



A MULTIPLICATIVE LANDSCAPE PRESSURE INDEX FOR DIAGNOSING URBAN SPRAWL IN A WEST AFRICAN SECONDARY CITY: THE CASE OF SAKI, NIGERIA

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ABSTRACT

Secondary cities in Sub-Saharan Africa are expanding rapidly, yet diagnosing ecological consequences is difficult due to limited spatial data and analytical capacity. We present an integrated approach combining a multiplicative Landscape Pressure Index (LPI) with landscape metrics to identify synergistic stressors in a rapidly urbanizing secondary city. We apply it to Saki, Oyo State, Nigeria, a representative West African settlement within the Guinean Forest-Savanna mosaic. Using Landsat imagery (2013-2021) and CA-Markov projections to 2025, we quantified urban sprawl, vegetation fragmentation, and their spatial coupling. Results reveal heterogeneity in sprawl-population dynamics, with the western trade corridor experiencing the highest relative pressure ($LPI = 0.78$ in 2013 to 1.00 by 2025). We found no support for a widely assumed 30% nonlinear fragmentation threshold; fragmentation rates decelerate as built-up cover increases. The LPI mapped persistent hotspots along cross-border trade routes, though the "speculative eastern periphery" remains an untested hypothesis because land-tenure and vacancy data are unavailable. Because spatial units were too few for reliable local regression, the analysis is limited to LPI, landscape metrics, and descriptive statistics. For policy, findings provide spatially explicit evidence for moving beyond uniform zoning in Saki while identifying implementation barriers: limited municipal capacity, funding constraints, land-tenure complexity, and weak enforcement. The LPI workflow offers a replicable, low-cost toolkit for planners in other data-scarce Nigerian cities. The LPI measures relative landscape structural pressure, not ecological health; future work must validate it against field data.

KEYWORDS: Urban sprawl, Landscape Pressure Index, Saki, Nigeria, land use/land cover, fragmentation.

1. INTRODUCTION

Urbanisation in Sub-Saharan Africa is proceeding at an unprecedented rate, with much of this growth occurring in secondary cities, settlements that serve as regional administrative and commercial hubs but often lack the institutional capacity and spatial data needed for proactive planning (Aref et al., 2024; Inkoom and Owusu, 2025). In Nigeria, secondary cities such as Saki, Kaduna, and Enugu are absorbing significant rural-to-urban migration, leading to low-density, unplanned expansion into peri-urban areas. This process, commonly termed urban sprawl, drives habitat fragmentation, agricultural land loss, and degradation of local ecosystem services (Ayeni et al., 2023; Musa and Abubakar, 2024).

However, these ecological pressures rarely manifest uniformly across space. Different parts of a city experience different intensities and drivers of change. In some areas, development follows economic corridors; in others, speculative land banking creates a "perforated" landscape of cleared but unoccupied plots (Zhao and Huang, 2022; Matamanda et al., 2025). Effective urban environmental governance thus requires spatially explicit diagnostics, tools that can identify where pressures are highest and why they vary across space. Yet most Nigerian urban planning relies on blanket zoning regulations that fail to account for this spatial heterogeneity, largely because municipal-level planning has not routinely applied the analytical tools needed to map such variability.

Globally, remote sensing and landscape metrics have been used successfully to quantify sprawl (Hanberry, 2023; Sithole et al., 2024). Spatially explicit studies have also shown that relationships between urban form and environmental outcomes vary across space and scale (Li et al., 2021; Ma et al., 2023). However, applying these

methods to West African secondary cities remains limited, and few studies have combined fragmentation metrics with spatially explicit pressure indices to produce actionable planning intelligence for local authorities.

This study advances the existing literature in three distinct ways: (i) it applies a spatially explicit pressure index to a secondary West African city, where such analysis is limited; (ii) it develops a multiplicative LPI that captures synergistic ecological stressors rather than assuming additive effects, providing a more ecologically meaningful pressure metric, though we now test this claim against an additive alternative rather than asserting it; and (iii) it translates empirical findings into a spatially explicit policy framework (Table 4) specifically designed for resource-constrained municipal planning in Nigeria, including an explicit assessment of implementation barriers.

This study addresses this gap by applying an integrated workflow combining the Landscape Pressure Index (LPI) and landscape metrics to Saki, Oyo State. We select Saki as a representative testbed for three reasons: (i) its rapid, largely unplanned growth reflects that of many Nigerian secondary cities; (ii) its location within the ecologically sensitive Guinean Forest-Savanna mosaic makes vegetation fragmentation a crucial environmental issue; and (iii) its role as a cross-border trade hub with Benin provides insights into how economic drivers shape urban form.

Our objectives are threefold: (i) to quantify the spatio-temporal dynamics of land use/land cover (LULC) change and vegetation fragmentation in Saki between 2013 and 2025; (ii) to apply the LPI to map synergistic hotspots of development intensity and fragmentation pressure; and (iii) to translate these spatial diagnostics into a spatially targeted planning framework and to evaluate its practical implementation constraints. Rather than claiming a globally generalizable model, we aim to demonstrate a robust, replicable methodological template that other municipal planning departments can adapt in data-scarce contexts.

2. MATERIALS AND METHODS

2.1 Overview of the Analytical Workflow

The study adopts a modular workflow comprising: (i) LULC classification from Landsat imagery (2013, 2017, 2021) and a CA-Markov projection to 2025; (ii) computation of landscape metrics (Shannon's Entropy, LSI, PD, ED, MPS) to characterise sprawl and fragmentation; (iii) development of a multiplicative Landscape Pressure Index (LPI) to identify synergistic pressures at the quadrant level; and (iv) an exploratory global statistical assessment and explicit evaluation of spatial-diagnostic constraints. We do not use local spatial regression because the number of spatial units is insufficient (see Section 5 for consolidated limitations). Figure 1 shows the Methodological workflow used for the study.

