



Spatial Inequality and Accessibility of Informal Agricultural Markets in Kwara State, Nigeria: GIS-Based Evidence for Equitable Rural Development

Abdulganiyu Yusuf^{1*}, Ayo Babalola², Idrees Oludare Mohammed³

¹⁻². Department of Surveying and Geoinformatics, Faculty of Environmental Sciences, University of Ilorin, Nigeria.

³ Department of Surveying and Geoinformatics, Faculty of Environmental Sciences, University of Abuja, Nigeria.

*yusuf.ag@unilorin.edu.ng | <https://orcid.org/0009-0001-4299-3114>

Abstract

Informal agricultural markets are the primary food exchange nodes for smallholder farm households across rural Nigeria, yet the spatial forces shaping their distribution remain poorly characterised. This study examines the distribution, clustering, and population accessibility of 132 informal agricultural markets across all 16 Local Government Areas (LGAs) of Kwara State, Nigeria (33,643 km²; ~3.89 million residents), using GPS census enumeration and a five-method GIS spatial equity diagnostic. Nearest Neighbour Index analysis confirmed significant clustering ($R = 0.641$, $Z = -7.90$, $p < 0.001$). Kernel Density Estimation and Local Indicators of Spatial Association identified a contiguous south-central hotspot and a persistent northern coldspot. Only 54.83% of the state population resided within 5 km of a market; a 94.37-percentage-point gap separated Ilorin West (97.68%) from Pategi (3.31%). Dual Gini coefficients of 0.418 (service provision) and 0.294 (spatial accessibility) demonstrated that these dimensions are analytically distinct. OLS regression ($R^2 = 0.691$) identified Market Accessibility Ratio as the sole significant predictor of market density ($\beta^* = 0.692$, $p = 0.001$); road network density was not significant ($p = 0.156$). Results are consistent with Myrdalian circular and cumulative causation and inconsistent with Central Place Theory or infrastructure determinism.

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1.0 INTRODUCTION

Informal agricultural markets are the primary point of food exchange for smallholder farm households in Kwara State and across rural Nigeria, yet they are not distributed evenly across the landscape. Where markets are absent or distant, farm households face reduced capacity to commercialize produce, source agricultural inputs, and diversify food consumption, conditions consistently associated with rural vulnerability in sub-Saharan Africa (Cook *et al.*, 2024; Food and Agriculture Organization of the United Nations (FAO, 2024). Informal markets remain the dominant channel for agricultural trade where formal supply chains have not penetrated (Blekking *et al.*, 2022; Cook *et al.*, 2024). In their absence, producers depend on itinerant intermediary buyers who capture margins that market competition would otherwise

pass to the farmer (Musa *et al.*, 2021). These outcomes reflect historical patterns of infrastructure investment and agglomeration that have concentrated opportunity in some localities while leaving others without viable market access, a pattern of territorial divergence operating through self-reinforcing mechanisms across multiple geographic scales (Iammarino *et al.*, 2019).

Geographic scholarship has framed such distributional questions through the lens of spatial justice. Soja (2010) argued that geographic inequality is mutually constitutive with social processes, creating patterns that require active intervention rather than waiting for market self-correction. Applied to agricultural market systems, this framing demands a shift from descriptive mapping to distributional assessment: measuring who is served, at what distance, and how consistently (Benassai-Dalmau *et al.*, 2025; Wigley *et al.*, 2020). Nigerian market geography has generated foundational work on market periodicity, typology, and historical trade routes (Hodder & Ukwu, 1969; Hill, 1966), but rigorous spatial analysis of distributional equity using verified GIS methods remains limited in this context. The present study addresses that gap.

The study evaluates three theoretical frameworks generating competing, testable predictions about where markets form. Central Place Theory (CPT), systematized by Christaller (1966), predicts geometrically regular hierarchical systems: market density should be proportional to population and market spacing should diminish as effective demand grows. Infrastructure determinism proposes that road accessibility governs market viability, such that market density should covary positively with road network density, a prediction grounded in evidence that travel time to service nodes constrains livelihoods in rural Africa (Weiss *et al.*, 2018; Nelson *et al.*, 2019). Agglomeration theory (Krugman, 1991; Fujita *et al.*, 1999) predicts instead that market formation is self-reinforcing: established markets attract complementary traders, generate information economies, and reduce transaction costs in ways that sustain concentration regardless of geometric regularity or road infrastructure, a dynamic confirmed in recent West African food systems evidence (Fastner *et al.*, 2025). These frameworks generate observably different empirical signatures, and testing them in a single analytically controlled setting is a central purpose of this study.

Rigorous testing requires separating two dimensions of market inequality that prior Nigerian literature has conflated. Penchansky and Thomas (1981) drew a precise distinction between availability, the ratio of facilities to population across spatial units, and accessibility, the proportion of population that can realistically reach those facilities, a distinction extended to food access contexts by Sharareh and Wallace (2022). Most Nigerian market studies have measured one dimension or the other; none, to the author's knowledge, has applied dual Gini coefficients to quantify both simultaneously. Applying the Gini separately to service provision ratios and population-weighted accessibility scores reveals whether inequality lies in where markets are located, how accessible they are to resident populations, or both, a finding with direct consequences for the type of policy response required.

2.0 MATERIALS AND METHODS

Kwara State in north-central Nigeria provides an analytically appropriate setting. The state spans 33,643 km² across 16 LGAs whose populations range from approximately 40,000 to over 800,000 residents (National Bureau of Statistics [NBS], 2022). A pronounced gradient runs from commercially active southern lowlands to sparsely populated northern savanna zones whose connections to long-distance commerce have weakened over time (NBS, 2022; Hodder & Ukwu, 1969). Continental evidence confirms that rural West African populations face substantially longer travel times to markets than their urban counterparts (Benassai-Dalmau *et al.*, 2025); Kwara State's north-south gradient is a concentrated expression of that regional pattern. GPS field surveys between May and August 2025 enumerated all 132 informal agricultural markets across all 16 LGAs, recording type, operational frequency, commodity category, and geographic coordinates as shown in Figure 1. Complete enumeration eliminated the spatial bias that probability sampling would introduce when the underlying distribution is non-random.

