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Analyzing Spatial Hierarchies of Short-Term Rentals using Core–Periphery and Rank-Size Rule: A case of Greater Banjul Area

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ABSTRACT

Short-Term Rental (STR) platforms increasingly reshape housing, tourism, and urban economies, yet their spatial organization in Sub-Saharan African cities remains poorly understood. This study addresses this gap by examining Airbnb market hierarchy in Greater Banjul Area, The Gambia, where tourism growth intersects with uneven urban development. Using 5,657 Airbnb listings collected between September 2024 and July 2025, the study applies an integrated framework combining K-Means clustering, DBSCAN, Global and Local Moran's I, sensitivity testing, and Zipf rank-size modelling. The results identify a significant core–periphery structure, with core listings concentrated along the Kololi–Senegambia–Fajara coastal corridor and peripheral listings dispersed inland. Positive spatial autocorrelation is robust (Moran's $I = 0.480$, $p < 0.001$). Market segmentation is driven mainly by host rating ($\eta^2 = 0.639$), guest satisfaction ($\eta^2 = 0.628$), and capacity, while price has negligible explanatory power ($\eta^2 = 0.009$). Supply follows a near-Zipfian hierarchy ($\alpha = 1.143$), whereas price and stay length remain flatter. The findings support differentiated STR regulation, improve tourism infrastructure planning, and guide resource allocation, housing protection, and investment strategies in African urban economies. Originality lies in linking spatial hierarchy with platform-mediated urban tourism governance and urban management.

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Highlights:	Contribution to the field statement:
- Core–periphery structure confirmed along the Kololi–Senegambia–Fajara coastal corridor. - Spatial autocorrelation is significant (Moran's I = 0.480); supply is near-Zipfian ($\alpha = 1.143$), hierarchy is supply-side. - Segmentation driven by host quality and capacity, not price ($\eta^2 = 0.009$). - Core–periphery theory transfers meaningfully to Sub-Saharan African STR markets. - Coastal concentration signals need for spatially differentiated regulation.	Contributions of this study include an integrated spatial analysis methodology for examining STRs, and empirical evidence that platform-mediated accommodation markets in Sub-Saharan Africa are structured hierarchically along core–periphery lines, suggesting that quality and capacity differentials mediate market hierarchy in tourism-dependent African urban economies, thereby extending core–periphery theory beyond its almost exclusive Global North applications.

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1. Introduction

1.1 Background and Context

Airbnb's rapid expansion since 2008 has transformed urban housing markets by converting residential properties into platform-mediated short-term rentals at scale, creating a structural tension between housing as a dwelling and housing as a commodity (Panahandeh et al. 2025; Sun et al., 2022). This tension is by design, quite built into the approach of many digital platforms. Peer-to-peer access does help get people into becoming hosts, but the way platforms rank and review listings determines not only who gets picked, strengthening local inequalities even before any market forces such as price come into play (Sridhar, 2022; Adamiak, 2022).

The benefits of Airbnb are enormous in scale, but they do carry a set of challenges. Airbnb's implications and governance are discussed in relation to theories about platform supply, which allow for some differentiation within this provision, such as between non-commercial or small-scale providers on the one hand and professionalized hosts on the other (Adamiak, 2022). Nevertheless, whether this can be considered as residential activity is one of the greatest points of contention, especially since many properties have transitioned from being occasional home sharing into a full-time rental business, stretching the boundaries between domestic and commercial land use. This change puts additional pressure on housing, because it reduces the amount of affordable stock with long-term rent and increases prices, as studies in dozens of cities show. (Garcia-López et al., 2020; Hidalgo et al., 2023). This study focuses empirically on Airbnb as the dominant and most data-accessible STR platform; while it may not capture the full spectrum of the STR market, this scope is justified by the limited availability of systematic data on competing platforms such as Vrbo or Booking.com, particularly in Sub-Saharan urban contexts.

The spatial dimension indicates that STRs tend to be concentrated in the heart of cities or in tourist magnets, leading to spatial inequities and urban inequalities. For instance, the proximity to the city center has been strongly associated with Airbnb distributions at a broad cross-city level (Sun et al. 2022). Such spatial concentration drives tourism-driven gentrification, a process that involves inflating real estate prices, changing the neighborhood's social fabric, and displacing vulnerable sub-populations. Airbnb listings consistently aggregate in attractive tourist areas, away from areas with similar hotel distributions, since this analytical unit heightens local housing demand pressure. (Gutiérrez *et al.*, 2017; Urquiaga et al., 2020). The distance to the city center has been strongly correlated with Airbnb distributions at a large inter-city scale (Sun et al., 2022; Gutiérrez *et al.*, 2017). In situations where visitor behaviour has been blamed, this has further aggravated resident dissatisfaction with and resistance to over-tourism as part of wider conflicting tourist-resident relations (Gutiérrez and Domènech, 2020). Besides the economic effects, STR development poses social and cultural strains on destination communities by impacting labor conditions, transport networks, and community structure (Albuquerque et al., 2024). This spatial concentration of pressures, increasing rents and displacement pressures as well as neighbourhood change driven by tourism is not coincidental; but rather the expected outcome of platform-mediated demand aggregation in advantaged locations (Gutiérrez *et al.*, 2017; Garcia-López et al., 2020; Hidalgo et al., 2023), a dynamic that core–periphery theory can explain. Urban planning is defined by commercial performance, with commercial spaces playing a significant role in both economies and landscapes (Roy, U. K., & Mishra, 2024), and short-term rental platforms have increasingly become a defining commercial force within that relationship .