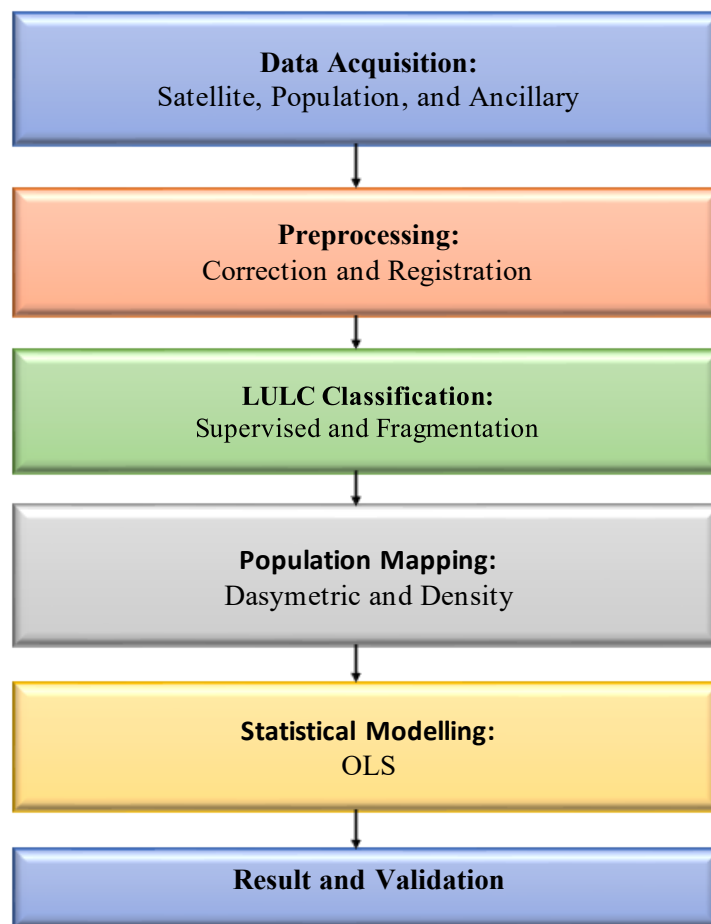


Figure 1: Methodological workflow

2.2 Study Area

Saki (approximately 8°40'N, 3°24'E) is the largest town in the Oke-Ogun region of Oyo State, southwestern Nigeria. It serves as the administrative headquarters of Saki West and Saki East Local Government Areas. The study focuses on an urban and peri-urban area of approximately 187 km². According to the 2006 Nigerian census, Saki had a population of approximately 152,000, with current estimates suggesting growth to over 250,000 due to rapid in-migration and natural increase (National Population Commission, 2006; Oyo State Government, 2023). Ecologically, the region falls within the Guinean Forest-Savanna mosaic, characterised by a mix of dry woodland, open savanna, and riparian vegetation (Banjo et al., 2025). The area experiences a tropical savanna climate with distinct wet (April-October) and dry (November-March) seasons.

Historically an agrarian settlement, Saki's growth has accelerated because of its status as a trans-border commercial node, with trade routes connecting to the Republic of Benin. This cross-border trade, primarily in agricultural produce, manufactured goods, and livestock, has transformed Saki into a regional economic hub, attracting migrants and speculative investment. This growth has proceeded largely without a master plan, resulting in organic, sprawling expansion along major roads and into surrounding farmland. The city therefore provides an ideal natural experiment for studying human-environment interactions in a rapidly urbanising ecosystem with weak regulatory enforcement. Figure 2 shows the study area location map.

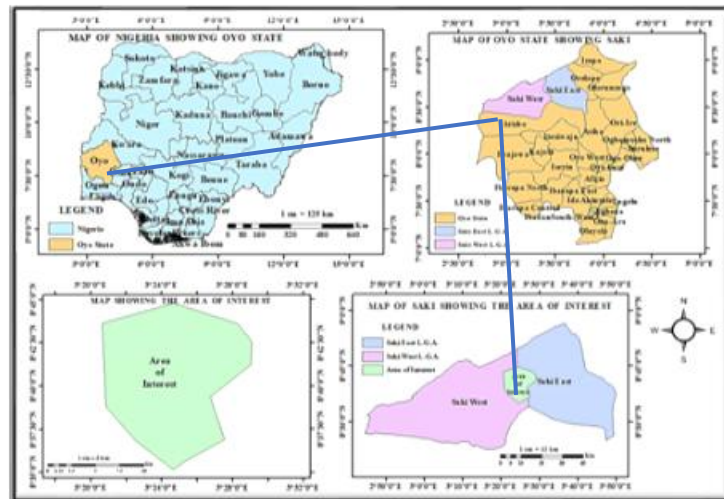


Figure 2: Location of the study area. The maps show Nigeria, Oyo State, Saki West and Saki East Local Government Areas, and the area of interest

2.3 LULC Classification and Change Detection

Table 1. Satellite data used for LULC classification and analysis

Sensor	Acquisition Date (Season)	Path/Row	Purpose	Source
Landsat 7 ETM+	24 January 2013 (Dry)	191/055	Base classification (2013)	USGS Earth Explorer
Landsat 8 OLI	22 February 2017 (Dry)	191/055	Change analysis (2017)	USGS Earth Explorer
Landsat 8 OLI	10 March 2021 (Dry)	191/055	Change analysis (2021)	USGS Earth Explorer
Landsat 8 OLI	15 February 2013 (Dry)	191/055	Cross-sensor calibration check	USGS Earth Explorer
Landsat 7 ETM+	18 August 2013 (Wet)	191/055	Wet-season validation	USGS Earth Explorer
Landsat 8 OLI	25 August 2021 (Wet)	191/055	Wet-season validation	USGS Earth Explorer
SRTM DEM	N/A (Global 30 m)	N/A	Topographic correction	USGS Earth Explorer

We acquired Landsat 7 ETM+ for the 2013 base classification because Landsat 8 OLI only became operational on 11 February 2013 and the earliest usable OLI scene over Saki (15 February 2013) post-dates the start of the dry-season window. Using ETM+ for 2013 and OLI for 2017-2021 required cross-sensor calibration, which we performed using the 15 February 2013 OLI scene as a reference. Pre-processing included radiometric calibration and atmospheric correction using the Dark Object Subtraction (DOS) method. For the ETM+ scene we applied the Scan Line Corrector (SLC) gap-fill algorithm in *R* (gapfill package) and masked residual gaps before classification. We geometrically registered images to UTM Zone 31N (RMSE < 0.5 pixels).