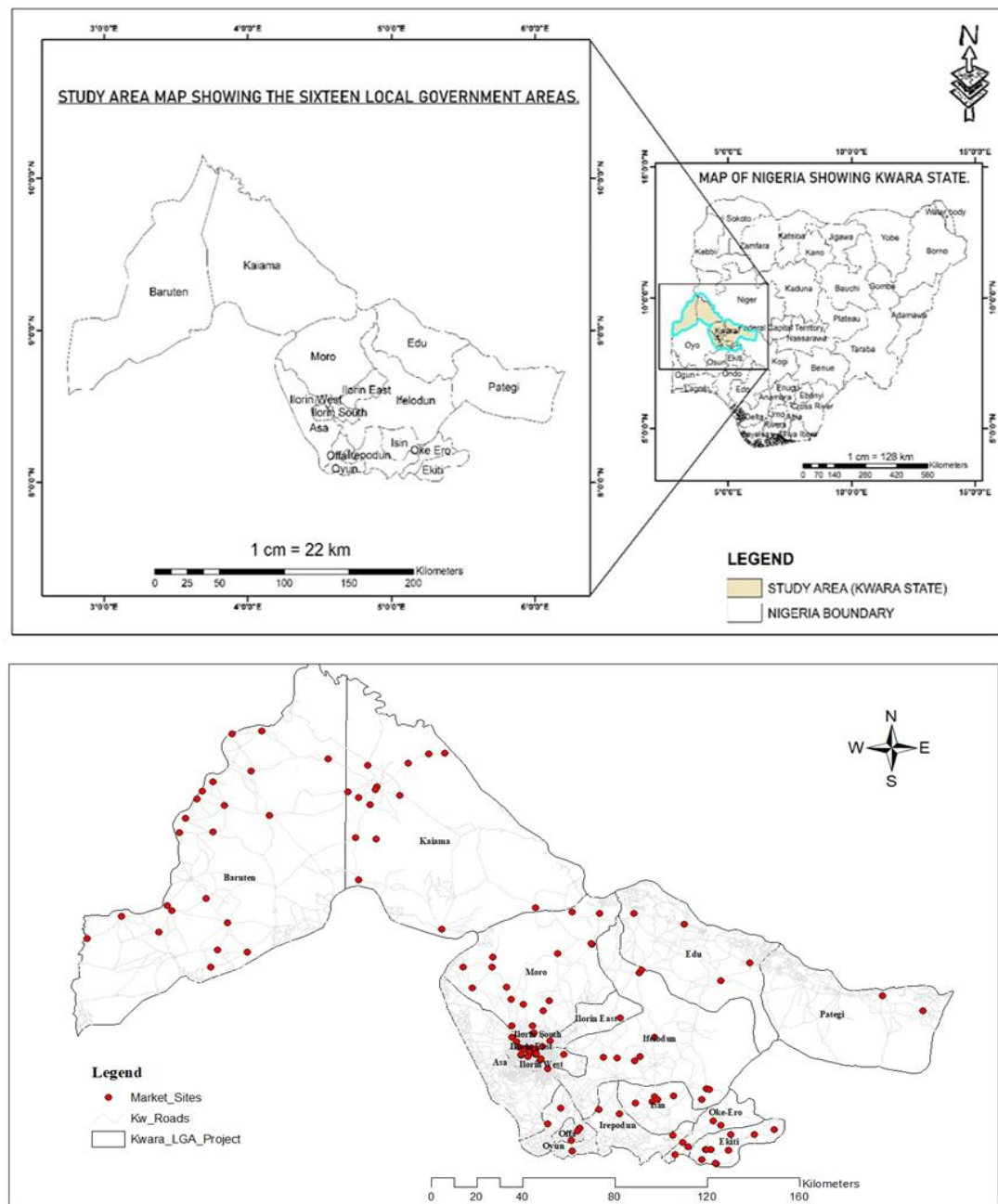


Figure 1. Study area map of Kwara State showing the 16 Local Government Areas and the 132 surveyed informal agricultural markets.
Source: Authors (2025).

This study pursues four objectives: to characterise market distribution and density across Kwara State's 16 LGAs; to identify clustering patterns using a five-method spatial statistical sequence; to quantify accessibility and its distributional inequality; and to determine the explanatory power of population density, road network density, and market accessibility in predicting market density. Three contributions follow: a dual Gini accessibility framework operationalising Penchansky and Thomas's (1981) availability-accessibility distinction; a replicable five-method spatial equity diagnostic applicable across data-constrained sub-Saharan African settings; and, to the author's knowledge, the first GPS-verified distributional equity analysis of informal agricultural markets across all LGAs of Kwara State.

2.2 Study Design and Data Sources

Administrative records of informal agricultural markets in Kwara State are incomplete: small periodic markets in northern LGAs are systematically under-recorded, and spatial bias from an incomplete sampling frame cannot be corrected after data collection. Under these conditions, probability sampling would produce biased estimates whose spatial representativeness could not be verified. Complete enumeration eliminates this problem and was accordingly adopted.

Field data collection followed a three-stage protocol between May and August 2025. In Stage 1, a candidate market list was compiled from LGA agricultural offices, the state Ministry of Agriculture, and prior academic literature. In Stage 2, all candidate sites were verified through systematic field visits using a Garmin Map76 GPS receiver (± 10 m accuracy). Each market was visited on an active market day and a non-market day to confirm operational status and record coordinates. Twelve candidates were excluded after field verification; all 132 confirmed markets were retained. In Stage 3, four variables were recorded per market: type (daily or periodic), operational frequency, commodity category (food staples, livestock, agricultural inputs, or mixed), and GPS coordinates.