Yet the mechanisms driving these outcomes, agglomeration, locational rent, and platform-reinforced spatial inequality, are not exclusive to Global North cities (Rogerson and Visser, 2011; Christie et al., 2014). We focus on the Greater Banjul Area theoretically because it is a productive case in this sense, as it manifests core–periphery spatial structure. GBA is under the management of tourism revenue concentration, and post-colonial spatial legacies and weak regulatory infrastructure, where the same platform dynamics prevail but without institutional buffers that undermine their impacts elsewhere

(Gössling and Hall, 2019), such that the same platform dynamics are independent of institutional buffers, which temper their effects elsewhere. Thus, situating the GBA in African urban tourism scholarship is not a concession to available data but rather a deliberate theoretical choice.

1.1.2. Theoretical Framing: Core–Periphery and Urban Hierarchy

This study is based on a combined theoretical framework of core–periphery theory and urban hierarchy to explain the spatial distribution of the economic system across different types of urban systems. The economic-geographic general equilibrium model, also known as core–periphery theory, was originally formalized by Paul Krugman (1991), which includes both agglomeration and uneven development (Ohtake, 2025). Earlier work by John Friedmann in 1996 described space as divided into two parts: dominant, economically powerful core regions and weaker, disadvantaged peripheral areas (Klimczuk, 2021). Core areas are characterized by close network connectivity, rapid economic growth, developed transport infrastructure, and a connection center, while peripheral areas have weak integration and dependencies (Shen et al. 2021; Na and Liu 2025). This is how the study framework has been used to justify urban dynamics, the spatial organization of economic activity, and interregional divergence, respectively.

Core–periphery theory explains why spatial inequality emerges and persists, but it does not, on its own, explain how the resulting hierarchy is organized across multiple tiers (Shen et al. 2021; Na and Liu 2025). Urban hierarchy theory addresses this by showing that cities and districts arrange themselves into ranked systems of functional specialization, in which the rank-size distribution of activities follows predictable power-law regularities (Sateriano *et al.*, 2024; Bonaventura et al., 2021). Both frameworks provide useful but different perspectives: core–periphery theory identifies the processes at the heart of uneven development, while urban hierarchy is an empirical framework for measuring and describing its configuration (Ying *et al.*, 2024), which explains why this study employs both.

In contrast, with globalization and digitalization, urban hierarchies are becoming ever more networked, moving beyond simple center-hinterland relationships to complex inter-city linkages (Bonaventura et al., 2021). More recently, this center–hinterland dyadic model has undergone substantial reformulation, as urban hierarchies are increasingly articulated both within and beyond traditional city hinterlands under the influence of globalization and digital transformation (Wen and Jansen, 2025). In addition, hierarchical agglomeration continues to play an important role in economic growth and the formation of spatial development modes (Ying *et al.*, 2024).

One method for empirically identifying hierarchical structures is the rank-size rule, proposed by George Zipf. Dombrowski et al. (2023) used a log-linear form that captured a stable empirical relationship between city size and city rank, one of the most important stylized facts observed in urban systems. Zipf's law is useful for detecting deviations from ideal hierarchically distributed data, but its validity depends heavily on sample selection and scale (Duran 2021; Ioannides and Skouras 2013).

While core–periphery and urban hierarchy frameworks have been extensively applied in urban and regional studies (Krugman 1991; Gabaix, 1999), their joint application to platform-mediated STR markets remains underdeveloped (Tianren & Yang 2025; Xiaoqian et al., 2023), and their application to Sub-Saharan African cities is virtually absent (Rogerson and Visser, 2011). STR growth in Sub-Saharan Africa is an important concern, since if the mechanisms of spatial concentration function differently under conditions of informality, weak governance, and tourism dependence than in STR markets elsewhere in Europe or North America, then findings cannot be easily transferred (Gössling and Hall, 2019). The GBA is therefore not merely an underrepresented case but a theoretically necessary one for testing whether these frameworks travel across urban contexts. In addition, this study addresses that gap by investigating how platform-mediated STR activity reproduces or departs from core–periphery spatial structures in a Sub-Saharan city.