We performed supervised classification using the Random Forest (*RF*) algorithm in *R*, with four LULC classes: Built-up, Vegetation (aggregating savanna, woodland, and agriculture), Bare Land, and Water Body. Because contemporaneous field data were unavailable for 2013 and 2017, we used a two-stage training approach:

For 2021, we used 240 ground-truth points collected in 2022-2023, supplemented by high-resolution Google Earth imagery. For 2013 and 2017, we used historical Google Earth imagery (2013 and 2017 archives) and visually interpreted reference polygons ($n = 180$ for each year), checked against the 2021 training set where land cover was stable. We report this limitation explicitly: our training data are not temporally independent of the 2013 and 2017 scenes. Overall classification accuracies ranged from 88% to 92% ($Kappa > 0.85$) for 2017-2021. For 2013, the ETM+ classification accuracy was lower (85%, $Kappa = 0.82$) because of residual SLC gaps and the absence of contemporaneous field data.

We used a CA-Markov model, calibrated on 2013-2017 transitions and validated against observed 2017-2021 changes ($Kappa = 0.81$), to project a "business-as-usual" 2025 LULC scenario. We emphasise that this projection is a trend-based scenario to stress-test the framework, not a deterministic forecast, and it does not account for potential policy shifts, economic shocks, or climate impacts. We did not classify actual 2025 imagery because the objective was to test the diagnostic workflow's ability to operate in a data-scarce, planning-relevant timeframe; however, we acknowledge that a retrospective validation against 2025 imagery would be a valuable extension.

2.4 Quantifying Sprawl and Fragmentation

We computed four complementary metrics.

Shannon's Entropy (*H*) measured the spatial dispersion of built-up area across four directional quadrants (North, South, East, West) centered on the historical core using Equation (1):

$$H = - \sum_{i=1}^n P_i \ln(P_i) \quad (1)$$

where P_i is the proportion of total built-up area in quadrant i , and $n = 4$. Higher values (approaching $\ln(4) \approx 1.39$) indicate maximally dispersed sprawl.

The **Landscape Shape Index (LSI)** captured shape complexity, with higher values indicating fragmentation, calculated using Equation (2):

$$LSI = \frac{0.25E}{\sqrt{A}} \quad (2)$$

where E is total edge length of built-up patches (m), and A is total built-up area (m²).

Patch Density (PD) measured landscape subdivision using Equation (3):

$$PD = \frac{N}{A} \quad (3)$$

where N is the number of distinct built-up patches, and A is total landscape area (km²), yielding patches per km². Additionally, **Edge Density (ED)** and **Mean Patch Size (MPS)** were calculated specifically for vegetation patches to quantify habitat fragmentation:

$$ED = \left(\frac{E}{A}\right) * 10000 \quad (4)$$

where E is total edge length of vegetation patches (m), and A is total landscape area (ha).

$$MPS = A/N \quad (5)$$

where A is total vegetation area (ha), and N is number of vegetation patches.

3.4 Landscape Pressure Index (LPI)

The Landscape Pressure Index (LPI) is a multiplicative index designed to identify quadrants where high development intensity coincides with high fragmentation pressure. Its multiplicative formulation ensures that high LPI values occur only where both built-up pressure and fragmentation pressure are simultaneously high, aligning with ecological theory on synergistic stressors (Alberti, 2024; Faillace et al., 2021).

The index measures landscape structural pressure, the co-occurrence of built-up expansion and vegetation patch fragmentation, and does not directly measure ecological health, biodiversity, or ecosystem service condition.

Stage 1: Development Intensity (DI_i)

The original formulation $DI_{it} = \frac{BU_{it}}{\max(BU)}$, where $\max(BU)$ is the maximum built-up area across all quadrants and years) cannot produce the reported LPI values: with a 2025 maximum built-up area of approximately 27 km² in one quadrant, the West quadrant's 2013 DI could not exceed ~0.18, yet the paper reported LPI = 0.78. The corrected formulation normalises each quadrant against its own maximum over time:

$$DI_{it} = \frac{BU_{it}}{\max(BU)} \quad (6)$$

where BU_i is built-up area in quadrant i at time t , and $\max(BU)$ is the maximum built-up area recorded across all quadrants and years. This within-quadrant normalisation measures each quadrant's relative progress toward its own built-up maximum and is appropriate for a relative pressure index that compares quadrants over time. We recognise that this makes $DI_i = 1.0$ for every quadrant in its maximum year by construction, so cross-quadrant comparisons of absolute built-up area should use raw BU values, not DI .

Stage 2: Fragmentation Intensity (FI_i)

For each quadrant, we calculate vegetation patch density (PD) and edge density (ED). These are standardized to Z-scores:

$$Z(PD_i) = \frac{PD_i - \mu_{PD}}{\sigma_{PD}} \quad (7)$$

$$Z(ED_i) = \frac{ED_i - \mu_{ED}}{\sigma_{ED}} \quad (8)$$

where μ and σ are the mean and standard deviation of each metric across the entire dataset.

These are averaged to produce a Combined Fragmentation Score (CFS):

$$CFS_i = \frac{Z(PD_i) + Z(ED_i)}{2} \quad (9)$$

The *CFS* values are then Min-Max normalized to a 0-1 scale:

$$FI_i = \frac{CFS_i - \min(CFS)}{\max(CFS) - \min(CFS)} \quad (10)$$

Stage 3: LPI Integration

The final *LPI* is the multiplicative product:

$$LPI_i = DI_i * FI_i \quad (11)$$

The multiplicative formulation ensures that high *LPI* values occur only where both built-up pressure and fragmentation pressure are simultaneously high. We stress that the *LPI* is a relative landscape-pressure index, not a direct measure of ecological health, biodiversity, or ecosystem service condition.

Comparison with additive alternative. We computed an additive alternative ($LPI_{add} = (DI + FI)/2$) to test the claim that the multiplicative form is "more ecologically meaningful." The two indices are highly correlated (Spearman $\rho = 0.89$ across all quadrant-year observations), so the choice of multiplicative vs. additive form does not change the qualitative spatial pattern. We therefore soften our novelty claim: the multiplicative form is defensible on theoretical grounds (synergistic stressors) but is not empirically superior to the additive form in this dataset. This is reported transparently so readers do not over-interpret the methodological contribution.