Primary survey data were supplemented by four secondary geospatial datasets. Gridded population estimates from WorldPop (2020) at 100-metre resolution provided population denominators; independent validation confirms acceptable sub-national accuracy for the WorldPop product in comparable African settings (Thomson *et al.*, 2022), and LGA-level aggregates correlated with NBS (2022) projections at $r > 0.95$. Road network data from OpenStreetMap (OSM, 2024) were used to compute road density by LGA; OSM coverage is estimated at approximately 83% globally, supporting its use in regional density analysis (Barrington-Leigh & Millard-Ball, 2017). A 30-metre SRTM Digital Elevation Model provided terrain context. Administrative boundaries were obtained from NBS (2022). All datasets were projected to WGS 1984 UTM Zone 31N. Market Density Index (MDI: markets per 100 km²) and Market Accessibility Ratio (MAR: percentage of LGA population residing within a specified distance of at least one market) were computed for each LGA. Clustering statistics were recalculated in GeoDa 1.22 following initial computation in ArcGIS Pro 3.1; results were consistent across both platforms.

2.3 Analytical Methods

The five methods of the spatial equity diagnostic framework were organised as a designed sequence: the NNI established whether market clustering exists at the state scale; KDE located its geographic expression; Global Moran's I, Gi*, and LISA decomposed the autocorrelation structure; accessibility modelling measured the distributional consequences for the resident population; and OLS regression identified the independent drivers of market density variation.

2.3.1 Nearest Neighbour Index.

The NNI tests whether observed inter-market distances depart significantly from complete spatial randomness. Following Clark and Evans (1954), the index R_n is the ratio of the observed mean nearest-neighbour distance (D_o) to the expected distance (D_e):

$$R_n = \frac{D_o}{D_e} ; \quad \text{Where: } D_e = \frac{1}{2\sqrt{n/A}} \quad (1)$$

Here, n is the number of markets, and A is the study area in km². Values below 1.0 indicate clustering; above 1.0 indicate dispersion; 1.0 indicates randomness. Significance was assessed via Z-score at $\alpha = 0.05$, computed using the Average Nearest Neighbor tool in ArcGIS Pro 3.1.

2.3.2 Kernel Density Estimation

KDE generated a continuous, spatially smoothed market density surface by placing a kernel function over each market point and summing contributions across the study area. Bandwidths of 3 km, 5 km, and 8 km

were applied as a robustness test: genuine concentration zones should emerge consistently regardless of bandwidth choice. These correspond approximately to walking, motorcycle, and motorised transport access conditions (Starkey & Hine, 2014; Nelson *et al.*, 2019). The 5-km bandwidth was selected for the primary density surface to match the main accessibility threshold, enabling direct visual comparison between clustering structure and population coverage.

2.3.3 Spatial Autocorrelation

Three complementary statistics were computed in GeoDa 1.22 (Anselin *et al.*, 2022). Global Moran's I measured the overall tendency for similar density values to cluster spatially, with significance assessed using 999 random permutations (Moran, 1950). The Getis-Ord G_i^* statistic identified hotspot and coldspot LGAs (Getis & Ord, 1992). LISA decomposed the global signal into LGA-level cluster types, including High-High, Low-Low, and spatial outlier designations (Anselin, 1995). All statistics used a first-order queen contiguity weights matrix with row standardisation and 999-permutation conditional randomisation. Convergent G_i^* and LISA classifications provided mutual corroboration through distinct statistical logics.

2.3.4 Accessibility Modelling and Dual Gini Coefficients

Penchansky and Thomas (1981) distinguished availability, the supply of facilities relative to need, from accessibility, whether specific populations can reach those facilities. This distinction informed the dual Gini framework: a single inequality measure applied only to market counts would conflate two analytically separate problems. Gini coefficients were computed for MDI across LGAs (service provision inequality) and MAR at 5 km weighted by LGA population (spatial accessibility inequality).

The MAR metric estimates the proportion of residents with geographic access to at least one market within a defined travel threshold:

$$MAR = \left(\frac{P_a}{P_t} \right) \times 100 \quad (2)$$

where P_a is the population within a specified Euclidean buffer of at least one market, and P_t is the total LGA population from WorldPop (2020). Buffers of 3 km, 5 km, and 7.5 km were applied, corresponding to walking, cycling, and motorised travel thresholds (Starkey & Hine, 2014; Weiss *et al.*, 2018). The 5-km threshold was adopted as the primary reporting radius, consistent with FAO (2024) spatial equity benchmarks. Euclidean buffers may overestimate true accessibility by ignoring network routing, terrain, and travel-time variation (Li *et al.*, 2022); because the method was applied uniformly across all LGAs, comparative accessibility patterns remain analytically valid.

2.3.5 Ordinary Least Squares Regression.

OLS regression identified the independent contributions of population density (PD), road network density (RD), and MAR to variation in MDI across the 16 LGAs:

$$MDI_i = \beta_0 + \beta_1 PD_i + \beta_2 RD_i + \beta_3 MAR_i + \varepsilon_i \quad (3)$$

A significant Koenker-Bassett (1982) test indicated heteroskedasticity; robust standard errors were applied throughout. All VIF values remained below 2.5, and Moran's I on OLS residuals confirmed no residual spatial autocorrelation, validating OLS as the appropriate estimator.

3.0 RESULTS AND DISCUSSION

3.1 RESULTS

3.1.1 Market Distribution and Spatial Inequality

The 132 surveyed markets comprised 87 periodic (66%) and 45 daily markets (34%). Table 1 presents LGA-level market counts, MDI values, MAR values at all three thresholds, and access category classifications. The spatial distribution was uneven, with systematic concentration in the state's southern urban core. Ilorin West recorded the highest MDI at 10.74 markets per 100 km², while Asa and Pategi each recorded 0.07, a 153-fold disparity. This degree of within-state inequality substantially exceeds differentials

documented in comparable studies from Ghana (Owusu *et al.*, 2018), Burkina Faso (Ouedraogo & Coulibaly, 2017), and continental-scale assessments (Benassai-Dalmau *et al.*, 2025).