1.1.3. Theoretical Justification for Applying Zipf's Law to STR Markets

While Zipf's Law has been widely validated, its applicability as a functional form for platform-mediated STR markets requires explicit theoretical justification rather than mere assumption. Three mechanisms in the literature provide a theoretical basis for applying Zipf's Law to Airbnb listings. First, the algorithm that reviews and ranks listings for platform visibility is an example of cumulative advantage, where popular listings receive more visibility and bookings, leading to power-law distributions with scale-free concentration (Albert & Barabási, 2002). Second, the fact that listings cluster spatially within cities in a way whose distribution is itself Zipfian, means that STR concentration inside cities is partly drawn from the underlying urban hierarchy. This study situates Zipf's Law as a theoretically grounded extension of city systems to platform markets, superseding them. Third, earlier work noting the power-law of participation and revenues on digital platforms more generally predicts a world in which STR markets are organized hierarchically rather than uniformly (Brynjolfsson et al., 2010). Rank-size plots can appear similar on the surface, whether the underlying distribution is a power law, log-normal, or exponential, yet the structural implications of each differ fundamentally. Accepting Zipf's Law without formal testing risks building hierarchical insights on a flawed distributional assumption. To address this, the fit is evaluated using the maximum-likelihood framework of Clauset et al. (2009), which tests Zipf as a falsifiable hypothesis rather than assuming it based on visual inspection, ensuring that the subsequent empirical and hierarchical analyses rest on explicitly verified distributional foundations.

The core–periphery framework seems particularly suitable for STR markets, because it allows for a coherent causal chain. In Krugman's (1991) core-periphery model, a feedback mechanism in which circular causation gives rise to core zones, agglomeration draws in demand, strengthens infrastructure, and further reinforces concentration. Short-term rental markets appear particularly prone to self-reinforcing feedback loops. Tourists flock to better-connected parts of the city, while hosts in those neighborhoods get reviews fast. Airbnb's algorithm rewards this momentum by ranking popular listings even higher, with the result that they become ever harder to compete with altogether (Albert & Barabási, 2002). Areas excluded from this dynamic lose their chances of catching up: they obtain less visitors and lower prices due to their lack of centrality in agreement with the well-known relationship between accessibility and rental value (Köksal & Yoğurtçu 2024), and remain structurally weak (Hidalgo et al., 2023; Adamiak, 2022). Therefore, the core–periphery distinction employed here is not an externally imposed category but, rather, is a pattern of spatial imbalance that emerges from the theory itself (Storper and Scott, 2016).

1.1.4. Problem Statement and Research Gap

The empirical literature on short-term rental (STR) markets has expanded rapidly, yet it remains fragmented in both scope and methodological integration. Existing literature on Short-term rentals predominantly focuses on three main areas: pricing determinants (Nawaro 2021; Álvarez-herranz and Macedo-ruíz, 2025; Panahandeh et al., 2025; Toader et al., 2022), spatial clustering of STRs (Rabiei-dastjerdi *et al.*, 2021). Other studies examined the broader impacts of STRs on gentrification (Jiao and Bai 2020; Mermet 2021; Grisdale 2021; Adamiak and Marjavaara 2023; Hübscher and Borst 2023; Nalin *et al.*, 2023). Some scholars also looked at housing market issues such as displacement, accessibility, and affordability (He and Jin 2024; Aritenang and Iskandar 2023; Xu and Xu 2021; Hur et al., 2024; Carollo et al. 2024; Bao and Shah 2020; de Arenaza et al., 2022; Zou 2020; Franco and Santos 2021; Zhu and Liu, 2024). Earlier works on pricing generally consider features such as location, amenities, and host characteristics (Jiao and Bai 2020 ; Chica-Olmo et al., 2020; Mermet, 2021; Harten and Boeing 2024), while spatial analyses often rely on a single method, e.g., clustering algorithms to reveal geographic concentrations of listings. Interest in the role of STRs has led a growing number of studies to explore their potential impact on neighborhood change, struggling communities, displacement pressure, and housing affordability. While much work has focused on STR and urban markets globally, it is worth noting that Sub-Saharan African cities remain almost entirely lacking from the STR literature base, despite being one of the regions within which rapid urban tourism economies are developing, with very different housing market dynamics representing a specific geographical limit in current work. Few studies utilize core–periphery classifications that synthesize STR market organization and the empirically derived quantitative indicator of urban hierarchy provided by the Zipf exponent in rank–size domain analysis (Gomez-lievano and Youn, 2012). However, they are seldom integrated into study design in this regard. Moreover, many studies consider a limited number of analytic approaches (e.g. clustering, spatial autocorrelation, or rank–size distributions respectively) in order to summarize and integrate information from the analysis. This thus points to a clear gap in the STR literature concerning multi-method validation frameworks.

1.1.5 Research Objectives and Questions

This study is framed around two interrelated aims that address a critical gap in the literature concerning the spatial organization and hierarchical structure of short-term rental markets in developing urban contexts. First, the study integrates complementary clustering algorithms (K-Means and DBSCAN) with spatial autocorrelation analysis (Global and Local Moran's I) to empirically identify and validate core–periphery structures within the Greater Banjul Area's Airbnb STR market. The synergy of these approaches enhances the reliability of spatial pattern detection, improving the characterization of core, transitional, and peripheral market zones and their associated pricing differentials. Second, by applying Zipf's Law (Rank–Size Rule) to listing supply, nightly price, and stay length, the study tests the degree to which STR activity in the GBA follows a hierarchically organized, power-law distribution, one consistent with urban market concentration theory. These aims are operationalized through two research questions:

RQ1: Does the Greater Banjul Area's Airbnb STR market exhibit a statistically significant core–periphery spatial structure, as evidenced by spatially autocorrelated listing density and systematic price variation across identified clusters?