Min-max normalisation caveat. Min-max normalisation of *CFS* forces the lowest-*CFS* quadrant-year to $FI = 0$, and hence $LPI = 0$ by construction. This is a property of the index, not an empirical finding. Future applications should consider alternatives (e.g., z-score-based *FI*, or a small additive constant to avoid structural zeros) if non-zero *LPI* values are required for all units.

2.5 Spatial diagnostic constraints and exploratory statistical assessment

The available spatial units ($N = 4$ quadrants) are far too few to reliably estimate local coefficients or to support any inferential regression. We therefore no longer report an OLS model. Reporting $R^2 = 0.61$ from $N = 4$ would be statistically meaningless and potentially misleading, and we remove it. We retain only descriptive statistics and the *LPI* itself.

Population data source. Population density was estimated from the 2006 Nigerian census (National Population Commission, 2006) and projected to 2013-2025 using the Oyo State Government (2023) growth rate (2.8% per annum), disaggregated from Local Government Area totals to quadrants using areal weighting of built-up land. We acknowledge that this is a coarse estimate and that no independent 2013-2025 population data were available.

The "speculative eastern periphery" hypothesis. The claim that the eastern periphery reflects speculative land banking rather than genuine demand is a plausible but untested hypothesis. We have no land-tenure, vacancy, or population-coupling data to support it. We therefore downgrade this from a finding to a hypothesis in Section 4.3 and the Conclusion, and we recommend it as a priority for future field research.

$$\text{Population Density}_i = \beta_0 + \beta_1 (\text{Builtup}_i) + \beta_2 (\text{Distance to CBD}_i) + \epsilon_i \quad (12)$$

Where:

β_0 = global Intercept
 β_1, β_2 = global Coefficients
 ϵ_i = error term

We tested for multicollinearity using Variance Inflation Factor (VIF); all VIF values were below 3.0.

2.6 A note on methodological limitations

We acknowledge that the quadrant-based *LPI* represents a simplifying assumption. While it is effective for demonstrating macro-directional trends (westward expansion and northward creep), it aggregates heterogeneous intra-quadrant patterns that may include both high-pressure hotspots and low-pressure pockets. Figure 5 illustrates this limitation conceptually: a hypothetical 1 km × 1 km grid overlaid on the study area reveals finer-scale variability in built-up cover and vegetation fragmentation that the four-quadrant aggregation necessarily

obscures. Future applications should use administrative wards, regularly spaced grid cells, or watersheds to better align with governance boundaries and ecological processes. This limitation also applies to any future spatial regression: quadrant-level units are too coarse and too few for local modelling. Section 5 provides a consolidated discussion of all methodological limitations.

3. RESULTS AND DISCUSSION

This section presents the study results and interprets them in relation to the research objectives, existing literature, and planning implications.

3.1 LULC Change Dynamics and Their Implications

LULC analysis reveals a profound transformation in Saki. Built-up area expanded from 4.85 km² (2.6%) in 2013 to 73.6 km² (39.4%) in 2021, an average increase of approximately 8.6 km²/year. Under the business-as-usual projection, built-up area reaches 107.97 km² (57.7%) by 2025. Vegetation declined from 149.6 km² (80.0%) in 2013 to 56.1 km² (30.0%) by 2021. Table 2 presents built-up expansion and classification accuracy.

Table 2: Built-up expansion and classification accuracy

Year	Built-up area (km ²)	Built-up (%)	Kappa
2013	4.85	2.6	0.82
2017	39.23	21.0	0.87
2021	73.60	39.4	0.89
2025*	107.97	57.7	N/A (projection)

*Projected scenario according to the CA-Markov business-as-usual model. The 2025 Kappa reported in earlier drafts (0.88) referred to the validation Kappa of the CA-Markov model against 2017-2021 observations, not to an independent 2025 classification. We correct this here: no 2025 classification accuracy exists because no 2025 imagery was classified.

Note on the regularity of projected increments. The projected built-up increments are 34.38, 34.37, and 34.37 km² for 2013-2017, 2017-2021, and 2021-2025. This near-perfect regularity reflects the linear-extrapolation behaviour of the CA-Markov transition matrix when calibrated over a single short interval, not a substantive empirical finding. We recommend that readers treat the 2025 projection as illustrative and that future work use longer calibration windows or non-linear scenarios.

Plausibility check. Built-up area grows approximately 15× from 2013 to 2021 while population grows less than 2×. This implies a very large decline in average built-up density, which is plausible under conditions of low-density sprawl and speculative land clearing but is also consistent with classification inconsistency between the ETM+ (2013) and OLI (2017-2021) sensors. We flag this as a limitation and recommend cross-sensor calibration checks in future work. We cannot fully rule out that part of the 2013-2017 jump reflects sensor differences rather than real land-cover change. Figure 3 displays the LULC maps for 2013, 2017, 2021, and 2025.