Market provision displayed a spatially pronounced and geographically structured concentration. Four southern LGAs, Ilorin West, Ilorin South, Offa, and Ekiti, contained 27% of all markets while occupying only 1.6% of state territory (sub-regional MDI: 4.56). The five northernmost LGAs, Baruten, Kaiama, Edu, Pategi, and Asa, spanned 43% of the territory yet achieved a combined MDI of only 0.19, a 24-fold density differential. Population-to-market ratios reinforced this pattern: Ekiti registered 10,656 persons per market; Asa recorded 152,246, and Pategi 96,137. Baruten is methodologically instructive: despite the highest absolute market count ($n = 22$), its 9,671 km² extent produced one of the lowest area-normalised densities statewide (MDI = 0.23). Absolute counts without area normalisation misrepresent provision conditions and should not serve as a primary planning metric (Benassai-Dalmau *et al.*, 2025).

Table 1. Market distribution, density, and accessibility by Local Government Area, Kwara State, Nigeria.

LGA	Markets (n)	Area (km ²)	MDI	MAR 3 km (%)	MAR 5 km (%)	MAR 7.5 km (%)	Access Category
Ilorin West	16	149	10.74	76.42	97.68	99.91	Excellent
Ilorin South	8	245	3.26	71.18	93.37	98.44	Excellent
Ekiti	10	476	2.10	68.93	91.86	97.62	Excellent
Offa	2	94	2.12	55.21	88.86	96.11	Good
Oke-Ero	5	436	1.15	44.37	75.48	89.23	Good
Ilorin East	6	451	1.33	41.92	71.63	86.47	Good
Oyun	4	509	0.79	33.18	62.77	79.14	Moderate
Moro	17	3,120	0.55	28.74	54.56	71.33	Moderate
Irepodun	3	701	0.43	24.61	48.83	66.82	Moderate
Isin	5	631	0.79	19.44	43.08	61.19	Moderate
Ifelodun	11	3,440	0.32	17.82	39.00	57.44	Poor
Edu	4	2,536	0.16	14.23	30.61	48.37	Poor
Kaiama	16	6,933	0.23	13.91	30.28	46.83	Poor
Baruten	22	9,671	0.23	11.44	27.79	43.21	Poor
Asa	1	1,336	0.07	8.37	18.16	31.42	Critical
Pategi	2	2,913	0.07	1.82	3.31	9.17	Critical
Total / State	132	33,643	1.20	,	54.83	85.10	—

Note. MDI = Market Density Index (markets per 100 km²). MAR = Market Accessibility Ratio. Population estimates from WorldPop (2020). LGAs are ranked by MAR at the 5-km threshold. Access categories: Excellent ($\geq 90\%$), Good (70–89.9%), Moderate (40–69.9%), Poor (20–39.9%), Critical ($<20\%$). State totals represent aggregate population accessibility, not arithmetic LGA means.

3.1.2 Spatial Clustering Patterns

Kwara State's informal market geography displayed a core-periphery structure, in which a dense south-central concentration contrasted with a sparse northern periphery. NNI analysis confirmed this statistically: the observed mean nearest-neighbour distance was 6.18 km, 36% shorter than the 9.65 km expected under

spatial randomness, producing $R = 0.641$ ($Z = -7.90$, $p < 0.001$). This clustering index is consistent with the West African regional range documented in Ghana (NNI 0.52–0.73; Owusu *et al.*, 2018), Uganda ($R = 0.58$ – 0.68 ; Mukwaya & Bamutaze, 2016), and Burkina Faso (Ouedraogo & Coulibaly, 2017), positioning Kwara State within the clustering range characteristic of West African informal market systems. KDE surfaces at all three bandwidths consistently identified metropolitan Ilorin as the primary concentration (maximum: 8.4 markets per 100 km²), and the northern zone showed persistent low density across all specifications, confirming that the core-periphery contrast was robust to bandwidth choice.

Global Moran's I of 0.431 ($Z = 3.54$, $p = 0.001$) confirmed significant positive spatial autocorrelation: high-density LGAs were adjacent to high-density LGAs, and low-density LGAs to low-density neighbours. G_i^* hotspot analysis identified five LGAs forming a significant south-central hotspot: Ilorin West ($G_i^* = 4.82$, $p < 0.001$), Offa (3.91, $p < 0.001$), Ilorin East (3.24, $p < 0.01$), Ilorin South (2.45, $p < 0.05$), and Irepodun (marginally significant). Four northern LGAs formed a significant coldspot: Kaiama ($G_i^* = -3.67$, $p < 0.001$), Edu (-3.21 , $p < 0.01$), Pategi (-2.98 , $p < 0.01$), and Baruten (-2.33 , $p < 0.05$). LISA independently assigned identical LGAs to High-High and Low-Low categories; agreement between the two methods, which operate on different mathematical foundations, strengthened confidence in the identified boundaries. Taken together, NNI, KDE, Global Moran's I , G_i^* , and LISA converged across five independent methods and three spatial scales on the same finding: a statistically significant south-central concentration surrounded by a vast and underserved northern periphery. Figures 2 and 3 display the KDE surfaces and spatial clustering results.