RQ2: To what extent does the spatial distribution of Airbnb STR activity in the Greater Banjul Area follow a Zipfian rank–size hierarchy, and what does this reveal about the degree and structure of STR market concentration?

1.1.6. Significance and Structure of the Paper

This research provides two main contributions. Methodologically, it outlines a novel and replicable multi-method sequence, including data analysis methods such as K-Means and DBSCAN clustering, global and local Moran's I spatial statistics, Zipf rank-size modeling, and bootstrapping validation. Collectively, these tools constitute a new analytical framework for conducting STR spatial analyses in data-poor urban environments. The study provides empirical evidence that platform-mediated accommodation markets in Sub-Saharan Africa are structured hierarchically in a core-periphery pattern. Notably, this hierarchical structure of tourism hosting in African cities is driven not by differences in land-rent gradients that dominate core–periphery applications in the Global North, but rather by differences in host quality and the number of available properties. The combined contributions expand upon core–periphery and urban hierarchy frameworks to a context previously untested in empirical research, and they challenge the implicit assumption that findings from European and North American STR markets have universal applicability.

The rest of this paper is organized as follows. In Section 2, we describe the study area, the data that comprise it, and the methodological framework. Section 3 presents clustering, statistical validation of the findings, spatial autocorrelation, and the rank-size outcomes. Findings are compared with previous literature and implications for policy, limitations and future research are discussed in Section 4. Section 5 provides the conclusion.

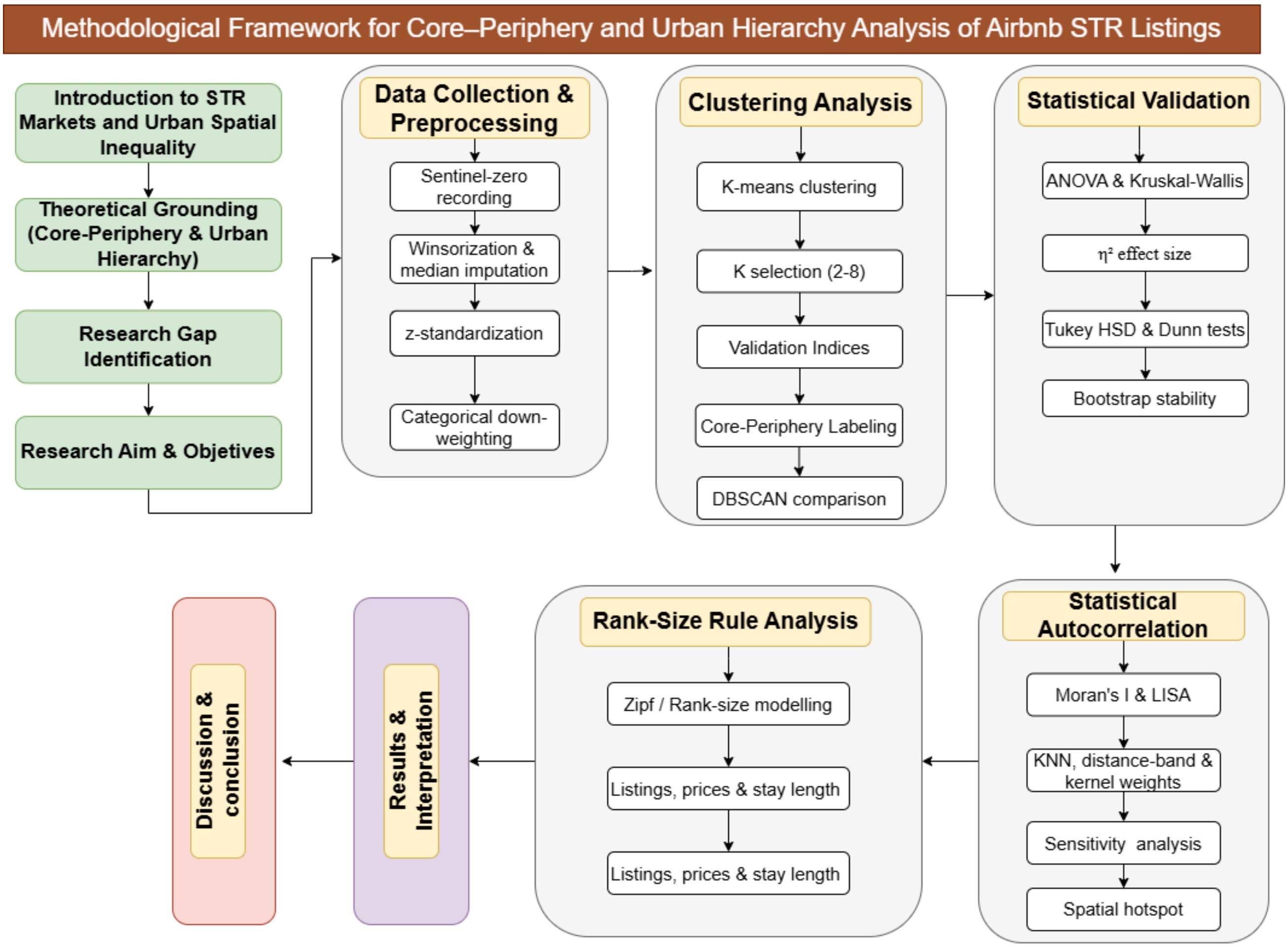

Figure 1. Structure of the Study.