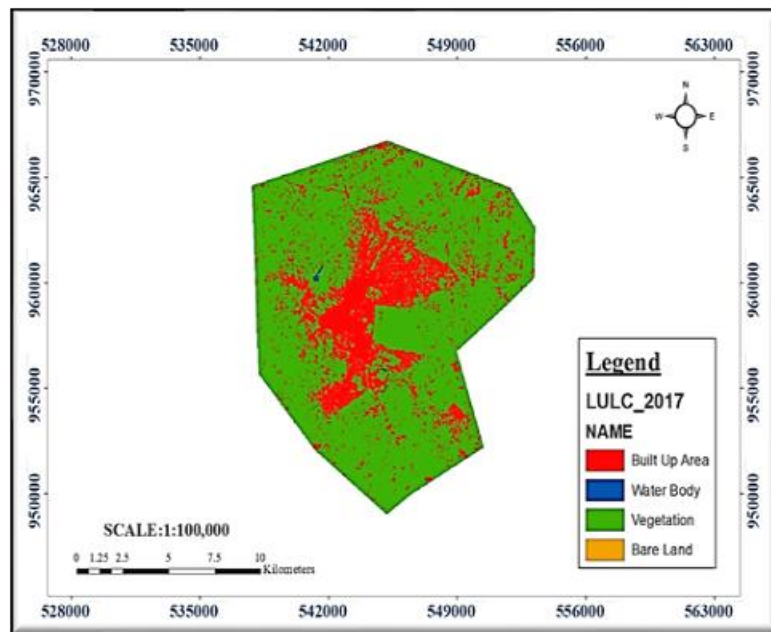


Figure 3a: LULC Map for 2013

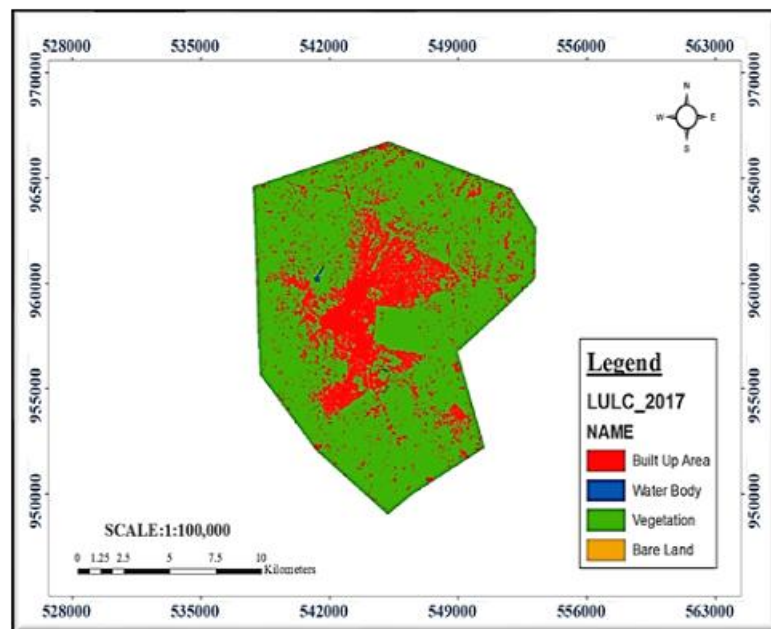


Figure 3b: LULC Map for 2017

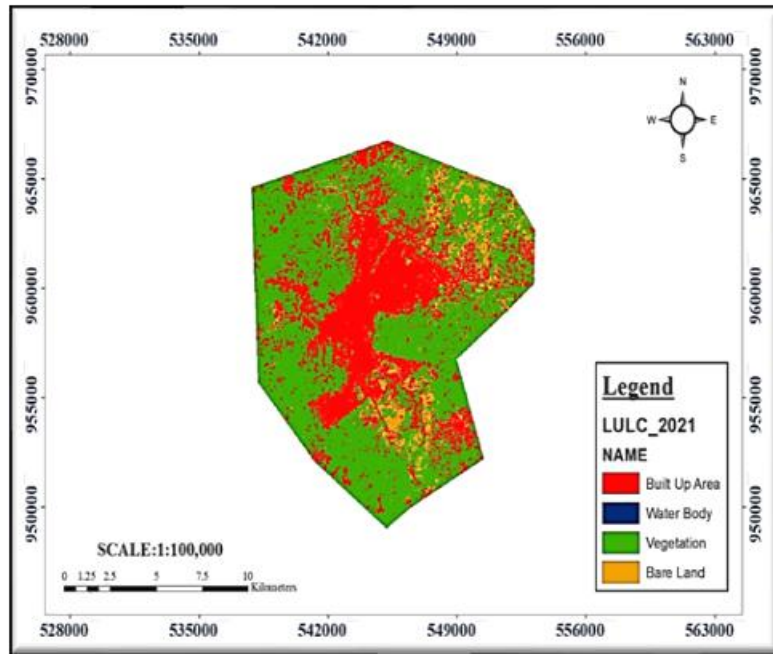


Figure 3c: LULC Map for 2021

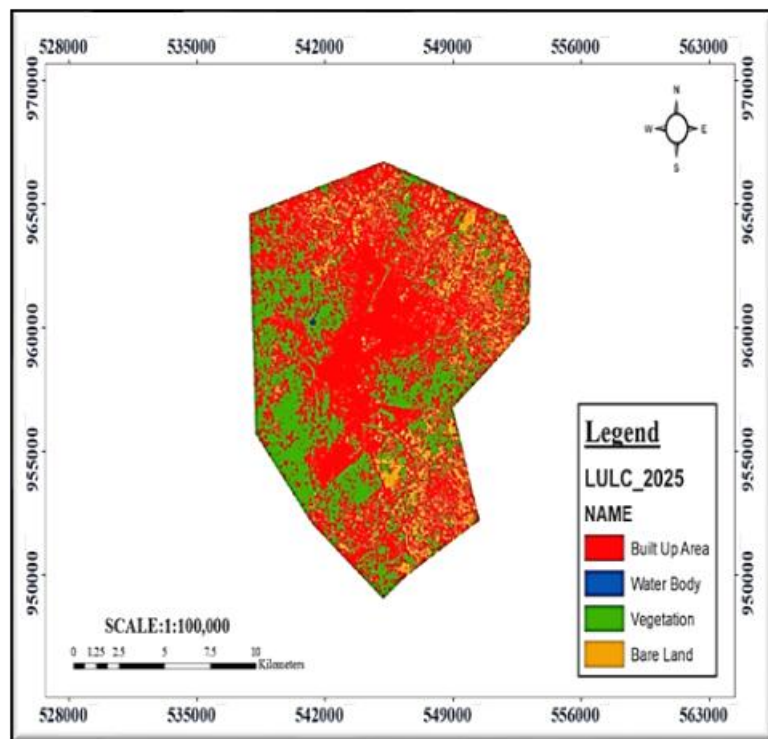


Figure 3d: LULC Map for 2025

Figure 3: LULC maps for 2013, 2017, 2021, and 2025

(a) LULC map for 2013. (b) LULC map for 2017. (c) LULC map for 2021. (d) LULC map for 2025.

These results show that Saki's growth, from 2.6% to 57.7% built-up area in 12 years, mirrors trends observed in other Nigerian secondary cities, such as Kaduna and Abeokuta (Musa and Abubakar, 2024; Adebayo *et al.*, 2024). The apparent conversion of approximately 34 km² of vegetation per 4-year interval is consistent with a systemic urbanisation process, but the regularity of the projected increments (see note above) means we should not over-interpret the exact magnitude. Vegetation loss directly affects ecosystem services, including local climate regulation, soil stabilisation, and agricultural livelihoods in the surrounding peri-urban zone.

