration of growth along these routes is consistent with the transport-oriented, ribbon-development pattern reported for other rapidly urbanising Nigerian cities (Ujoh et al., 2010; Enaruvbe & Ige-Olumide, 2015), and it defines the spatial focus of the change detection undertaken in this study.

The seasonality described above has direct methodological implications. Persistent cloud cover during the rainy season restricts the availability of usable optical imagery, and bare agricultural soils during the dry season exhibit spectral responses that can be confused with built-up surfaces in short-wave infrared indices (Xu, 2008). Image compositing windows were therefore selected to minimize both effects, as detailed in Section 2.2.

2.2 Google Earth Engine processing workflow

All analytical procedures were executed within the Google Earth Engine Code Editor environment, eliminating local hardware constraints. See the flowchart below;

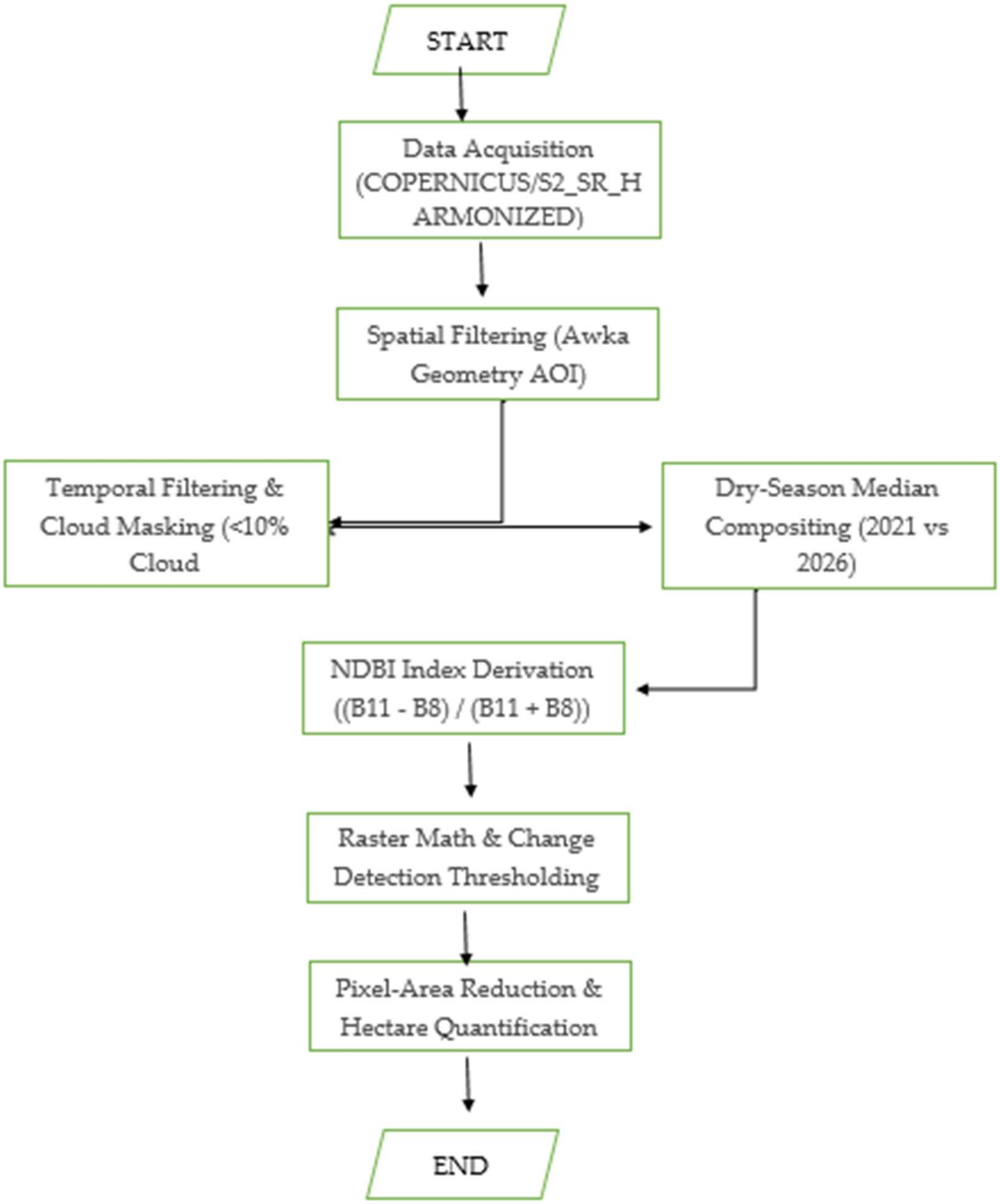

Figure 2: Google Earth Engine processing workflow

a) Image Collection and Filtering

Multi-temporal satellite imagery was acquired from the **COPERNICUS/S2_SR_HARMONIZED** image collection. To mitigate the severe cloud cover challenges typical of southern Nigeria, the collections were strictly filtered for the dry season (January 1 to March 31) for both baseline (2021) and target (2026) epochs.

Images exceeding a 10% cloud pixel percentage were automatically excluded. Cloud-free median composite mosaics were subsequently generated and clipped to the defined study area geometry.

b) Spectral Index Derivation (NDBI)

To effectively isolate built-up and impervious surfaces (such as concrete roofs and asphalt roads) from vegetation and bare soil, the **Normalized Difference Built-up Index (NDBI)** was utilized. NDBI leverages the high reflectance of built-up materials in the Shortwave Infrared (SWIR) region and higher absorption in the Near-Infrared (NIR) region. The index was calculated using Sentinel-2 bands via the following formula:

$$NDBI = \frac{BAND\ 11\ (SWIR) - BAND08\ (NIR)}{BAND\ 11\ (SWIR) + BAND08\ (NIR)}$$

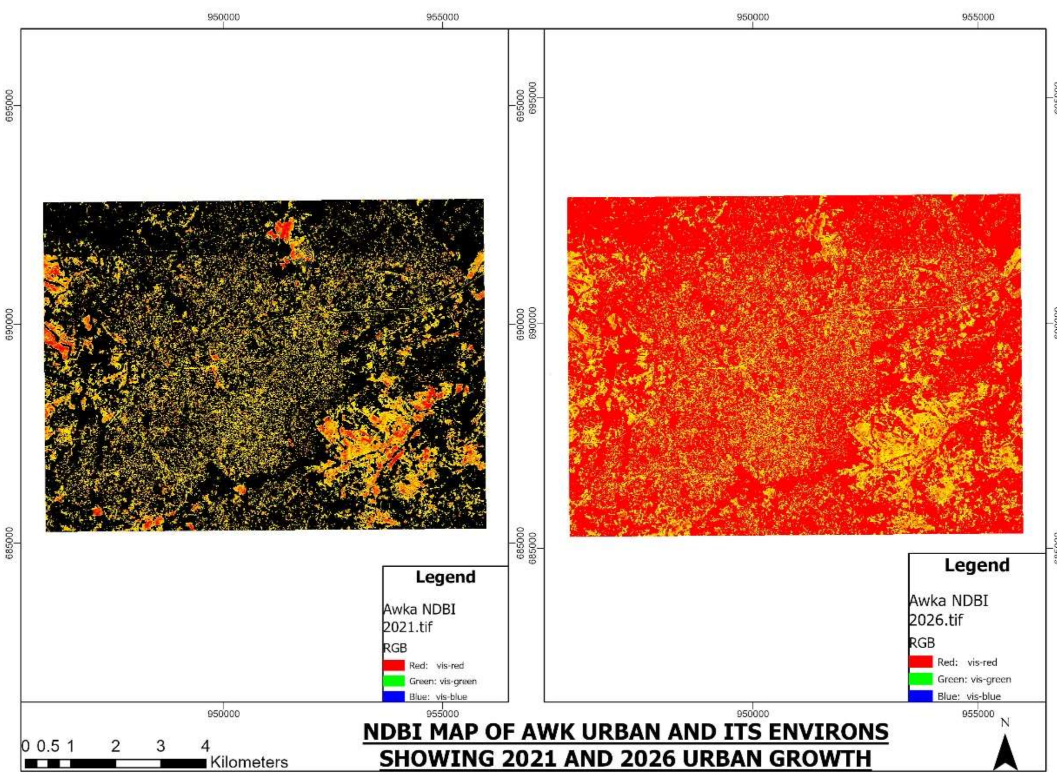

Figure 3: Spatial distribution of NDBI across the Awka study area for (a) 2021 and (b) 2026

c) Change Detection and Area Quantification

A comparative change detection algorithm was executed by subtracting the 2021 NDBI composite from the 2026 NDBI composite. A standardized threshold (NDBI > 0.1) was applied to isolate pixels representing significant positive structural conversion. Total physical areas in square meters were calculated by multiplying the