2. Materials and Methods

2.1. Study Area

The study setting is in the Greater Banjul Area (GBA), which is the most urbanized part of The Gambia, located at latitudes 16·81°W–16. 57°W and latitudes 13.24°N–13. 49°N, spanning an area of 475.91 km²(Samb *et al.*, 2026). The GBA has three constituent municipalities (Kanifing, Banjul and Brikama). Gambia's urban population increased from 57.8% in 2013 to 62.6% in 2020, and the GBA has absorbed much of this growth with a consistent trend of significant annual growth rates observed over the past two decades, ranging between 3-7%. According to UNOPS 2020, the study area contained around 1.4 million persons, and a total of 223,764 households with a gross density of 2,858 person/km² (Samb *et al.*, 2026).

2.2. Data and Methodology

2.2.1. Data Preprocessing and feature engineering

We used a dataset from Airbnb.com comprising 5,657 Airbnb listings across the entire study area. The data were not collected over a continuous monthly sequence but through multiple discrete scraping intervals to capture temporal variability in STR activity. Specifically, data were collected on 9 September 2024, November 2024, December 2024, January 2025, February 2025, March 2025, April 2025, May 2025, June 2025, and July 2025. Although no scraping was conducted in October 2024, the September dataset captures October conditions through forward-looking availability and pricing based on standardized check-in and check-out dates. For each scraping instance, consistent stay periods were specified, allowing the dataset to reflect booking conditions beyond the exact scraping date. Temporal coverage, therefore, extends to adjacent months, ensuring continuous representation of STR dynamics despite gaps in scraping frequency. The dataset's structure further justifies the spatio-temporal nature of the analysis: each snapshot includes time-varying attributes such as price, availability, and booking dates, allowing seasonal demand patterns, particularly during the peak tourism period (November–March), to be implicitly represented in the data. Repeated observations of listings across time enable the identification of temporal clustering behavior and spatial evolution, such as the persistence, emergence, or disappearance of clusters. It should be noted, however, that denser coverage during the peak tourism period may underrepresent off-peak listing behavior, and readers should consider this when generalizing findings across the full annual tourism cycle. A raw CSV dataset was cleaned to retain only relevant numeric variables for property capacity, host characteristics, guest satisfaction, pricing, cancellation policies, and room type. We dropped identifier, free-text, and high-cardinality categorical fields to eliminate noise and redundancy. Boolean and object-typed numeric columns were cast to float for consistency.

2.2.2. Preprocessing

2.2.2.1 Handling Missing Ratings (Sentinel-Zero Recoding)

Airbnb marks listings with insufficient ratings as 0, rather than leaving those values blank. If taken at face value, these zeros create a problem. They pull unreviewed listings artificially close together in the feature space used by K-Means, distort cluster means, and obscure a meaningful distinction between a listing that has simply not been reviewed and one that has actually received a poor rating. To prevent this, any value at or below 0.5 in columns identified as rating-like was replaced with a missing value (NaN) before any further processing. In the current dataset, 1,592 host-rating entries (28.1% of that column) were sentinel zeros; the guest-satisfaction column had none. A binary flag called has_rating was added to the feature set so that the question of whether a listing has been reviewed at all could still inform the clustering, even after the problematic zeros were removed.

2.2.2.2. Winsorization and Imputation

Continuous features were winsorized at the 1st and 99th percentiles, preventing extreme outliers from driving our feature importances (Wicker, 2026). These thresholds were calculated from the genuine (non-zero) values, since sentinel-zero removal had already been carried out. Any remaining missing values were filled with the column median. Before imputation, missingness was recorded for every column; only the host-rating average had substantial gaps (28.1%, with a median of 4.77).

2.2.2.3. Standardization and Down-weighting Categorical Variables

All sixteen numeric features were converted to z-scores so that no single variable would dominate the distance calculations simply because of its scale (Wongoutong, 2024). However, the feature set combined six continuous variables with ten binary one-hot indicators, and equal weighting of both groups led to a degenerate outcome: a single cancellation-policy indicator (cancellationPolicies_Moderate) accounted for virtually all of the variance between clusters (eta-squared = 1.000). This was adjusted by multiplying the scaled categorical block by downweighting factor w. (Liu *et al.*, 2024). The parameter w = 0.3 was chosen through grid search upon w ∈ {1.0, 0.5, 0.3, 0.1} that yielded the largest silhouette score (0.311) for a given value of every feature $\eta^2 < 0.95$. This corrected a degenerate outcome under equal weighting, where a single categorical indicator dominated the partition ($\eta^2 = 1.000$) — a known problem when binary one-hot variables outnumber continuous features in Euclidean distance-based clustering (Huang, 1998; Hennig and Liao, 2013).