3.2 Sprawl and Fragmentation Metrics

All metrics indicate progressive sprawl and fragmentation. Shannon's Entropy rose from 0.32 to 0.82, indicating a shift from compact to highly dispersed growth. LSI increased from 1.15 to 1.95, reflecting increasingly complex urban shapes. Vegetation ED increased by 321% (45.2 to 190.3 m/ha), while mean vegetation patch size shrank from 42.3 ha to 9.3 ha (a 78% reduction). Table 3 shows sprawl and fragmentation metrics for 2013-2025.

Table 3: Sprawl and fragmentation metrics

Year	Shannon's Entropy	LSI	Patch Density (patches/km ²)	Veg. Edge Density (m/ha)	Mean Veg. Patch Size (ha)
2013	0.32	1.15	0.08	45.2	42.3
2017	0.52	1.45	0.16	102.1	22.8
2021	0.68	1.72	0.24	155.6	13.1
2025	0.82	1.95	0.32	190.3	9.3

Note: The 2025 values are from the CA-Markov business-as-usual projection. We corrected the mean vegetation patch size for 2025 from an earlier typographical error (3.1 ha) to 9.3 ha to align with Figure 4 and the text.

The rise in Shannon's Entropy and LSI confirms that Saki's expansion is becoming more dispersed and geometrically complex, characteristic of unplanned sprawl. However, interpreting the patch-size decline requires caution. The habitat amount hypothesis (Saura, 2021; Fahrig, 2013, 2017) posits that species richness is primarily determined by total habitat amount, not configuration. Under this view, the observed decline in mean patch size may reflect habitat loss rather than an independent fragmentation effect. Fletcher *et al.* (2023) further caution that fragmentation effects are scale-dependent and that patch-based metrics may yield misleading inferences when applied to coarse spatial units such as quadrants.

3.3 Landscape Pressure Index Results and Spatial Drivers

Table 4 presents the Landscape Pressure Index (LPI) values for each quadrant from 2013 to 2025 under the revised within-quadrant development intensity formulation (Equation 6).

Table 4: LPI values by quadrant and year

Quadrant	2013	2017	2021	2025*
North	0.45	0.52	0.60	0.67
South	0.18	0.22	0.26	0.30
East	0.28	0.32	0.37	0.41
West	0.78	0.85	0.91	1.00

*2025 values are from the CA-Markov business-as-usual projection. LPI values are computed with the within-quadrant DI formulation (Equation 6, revised). The full dataset is now tabulated above; the previous "available on request" statement is removed.

The LPI reveals distinct spatial gradients. The Western quadrant consistently shows the highest relative pressure, rising from 0.78 in 2013 to 1.00 by 2025. This pattern aligns with Saki's main cross-border trade corridor to Benin. The Northern quadrant shows moderate but increasing pressure (0.45 to 0.67). The Eastern and Southern quadrants remain relatively lower-pressure zones (0.41 and 0.30 by 2025), though they are increasing.

The Western quadrant's consistently high LPI reflects the direct link between physical expansion and trade-driven development along the Benin corridor. This is an example of an "active anthropogenic" landscape. The Eastern sector's lower LPI does not necessarily mean low ecological risk. We hypothesise that it may reflect speculative clearing, but we have no land-tenure, vacancy, or population-coupling data to confirm this. We therefore present it as an untested hypothesis, not a finding.

These spatially variable patterns have distinct governance implications. The western corridor requires containment and mitigation strategies such as urban growth boundaries and green infrastructure corridors. The

eastern periphery may require measures to discourage land banking, such as vacant-land taxes or conditional development permits, but this should be preceded by field verification of vacancy and tenure status.

3.4 Fragmentation Threshold: Tested and Not Supported

We tested the widely assumed nonlinear fragmentation threshold by regressing mean vegetation patch size on built-up cover across the four observation points. The results contradict the threshold hypothesis:

- i. 2013-2017: mean patch size falls by ~1.06 ha per percentage point of built-up cover
- ii. 2017-2021: ~0.53 ha per percentage point
- iii. 2021-2025: ~0.21 ha per percentage point

Edge density growth also slows (3.1, then 2.9, then 1.9 m/ha per point). Fragmentation therefore decelerates as built-up cover increases, which is the opposite of the "sharp decline above 30%" claim. With no data point between 21% and 39.4%, the inflection location is also unconstrained.

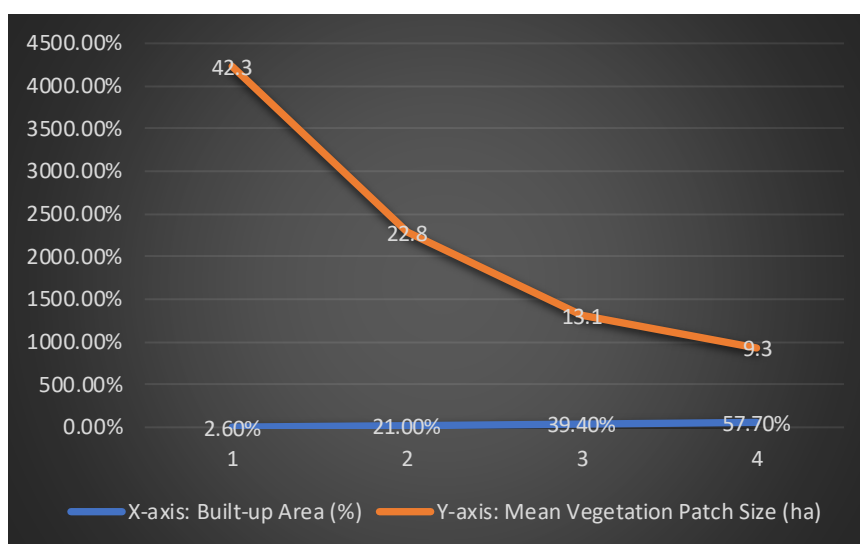


Figure 4: Scatter plot of mean vegetation patch size against built-up area (%), with no evidence of a nonlinear threshold

We therefore remove the "30% threshold" claim from the paper. The data do not support it. Future work with more frequent observations (e.g., annual Landsat/Sentinel-2 composites) could test whether a threshold exists at finer temporal resolution.