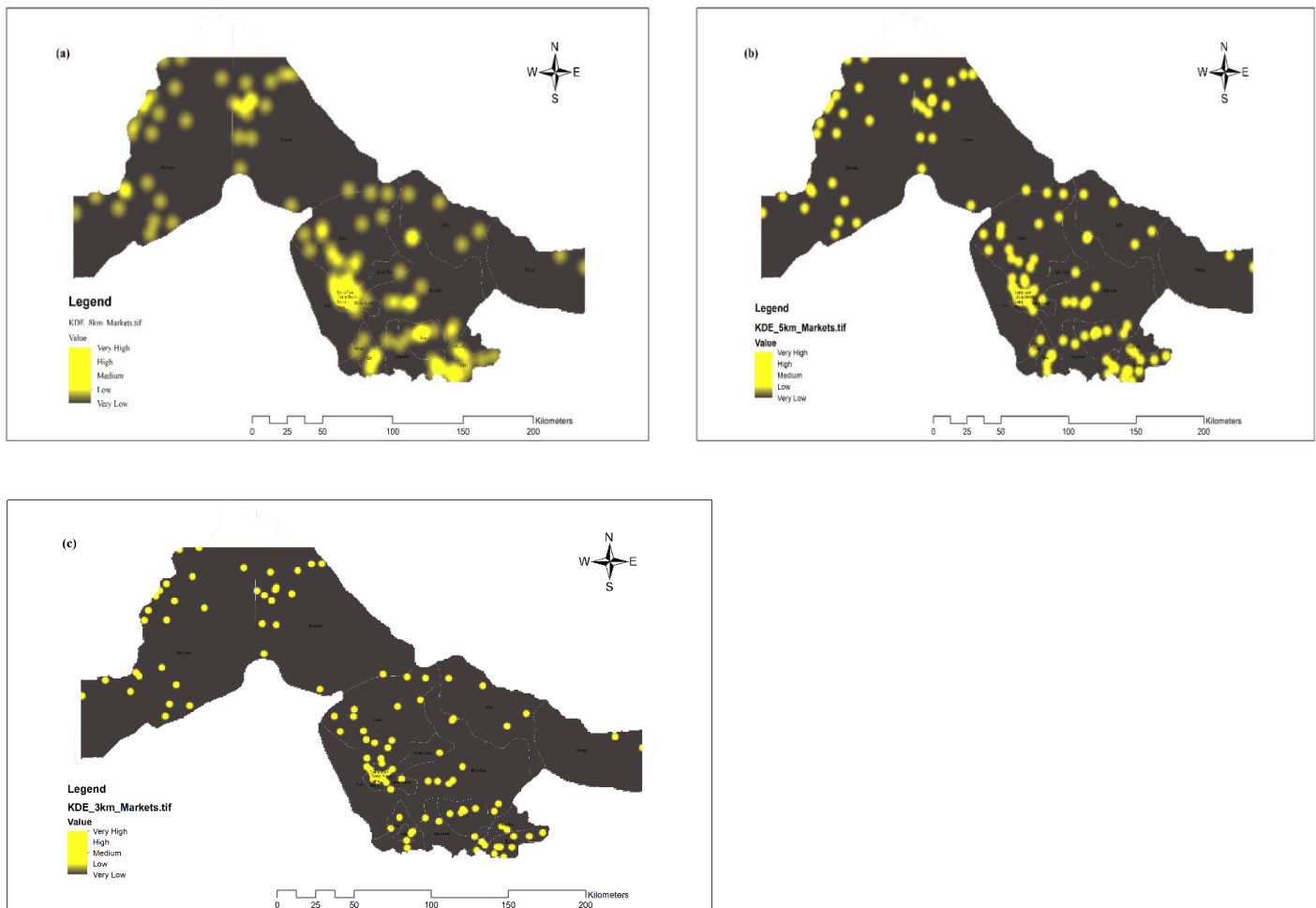


Figure 2. Kernel Density Estimation surfaces at (a) 8-km, (b) 5-km, and (c) 3-km bandwidths showing the metropolitan Ilorin hotspot and northern peripheral coldspot.

Source: Authors (2025).