2.2.3. Clustering

2.2.3.1. K-Means and Choosing the Number of Clusters

This procedure First K-Means to get a (5,657 by 16) normalized feature matrix minimizes the sum of the squares of the Euclidean distance of each listing belonging to the center assigned. Four internal validation measures that strongly correlate to cluster quality (the elbow point on inertia, silhouette width as a primary criteria, Davies-Bouldin index, and Caliński-Harabasz index) were used to calculate the optimal number of clusters K(2-8). The highest silhouette score (0.318) appeared at K = 2, with K = 3 close behind (0.311). K = 2 was adopted because it aligns well with the core-periphery framework motivating this study.

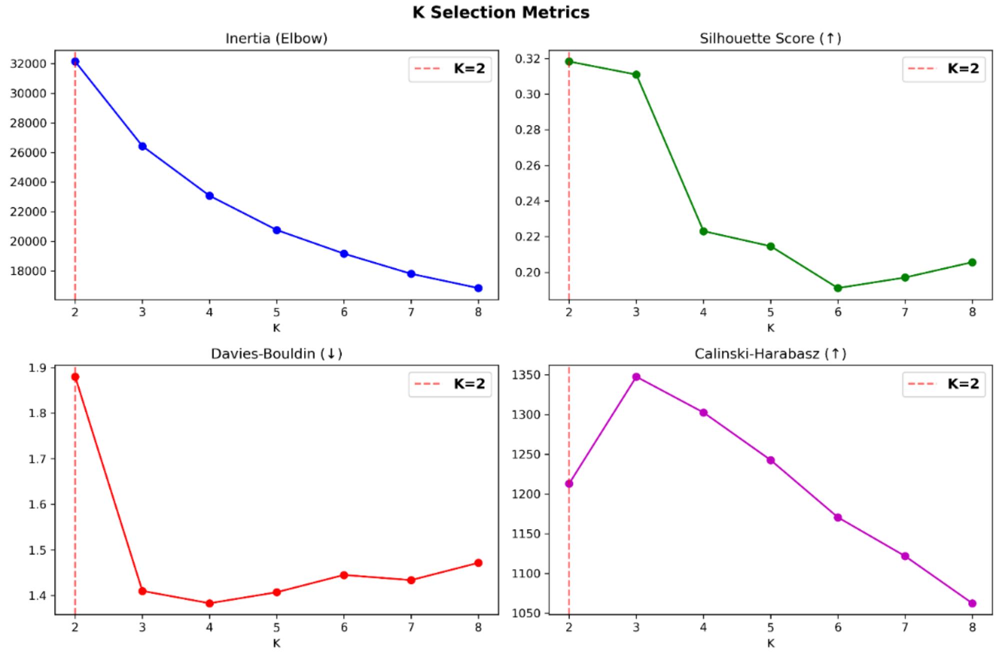

Figure 2. Optimal K Selection Metrics.

2.2.3.2. Labelling Clusters as Core and Periphery

Two clusters were labeled and ranked by average nightly price (USD). The nightly rate serves as a hedonic summary statistic within STR markets that could, implicitly, capture accessibility, land-use intensity, and tourism infrastructure in a single observable revealed by the market (Wang and Nicolau, 2017; Gyódi and Nawaro, 2021). On the other hand, both price and capacity are modeled as listing-level variables, with the nightly price serving as a market-clearing mechanism that combines (or summarizes) a range of factors related to a location's accessibility, agglomeration density, and tourist infrastructure into a single observable proxy (Alonso, 1964). This empirically supported by evidence that Airbnb rates decline with distance from city centers, rise near transport nodes, and correlate with neighborhood agglomeration intensity (Gyódi and Nawaro, 2021; Tong and Gunter, 2022). Consequently, price serves as a spatially embedded signal of locational advantage in the absence of detailed accessibility data, while capacity compounds this image by acting as a proxy to tourism investment scale (Gutiérrez *et al.*, 2017).

The one with the higher average price was labelled Core; the other Periphery. Core zones in core–periphery theory are defined by a mix of agglomeration advantages, accessibility, tourism infrastructure, and locational rent, capitalized into nightly price (Krugman 1991) which is structurally based rather than random quality variation (Wang and Nicolau, 2017). The periphery cluster reflects weaker agglomeration and depressed locational rents (Shen et al. 2021). Since price is not a rating-like variable, all listings were included in this ranking.

2.2.3.3. DBSCAN as a Density-Based Comparator

Alongside K-Means, DBSCAN was run as a second comparison model that does not require the number of clusters to be set beforehand. The k-distance elbow plot determined the neighbourhood radius (eps) which was further tuned by grid search over five values of eps (0.30, 0.50, 0.70, 1.00, and 1.50), and four minimum-sample thresholds (5,10,15 and 20). The configuration that maximized the silhouette (eps = 1.5, min_samples = 10) resulted in nine clusters and identified 330 listings (5.8%) as noise associated with outliers.