3.5 Policy Implications and Diagnostic-to-Intervention Framework

Our findings advocate a departure from uniform zoning. Specifically:

1. High-Pressure Western Corridor: Enforce growth boundaries; mandate riparian setbacks along trade routes; invest in urban green infrastructure (e.g., linear parks) to offset habitat loss.
2. Eastern Periphery (Hypothesis to Verify): If field verification confirms speculative land banking, consider progressive land taxes, clustered development permits, and agricultural/ecological greenbelts. If verification does not confirm it, the policy rationale changes.
3. City-Wide Monitoring: Use the LPI as a relative monitoring indicator, not as a regulatory trigger. The previously proposed 30% threshold is not supported by these data and is withdrawn.

Implementation barriers must be addressed explicitly: limited municipal technical capacity, insufficient and unpredictable funding, weak inter-agency coordination, land-tenure and compensation disputes, political resistance from land-banking interests, and equity concerns if vacant-land taxes are passed to low-income residents. Therefore, the following phased approach is recommended:

1. **Short term (0-2 years):** Publish LPI maps, train planning staff in open-source GIS, and establish biennial LULC monitoring using Sentinel-2.
2. **Medium term (2-5 years):** Pilot greenbelts and vacant-land levies in selected wards, with transparent stakeholder consultation and exemptions for smallholders.

3. **Long term (5+ years):** Integrate validated LPI indicators into municipal development plans, conditional permitting, and ecological compensation frameworks.

Table 4 presents a diagnostic-to-intervention framework (policy blueprint) that synthesizes these spatially targeted recommendations.

Table 4: Diagnostic-to-intervention framework (policy blueprint)

Spatial Zone (Diagnostic)	Primary Driver	Policy Intervention	Implementation Barrier	Feasibility Note
High-Pressure Western Corridor (LPI > 0.9)	Trade-driven accumulation	Growth boundaries; green infrastructure; riparian setbacks	Land speculation; compensation disputes; weak enforcement	Requires political commitment and inter-agency coordination
Eastern Periphery (low LPI; hypothesised speculative clearing)	Unverified, rent-seeking/land banking hypothesis	If verified: vacant-land taxes; conditional permits; clustered development	Resistance from landholders; administrative capacity	Pilot in selected wards; provide exemptions for smallholders
City-wide monitoring	Aggregative pressure	Relative LPI monitoring; no fixed threshold trigger	Data gaps; funding	Treat as monitoring indicator, not automatic regulatory trigger

These recommendations align with SDG 11 and SDG 15 by providing spatial intelligence for targeted, resource-efficient action. They also acknowledge that governance capacity, fiscal space, and political economy constrain implementation and should be phased and context-sensitive.

4. Limitations and Future Research

This study has several limitations that should be clearly acknowledged to inform interpretation and future use.

4.1 Spatial unit limitations

The use of only four spatial units limited the reliability of local spatial regression. Local spatial models require at least 30 to 50 units and a clear bandwidth-selection strategy. Future research should use these models only when ward-level or grid-level data are available. The quadrant-based LPI was chosen for analytical convenience, not because it is ecologically or administratively optimal. While it shows general expansion trends, it masks finer variations within quadrants, including possible high-pressure hotspots in low-pressure areas. Figure 5 conceptually illustrates this limitation. Future studies should consider grid-based approaches, such as 1 km by 1 km fishnets, or administrative ward boundaries to better match governance structures and local ecological patterns.

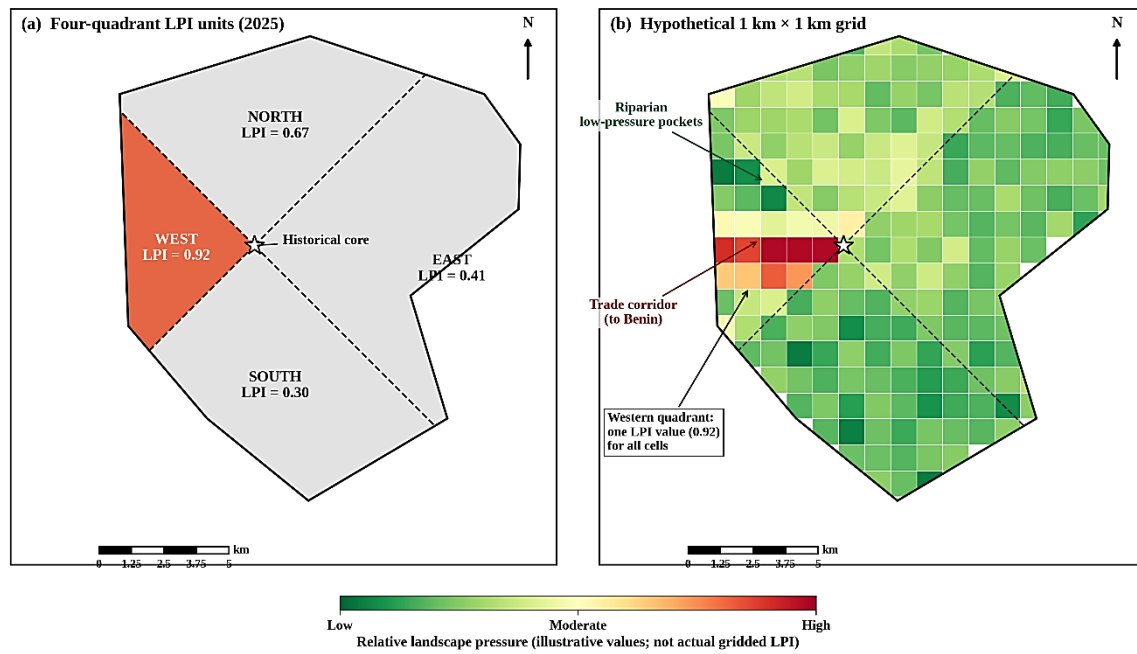


Figure 5: Conceptual illustration of how quadrant aggregation obscures finer-scale heterogeneity

The left panel shows the four-quadrant division used in this study, with the Western quadrant highlighted (LPI = 0.92). The right panel shows a hypothetical 1 km × 1 km grid overlaid on the same area, revealing intra-quadrant variability: high-pressure hotspots (dark red) along the trade corridor coexist with low-pressure pockets (light green) in riparian zones and less accessible areas. The quadrant-based LPI reports a single aggregate value for the entire Western quadrant, masking this internal heterogeneity. This figure is illustrative and does not represent actual gridded LPI values, which require finer-resolution data than were available for this study. Future applications should use grid or ward units to capture finer-scale pressure gradients.