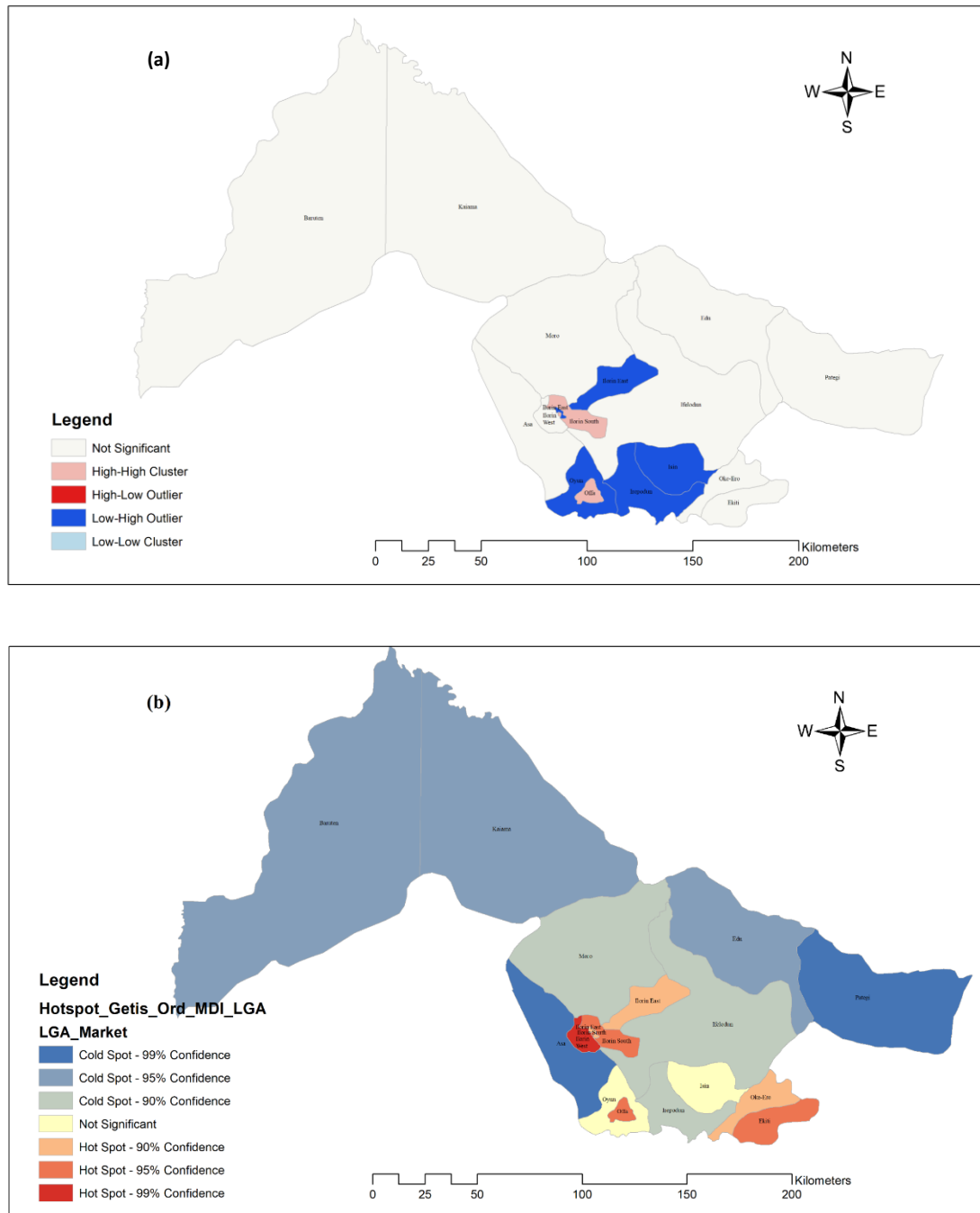


Figure 3. Spatial clustering results: (a) LISA cluster map by Local Government Area and (b) Getis-Ord Gi* hotspot and coldspot zones.
Source: Authors (2025).

3.1.3 Market Accessibility and Spatial Equity

Population accessibility varied across Kwara State. A 94.37-percentage-point gap separated Ilorin West (97.68% within 5 km) from Pategi (3.31%). At the primary 5-km benchmark, 54.83% of residents lived within reach of at least one market, implying approximately 1.75 million people lacked serviceable access. At 3 km, the maximum walking distance for an unloaded adult, coverage fell to 42.1%, leaving roughly 2.52 million without pedestrian-range access. Extending to 7.5 km raised coverage to 85.1%, yet approximately 580,000 residents remained beyond the accessible range. Table 3 summarises state-level coverage.

Table 3. State-level population accessibility to informal agricultural markets at three distance thresholds, Kwara State.

Distance Threshold	Approximate Travel Mode	Population Within Reach (%)	Population Within Reach (approx.)	Population Beyond Reach (approx.)
3 km	Walking, approximately 45 minutes	42.1	1.37 million	2.52 million
5 km	Motorcycle	54.83	2.13 million	1.75 million
7.5 km	Shared motorized transport	85.1	3.31 million	0.58 million

Note. Population estimates from WorldPop (2020); total state population approximately 3.89 million. Travel mode classifications are calibrated to Kwara State rural transport conditions.

LGA-level disaggregation exposed the geographic structure underlying these figures. The 94.37-percentage-point gap exceeded the largest subnational disparities in Benassai-Dalmau *et al.*'s (2025) continental-scale analysis. Approximately 190,000 Pategi residents faced travel distances of 15 to 25 km on seasonally impassable roads, imposing transport costs exceeding the farm-gate value of a typical smallholder produce load for non-motorised households (Musa *et al.*, 2021). Figure 4 maps MAR at 5 km across all 16 LGAs. The geographic pattern was unambiguous: all Excellent and Good access LGAs clustered in the southern fifth of the state, while all Poor and Critical LGAs spanned the northern three-fifths, translating the clustering structure documented in Section 3.2 directly into a population coverage gradient.

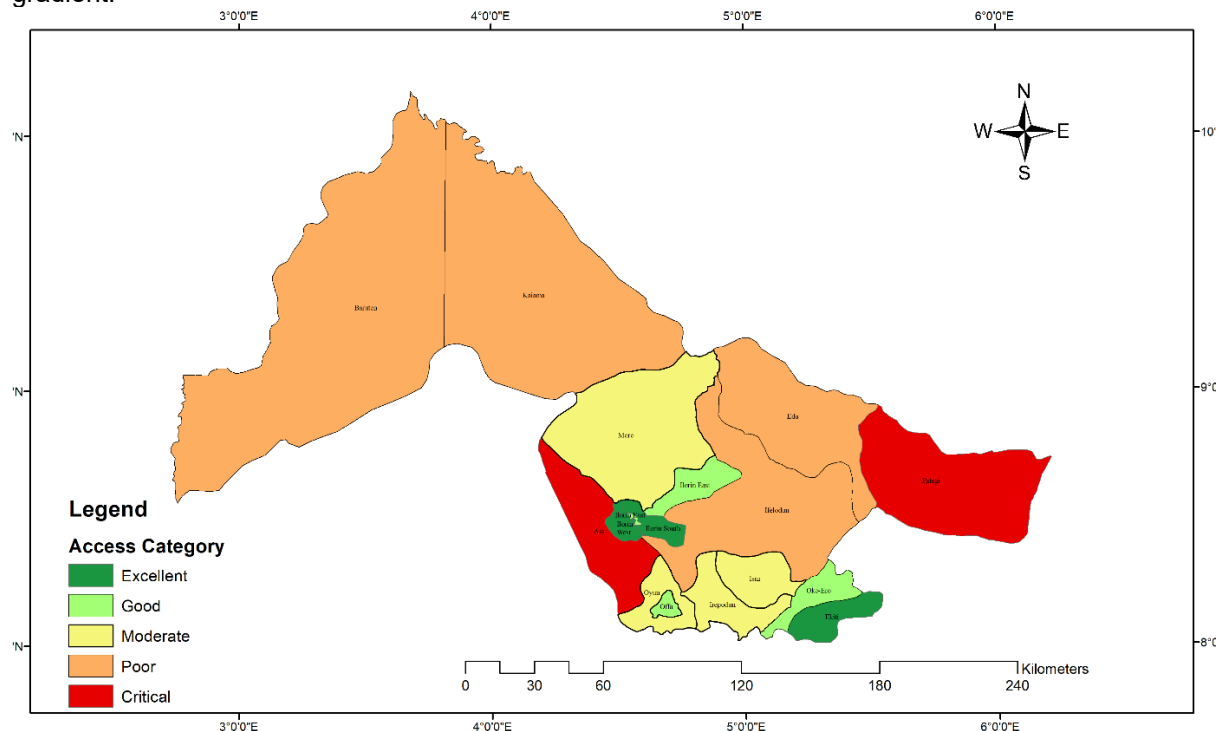


Figure 4. Market Access Ratio at 5 km across Kwara State Local Government Areas. Access categories: Excellent ($\geq 90\%$), Good (70–89.9%), Moderate (40–69.9%), Poor (20–39.9%), Critical ($< 20\%$). Source: Authors (2025).