2.2.4. Statistical Validation

Between cluster differences on all features were assessed using both a standard one-way ANOVA (F-statistic) and the Kruskal-Wallis non-parametric test, with optional eta-squared as a measure of effect size. For rating-like variables both tests used only the observed (non-sentinel) values to avoid producing results that could be artefacts of imputation rather than true differences. Post-hoc pairwise comparisons on price were performed using Tukey's HSD and Dunn's test with Bonferroni correction. Cluster stability was assessed using 200 non-parametric bootstrap resamples; confidence intervals for each cluster's mean silhouette score are reported at the 95th percentile.

The eta-squared effect size measures the proportion of total variance in a feature that is explained by cluster membership, computed as the ratio of between-cluster to total sum of squares:

$$eta^2 = \Sigma\, n_\mathrm{k}(\mu_\mathrm{k} - \mu)^2 \;/\; \Sigma\,(x_\mathrm{i} - \mu)^2 \quad \textbf{\textit{Eq.1}}$$

where n_k is the size of cluster k, mu_k is its mean, mu is the grand mean, and x_i are individual observations. Values approaching 1 indicate a feature that almost completely drives the partition; the eta-squared guard threshold of 0.95 flags this kind of single-feature dominance.

2.2.5. Spatial Autocorrelation and Weight-Matrix Sensitivity

To assess whether the core-periphery classification exhibits spatial clustering across the study area, we calculated Global Moran's I and Local Indicators of Spatial Association (Anselin, 1995). Data were standardised with row-standardized K-nearest-neighbour weights k = 8 (Kubara and Kopczewska, 2024), and tested using 499 conditional permutations as the baseline specification. Then positive Moran's I suggests that similar listings are located nearby each other. To assess the robustness of Moran's I to spatial weights specification, nine alternative configurations were tested across three families: K-nearest neighbors (k = 4, 8, 12, 20), fixed distance bands (500 m, 1 km, 2 km, projected in EPSG:3857), and adaptive-bandwidth kernel weights. The kernel family included inverse-distance and Gaussian decay functions, both anchored at k = 8 (Bivand and Wong, 2018). Consistent results across all specifications confirmed that the spatial autocorrelation findings are not an artifact of any single weighting scheme (Bivand and Wong, 2018). All matrices were row-standardized; kernel weights were built manually with explicit zero diagonals to ensure consistent behaviour across libpysal versions. For each specification, Global Moran's I, its permutation p-value, z-score, and LISA quadrant counts were recorded. Sign- and significance-consistency were calculated only across specifications that produced a finite value of I.

Table 1: Spatial Weight Matrix Specifications Tested.

Specification	Family	Definition	Mean neighbours	Role
KNN-4	K-nearest	k = 4 nearest neighbours	4.0	Fine-grained local
KNN-8 (baseline)	K-nearest	k = 8 nearest neighbours	8.0	Main analysis
KNN-12	K-nearest	k = 12 nearest neighbours	12.0	Broader neighbourhood
KNN-20	K-nearest	k = 20 nearest neighbours	20.0	Widest KNN span
DistBand-500m	Distance-band	Fixed radius 500 m (binary)	197.4	Local scale
DistBand-1km	Distance-band	Fixed radius 1,000 m (binary)	412.0	Neighbourhood scale
DistBand-2km	Distance-band	Fixed radius 2,000 m (binary)	993.1	District scale
Kernel-IDW-8	Kernel	Inverse-distance, k = 8 anchors	8.0	Smooth distance decay
Kernel-Gauss-8	Kernel	Gaussian, adaptive bandwidth, k = 8 anchors	8.0	Smooth distance decay

Note: All weight matrices were row-standardised. Distance bands were computed on coordinates projected to EPSG:3857; kernel weights were constructed manually with explicit zero diagonal and adaptive bandwidth set to each focal point's k-th nearest-neighbour distance.

2.2.6. Rank–Size Rule

Following Auerbach and Ciccone, (2023) and Gabaix (1999) the hierarchical organisation of the market was examined using the Rank-Size Rule also known as Zipf's Law (Rybski and Ciccone, 2023). Originally applied to city-size distributions, the rule has since been extended to economic and market hierarchies where platform-mediated activity is expected to concentrate unevenly across space (Gabaix 1999; Ioannides and Skouras, 2013). This states that the size of the r-th ranked unit follows a power law of its rank:

$$log\, S_{\mathrm{r}} = log\, C - \alpha \cdot log\, r \quad \boldsymbol{Eq.2}$$

where C is a constant, r is the rank, and alpha is the Zipf exponent estimated by ordinary least squares on the log-log relationship. While $\alpha \approx 1$ implies a scale-invariant size hierarchy, an exponent of $\alpha > 1$ indicates that higher ranked units dominate (primate behavior), while $\alpha < 1$ denotes a flatter more dispersed distribution (Gabaix 1999; Ioannides and Overman, 2003). Given that OLS estimation of Zipf exponents can introduce downward bias in small samples, results are interpreted accordingly (Gabaix and Ibragimov, 2012)

The rule was fitted to three theoretically motivated proxies: (i) listings per spatial grid cell (0.005-degree grid, ~500 m), serving as the primary macro-hierarchy test of supply concentration; (ii) mean price per night, capturing the value hierarchy and how locational rents are monetized across spatial tiers (Xiaoqian *et al.*, 2023). An and (iii) mean stay length, proxying demand intensity, tested as a potential discriminator between tourist-dominated core nodes and peripheral listings. Though as reported in the results, stay length shows no meaningful hierarchical organization across listing ranks ($\alpha = 0.044$), and does not differentiate Core from Periphery in this dataset.