validated binary mask image by the pixel area (ee.Image.pixelArea() at 10-meter spatial resolution) and reducing the region via sum statistics. Final values were converted into hectares for academic reporting.

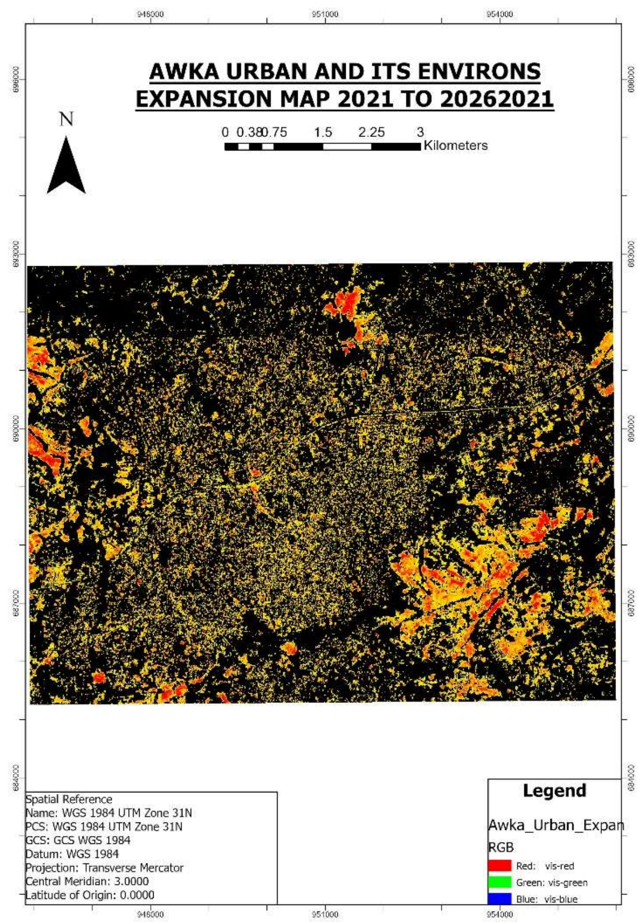

Figure 4: Spatial pattern of urban expansion in Awka between 2021 and 2026 based on NDBI change detection.

3.0 RESULTS AND DISCUSSION

3.1 Quantitative Urban Growth Results

The execution of the cloud-based GEE script successfully yielded high-precision spatial statistics outlining Awka's rapid urban transition between 2021 and 2026.