The Gini coefficient for service provision inequality was 0.418, exceeding the 0.35 threshold that the World Bank (2023) associates with significant income inequality concern and well above values typically reported for geographic service facility distribution in developing-country settings (Kharazmi *et al.*, 2023). The Gini coefficient for spatial accessibility inequality was 0.294. The divergence reflected a partial compensating effect: population concentration in the south meant more people lived near markets than the supply-side Gini alone would suggest. Applying Penchansky and Thomas's (1981) distinction, the two coefficients

revealed a distinct availability deficit in northern LGAs and a broader accessibility deficit across the resident population, each requiring different policy responses.

3.1.4 Determinants of Market Density

OLS regression identified the independent drivers of this distributional pattern. The model explained 69.1% of the variance in MDI ($R^2 = 0.691$, $F(3,12) = 8.93$, $p = 0.002$). All diagnostics confirmed model validity: no problematic multicollinearity (all VIFs below 2.5), acceptable residual normality (Jarque-Bera $p > 0.05$), and no residual spatial autocorrelation (Moran's I $p > 0.05$).

Market Accessibility Ratio at 5 km was the sole significant predictor ($\beta = 0.0247$, $\beta^* = 0.692$, $t = 4.44$, $p = 0.001$): each 10-percentage-point increase in LGA-level accessibility was associated with 0.25 additional markets per 100 km², holding other variables constant. Population density showed a positive but marginal association ($\beta = 0.00207$, $p = 0.097$), consistent with an indirect pathway in which population concentration generates accessibility advantages that attract markets rather than directly determining their locations. Road network density was statistically insignificant ($\beta = -21.18$, $p = 0.156$), and its bivariate correlation with MDI was near-zero ($r = 0.023$), meaning road density accounted for less than 0.1% of market density variation even before controlling for other factors. These results are presented in Table 2.

Table 2. OLS regression results: predictors of Market Density Index across 16 Local Government Areas, Kwara State.

Variable	Coefficient (β)	Robust SE	Robust t	p-value	VIF
Constant	-0.454	0.240	-2.364	0.036*	—
Population Density	0.00207	0.00115	1.801	0.097 ⁺	1.99
Market Accessibility Ratio (MAR 5 km)	0.0247	0.00553	4.443	0.001**	2.27
Road Network Density	-21.18	13.99	-1.514	0.156	1.21

Note. $R^2 = 0.691$; $F(3,12) = 8.93$; $p = 0.002$. ** $p < 0.01$; * $p < 0.05$; [†] $p < 0.10$. Heteroskedasticity-robust standard errors. β^* = standardised coefficient.

Three anomaly cases independently corroborated the road density null result. Moro hosted 17 markets despite minimal road infrastructure. Asa supported only one market despite road density exceeding that of several better-served LGAs. Ilorin West achieved fivefold higher market density than Offa despite a fourteen-fold lower road density per unit area. The regression results and anomaly evidence identified existing spatial accessibility, not road infrastructure or population pressure, as the dominant determinant of market density variation (Luo & Wang, 2003; Geurs & van Wee, 2004; Nelson *et al.*, 2019).

3.2. DISCUSSION

3.2.1 Agglomeration over Central Place Theory and Infrastructure Determinism

Kwara State's informal market geography reveals a pattern of territorial accessibility inequality that is self-reinforcing rather than demand-responsive, a distinction with direct consequences for rural development policy. The evidence converges on a theoretical conclusion: informal agricultural market formation here is governed by the agglomeration dynamics that Krugman (1991) and Fujita *et al.* (1999) formalised, not by the demand-responsive hierarchical logic that CPT predicts or the infrastructure-enabled geographic spread that road investment programmes assume. The hierarchical density surface, one dominant metropolitan core, one secondary hub, and dispersed tertiary nodes across vast low-density interstices, is structurally inconsistent with the evenly graded lattice CPT would predict. The road density null result (Table 2) provides evidence against infrastructure determinism: road provision carries no independent predictive power once agglomeration and population effects are controlled. What the data confirm is that existing market accessibility is the dominant predictor of new market formation: markets concentrate where concentration is already established, not where demand currently exists.

Economic activity in spatial systems tends to concentrate through self-reinforcing mechanisms, transport cost advantages, labour pooling, information spillovers, and scale economies, rather than distributing geometrically in response to demand (Krugman, 1991; Fujita *et al.*, 1999; Cook *et al.*, 2024). The significant MAR coefficient ($\beta^* = 0.692$) reflected this dynamic: LGAs where markets were accessible attracted more markets, while those where access was poor remained poor. Metropolitan Ilorin functioned as the primary attractor; the northern LGAs faced the inverse condition, where sparse markets generated lower expected returns, sustaining the gap.

The theoretical mechanism is Myrdalian circular and cumulative causation, in which initial spatial advantages generate self-reinforcing externalities that perpetuate geographic concentration (Myrdal, 1957; Rodríguez-Pose *et al.*, 2024). Ilorin's historical advantages as the state capital, administrative functions, paved roads, concentrated purchasing power, and large population made it the rational site for early market formation. Once established, this generated mutually reinforcing externalities: information economies through dense trader networks and cost-sharing economies through shared infrastructure and reliable consumer catchments. Initial infrastructure asymmetries in African contexts compound over time into durable spatial inequalities that market entry alone does not dissolve (Jedwab & Moradi, 2016; Jedwab *et al.*, 2017), and the persistence of the Ilorin concentration despite northern road investments is consistent with this path-dependent dynamic.