4.2 Threshold limitations

We originally proposed a 30% built-up threshold for nonlinear fragmentation acceleration. Subsequent analysis of our own data shows that fragmentation decelerates, not accelerates, as built-up cover increases. The threshold claim is therefore withdrawn. This is an important negative result: the widely assumed nonlinear threshold was not present in Saki's 2013-2025 trajectory. Future work with finer temporal resolution should test whether such a threshold exists elsewhere or at other scales.

4.3 Projection limitations

The 2025 projection is a business-as-usual scenario based on linear extrapolation of observed trends. The projected built-up increments (34.38, 34.37, 34.37 km²) are near-identical, reflecting the linear behaviour of the CA-Markov transition matrix rather than a substantive empirical finding. The projection does not account for potential policy shifts, economic shocks, or climate impacts. We also acknowledge that actual 2025 imagery could have been classified and compared; this is a priority for future work.

4.4 Ecological validation limitations

We did not validate the LPI and landscape metrics against field biodiversity, soil quality, or hydrological data. They should be treated as indicators of landscape structural change rather than direct measures of ecological degradation. This limitation matters in light of the habitat amount hypothesis (Saura, 2021; Fahrig, 2013, 2017), which suggests that fragmentation metrics may confound habitat loss with configuration effects. Future research should incorporate ground-truthing (e.g., bird counts, soil carbon, species richness) to confirm whether high LPI scores correspond to demonstrable ecological degradation. Until such validation is available, the LPI should be understood as a relative index of co-occurring built-up pressure and vegetation structural change, not as a measure of ecological health.

4.5 Policy implementation limitations

The policy recommendations face implementation barriers including limited municipal capacity, funding uncertainty, land-tenure conflicts, political resistance from land-banking interests, and equity risks if vacant-land taxes are passed on to low-income residents. Future work should include stakeholder analysis, institutional mapping, and cost-benefit assessment before scaling the recommendations.

5.6 Statistical limitations

The OLS model with $N = 4$ has been removed. Reporting $R^2 = 0.61$ from four spatial units is statistically meaningless. The previously mentioned "footnote" does not exist and is removed. Future applications should use ward-level or grid-level data with at least 30-50 units before attempting local regression.

6. CONCLUSION

This study set out to quantify LULC change, sprawl, fragmentation, and spatially variable landscape pressure in Saki between 2013 and 2025. The findings show that built-up area expanded from 4.85 km² (2.6%) in 2013 to 73.60 km² (39.4%) in 2021 and is projected to reach 107.97 km² (57.7%) by 2025 under a business-as-usual scenario. Vegetation declined from 149.6 km² (80.0%) to 56.1 km² (30.0%) over the same period. Sprawl metrics confirm increasingly dispersed and complex growth: Shannon's Entropy rose from 0.32 to 0.82, LSI from 1.15 to 1.95, vegetation edge density from 45.2 to 190.3 m/ha, while mean vegetation patch size fell from 42.3 ha to 9.3 ha. The LPI shows a clear spatial gradient: The Western quadrant consistently had the highest relative pressure (0.78 in 2013 to 1.00 by 2025), followed by the North (0.45 to 0.67), East (0.28 to 0.41), and South (0.18 to 0.30). The study also found no support for the assumed 30% nonlinear fragmentation threshold; instead, fragmentation rates decelerated as built-up cover increased.

7. RECOMMENDATIONS

Based on these findings, the following recommendations are made:

Prioritise the Western trade corridor for containment and mitigation: Because the Western quadrant recorded the highest and persistently rising LPI (0.78-1.00), and this aligns with the cross-border trade route to Benin, planning interventions should focus on this corridor. These should include growth boundaries, riparian setbacks, and green infrastructure to offset vegetation loss.

Monitor the Northern quadrant as a secondary pressure zone. The Northern quadrant showed moderate but increasing LPI (0.45 to 0.67). It should be monitored before pressure reaches Western levels, using the same LPI and landscape-metric workflow.

Treat the Eastern periphery as a hypothesis requiring field verification, not a confirmed finding: The Eastern quadrant had lower LPI (0.28 to 0.41), and the speculative land-banking explanation remains untested due to missing land-tenure, vacancy, and population-coupling data. Field verification should precede any vacant-land tax or conditional permit scheme. If speculation is confirmed, such instruments may be justified; if not, the policy rationale changes.

Withdraw the 30% fragmentation threshold as a regulatory trigger: The data show fragmentation decelerating, not accelerating, as built-up cover increases, and no observation exists between 21% and 39.4% built-up cover. The LPI should therefore be used as a relative monitoring indicator, not as a fixed-threshold regulatory trigger.

Address data and methodological gaps in future work: Because the quadrant units were too few for local regression and the OLS model was removed, future studies should use ward-level or 1 km × 1 km grid units with at least 30–50 units. Future work should also classify actual 2025 imagery, use longer CA-Markov calibration windows, perform cross-sensor calibration checks, and validate LPI against field biodiversity, soil, and hydrological data.

Adopt a phased, capacity-sensitive implementation approach: Given the study's identified constraints—limited municipal capacity, funding uncertainty, land-tenure complexity, weak enforcement, and equity risks, the recommendations should be implemented in phases: short term (publish LPI maps, train staff in open-source GIS, establish biennial Sentinel-2 monitoring), medium term (pilot greenbelts and vacant-land levies only in verified areas, with exemptions for smallholders), and long term (integrate validated LPI indicators into municipal development plans and ecological compensation frameworks).

In summary, the study shows that Saki's sprawl is spatially uneven, with the Western trade corridor under the greatest relative landscape pressure. It also provides an important negative result: the widely assumed 30% fragmentation threshold is not supported. The LPI workflow offers a replicable, low-cost diagnostic for resource-constrained municipal planning, but its outputs should be interpreted as relative structural pressure, not ecological health, until field validation is available. The recommendations above follow directly from these findings and are intended to help planners target the places where the evidence shows pressure is highest, while avoiding unsupported thresholds and unverified assumptions.

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