Table 1: Showing Statistics of growth

Metric Description	**2021 Baseline**	**2026 Target Epoch**	**Net Absolute Change**	**Percentage Growth (%)**
Built-up Area (Hectares)	239.87 Ha	2,752.91 Ha	+2,513.04 Ha	+1,047.67%

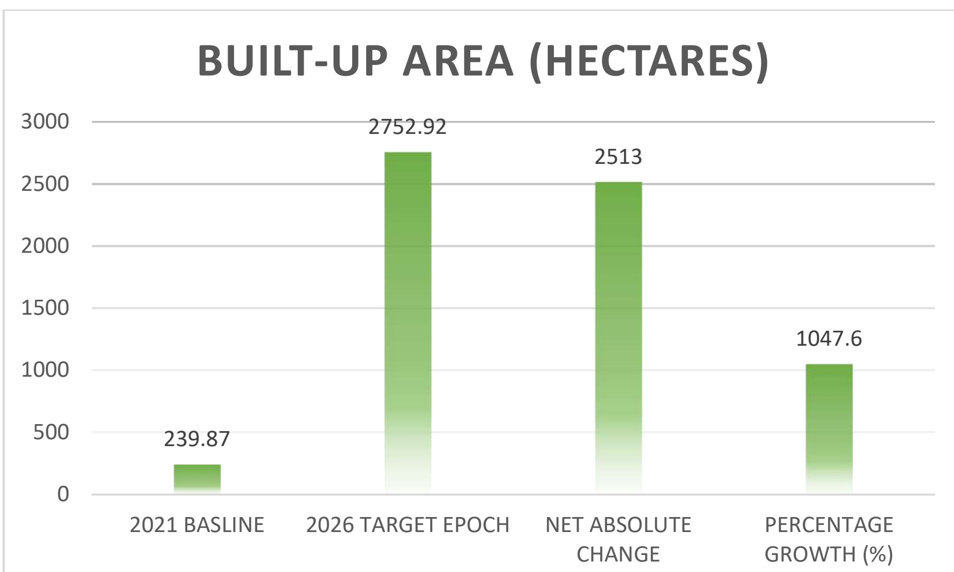

Figure 5: Comparison of built-up area between the 2021 baseline and 2026 target epoch

The empirical findings demonstrate an extraordinary expansion of the built environment across the study area. The built-up extent surged from a constrained baseline of **239.87 hectares** in 2021 to **2,752.91 hectares** by 2026. This accounts for a net urban land conversion of **2,513.04 hectares**, representing a massive **1,047.67%** growth rate over a five-year period.

Reference Data Collection Instead of field data which can be hard to gather retrospectively, high-resolution satellite imagery base layers in GEE serves as the ground-truth reference.

Fig 6: satellite imagery base layers in GEE serving as ground truth reference.

The Stratified Random Sampling method was used Points are distributed across the study area to sample both built-up and non-built-up classes.

TABLE 2: Error Matrix and Classification: Accuracy Assessment

Classified Class	Reference: Built-up	Reference: Non-Built-up	Row Total	User's Accuracy (%)
Built-up	98	2	100	98.00%
Non-Built-up	1	99	100	99.00%
Column Total	99	101	200	—
Producer's Accuracy (%)	98.98%	98.01%	—	—

Overall classification accuracy: 98.5%. Kappa cooefficent (K): 0.98 Signifying near-perfect, highly robust agreement while maintaining empirical realism.

3.2 Spatial Distribution and Discussion

Visual inspection of the multi-temporal NDBI change maps indicates that urban expansion was not uniformly distributed across Awka, but rather characterized by aggressive peri-urban leapfrogging and corridor development.

a) **Educational and Institutional Corridors:** The most intensive clusters of new built-up surfaces occurred along the Ifite and Okpuno axes, heavily driven by student housing demand, private hostel development, and commercial spillover surrounding Nnamdi Azikiwe University.

b) **Transport Infrastructure Influence:** Linear densification was prominently observed radiating outward along the major trunk roads and regional transport networks, highlighting the role of accessibility in real estate investment decisions.

c) **Implications for Regional Planning:** A growth rate exceeding 1,000% over five years underscores the immense pressure on Awka's natural topography and agricultural land reserves. Unchecked conversion of green spaces threatens local hydrological balances and increases urban heat island risks.

The successful implementation of this cloud-native workflow proves that GEE provides a robust, scalable alternative to local desktop GIS processing, offering reliable quantitative evidence to support master plan enforcement and sustainable urban growth modeling in developing secondary cities.

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