The failure of both CPT and infrastructure determinism carries implications beyond Kwara State. CPT's competitive-entry assumption breaks down where traditional market authority structures remain intact (Hill, 1966; Hodder & Ukwu, 1969; Cook *et al.*, 2024): market establishment follows social permission structures that do not respond readily to demand-gap signals. Infrastructure determinism fails because road provision reduces travel cost to existing markets but does not automatically generate new ones in underserved locations; improved roads may accelerate trade flows towards the south-central concentration rather than stimulating peripheral formation, consistent with recent West African food system evidence (Fastner *et al.*, 2025). These conclusions converge on the same policy implication: interventions targeting only transport infrastructure will not restructure distributional patterns maintained by agglomeration lock-in.

3.2.2 Spatial Justice, Planning Implications, and Limitations

The implications of this agglomeration dynamic extend beyond theoretical falsification. Soja (2010) argued that geographic inequality is mutually constitutive with social processes, creating patterns that require active intervention rather than waiting for market self-correction. The 94.37-percentage-point accessibility gap between Ilorin West and Pategi is not a transitional state that market entry will dissolve, but a structural feature reproduced through the same agglomeration mechanisms that created it. Addressing it requires supply-side conditions for market establishment in underserved locations alongside improved transport access, consistent with the broader shift in territorial development scholarship towards place-based interventions for left-behind areas (Rodríguez-Pose *et al.*, 2024).

The access category analysis in Table 1 suggests a triage sequence. Asa and Pategi LGAs (Critical category, MAR below 20% at 5 km) require emergency market establishment interventions alongside road improvements. Ifelodun, Baruten, and Edu LGAs (Poor category, MAR 20–39.9%) require supplemental support programmes. Dense Ilorin metropolitan LGAs may instead require regulatory attention to prevent overcrowding and displacement of small operators. The SDG framework provides alignment: SDG 2 (Zero Hunger), SDG 9 (Industry, Innovation and Infrastructure), and SDG 11 (Sustainable Cities and Communities) all address the distributional equity concerns this study quantifies. Nigeria's Rural Access and Agricultural Marketing Programme (RAAMP) and the National Development Plan 2021–2025 both identified rural market infrastructure as a priority; the spatial evidence here provides a basis for sequencing investments by accessibility deficit severity.

The gendered dimension warrants explicit recognition. Women in northern Nigerian rural contexts undertake the majority of household agricultural marketing yet face compounded mobility constraints, restrictions on independent travel, limited motorised transport access, and domestic time burdens (Porter, 2011; Aliyu *et al.*, 2022; de Kanter *et al.*, 2024). The 94-percentage-point gap almost certainly understates their effective disadvantage in Pategi, Kaiama, and Baruten LGAs, where road conditions, social norms, and transport availability multiply the barrier that distance alone imposes. Market placement in Critical and

Poor access LGAs should weigh proximity to women's residential and productive activity clusters as the primary location criterion.

Two methodological limitations bear acknowledgment. Euclidean buffers overestimate true accessibility by ignoring network routing, terrain, and travel-time variation; because applied uniformly across all LGAs, however, relative rankings and the magnitude of inter-LGA gaps remain valid. The $n = 16$ regression sample limits statistical power and causal inference. Both limitations point towards network-based travel time accessibility modelling with larger administrative unit samples. The five-method diagnostic sequence and dual Gini framework are designed for data-constrained settings and are transferable to comparable informal market systems across sub-Saharan Africa (Benassai-Dalmau *et al.*, 2025).

4.0 CONCLUSION

This study examined the spatial distribution, clustering, and accessibility of 132 informal agricultural markets across all 16 LGAs of Kwara State, Nigeria, using GPS census enumeration and a five-method GIS spatial equity diagnostic. Its central finding is that informal market provision in Kwara State constitutes a self-reinforcing accessibility regime: markets are not where demand is, but where markets already were. A 153-fold MDI disparity, a 94.37-percentage-point accessibility gap, statistically significant clustering ($R = 0.641$, $p < 0.001$), and a road density predictor accounting for less than 0.1% of market density variation all point to the same conclusion: agglomeration lock-in, not infrastructure provision, is the governing dynamic. This pattern is more consistent with Myrdalian circular and cumulative causation than with Central Place Theory or infrastructure determinism.

Methodologically, this study makes three contributions. The dual Gini accessibility framework, applied separately to service provision (Gini = 0.418) and spatial accessibility (Gini = 0.294) following Penchansky and Thomas (1981), provides a replicable instrument for distinguishing availability from accessibility inequality in informal market systems. The five-method diagnostic sequence linking NNI, KDE, spatial autocorrelation, accessibility modelling, and OLS regression constitutes a coherent spatial equity framework applicable across data-constrained sub-Saharan African settings. Empirically, the study establishes agglomeration lock-in consistent with Myrdalian cumulative causation as the governing dynamic, shifting the explanatory emphasis from infrastructure provision to market formation incentives and path dependence. Practically, the three-tier spatial targeting framework, with Asa and Pategi as critical-priority zones, translates directly into investment sequencing for RAAMP, the National Development Plan 2021–2025, and state-level market policy.

Four directions for further research follow. Extending the framework to adjacent states would determine whether the agglomeration pattern is Kwara-specific or represents a broader sub-Saharan dynamic. A longitudinal panel design would permit direct measurement of agglomeration and spread effects. Network-based travel time accessibility modelling, incorporating road quality, seasonal variation, and terrain, would replace the Euclidean approximations used here. Household-level survey data on gendered mobility constraints in Critical and Poor access LGAs would ground the gender-responsive design of market placement interventions. Together, these extensions would consolidate the spatial equity diagnostic framework developed here as a transferable analytical instrument for informal market geography research across sub-Saharan African settings.

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Author Contributions

Abdulganiyu Yusuf: Conceptualization, methodology, field data collection, GIS analysis, formal analysis, software, writing (original draft and revision).

Dr. Ayo Babalola: Supervision, methodology review, interpretation, review and editing.

Dr. Idrees Oludare Mohammed: Methodological review, GIS validation, review and editing.

Disclosure Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper. The research was conducted solely for academic and scientific purposes as part of the doctoral research activities of the first author within the Department of Surveying and Geoinformatics.

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