2.2.7. Reproducibility

All analyses were carried out in Python 3.11, drawing on the following libraries: scikit-learn for K-Means and DBSCAN; libpysal and esda for spatial weights and Moran's I; geopandas for spatial data handling; contextually for OpenStreetMap basemaps; statsmodels for statistical testing; and scikit-posthocs for post-hoc comparisons. A fixed random seed of 42 was used throughout to ensure results are fully replicable. The pipeline produces 34 output files, including audit CSVs for sentinel-zero recoding, pre-imputation missingness, the core-periphery ranking procedure, cluster-composition diagnostics, spatial-weights sensitivity checks, and bootstrap stability assessments.

2.2.8. Methodological Limitations

Three limitations are worth noting. In particular, first-distance band weights were calculated in the EPSG:3857 projection as this is sufficient for making local-level comparison within this scale, however larger areas of interest can experience minor geometric distortion and a local UTM would be preferable. Second, Moran's I has laudable properties including being consistent and double standardized; however its absolute magnitude declines with neighborhoods, either larger k or distance band sizes. Therefore, readers using results from several studies to compare/contrast should focus on the underlying weight-matrix specification used in a particular analysis rather than considering I values separately. K-Means, by construction, is a hard partition — each listing belongs to exactly one cluster. While the bootstrap stability analysis and the DBSCAN comparator assist in characterizing, they cannot remove sensitivity of this partition to feature scaling choices and the sample used.

3. Results

3.1. K-Means Core-Periphery Clusters

In the case of K = 2, the K-means clustering separated the 5,657 listings into two clearly defined, divergent market segments. However, their near-zero silhouette score (0.233) suggests that these clusters poorly discriminate between actual observations. In particular, they have substantial overlap, leading this partition to be better defined as a continuum of structured markets than as corresponding classes. Core (C1; n=1741) entries were more valuable and larger, with a mean price per night of $92.77 and a room capacity of 5.22 people (from 2.46 bedrooms). This segment mainly consists of Entire-place listings (91.67%), with only 8.33% for private rooms. The other findings were Guest satisfaction (4.81) and host rating (4.71) below the fringe, while Superhost share is low (8; 50%). The Periphery cluster (C0; n = 3916) includes cheaper, smaller listings (i.e., mean nightly rate: $52.86 and capacity: 2.72 persons across 1.82 bedrooms). Private rooms, comprising 27.91% of the listings, a more than three-fold share as compared with Core, suggest a combined supply in a less organized manner that is supplemented with informal and shared-space provisions. In comparison, Guest satisfaction (4.76) and host rating (4.59) are slightly lower, and the fraction of Superhosts is slightly higher (10.37%).

Table 3: K-Means Cluster Summary for Short-Term Rental Listings (K = 2).

Metric	Core (C1) n = 1,741	Periphery (C0) n = 3,916	Difference (Core − Periphery)
CLUSTER OVERVIEW			
Listings (n)	1,741	3,916	**-2,175**
Has observed rating (%)	69.39%	72.96%	**-3.57%**
PRICING & CAPACITY			
Price per night (USD, mean)	$92.77	$52.86	**$39.91**
Person capacity (mean)	5.2200	2.7200	**2.5000**
Bedrooms (mean)	2.4600	1.8200	**0.6400**
Beds (mean)	2.5700	1.7100	**0.8600**
QUALITY & HOST METRICS (observed only)			
Guest satisfaction (mean)	4.8147	4.7643	**0.0504**
Host rating average (mean)	4.7141	4.5912	**0.1229**

Superhost share (%)	8.50%	10.37%	**-1.87%**
ROOM TYPE MIX			
Entire place — implied (%)	91.67%	72.06%	**19.61%**
Private room (%)	8.33%	27.91%	**-19.58%**
Hotel room (%)	0.00%	0.05%	**-0.05%**
Shared room (%)	0.00%	0.03%	**-0.03%**
CANCELLATION POLICY MIX			
Flexible (%)	61.57%	65.27%	**-3.70%**
Moderate (%)	12.92%	9.63%	**3.29%**
Non-refundable (%)	5.86%	3.88%	**1.98%**
Strict (%)	10.34%	12.31%	**-1.97%**
Super Strict 60 days (%)	0.11%	0.00%	**0.11%**

Note: Rating columns (guest satisfaction, host rating) use observed values only sentinel zeros recoded to NaN before clustering. "Entire place" share is derived as 1 − private room − hotel − shared room. n = 5,657 listings total.

The Core–Periphery partition is driven more by property scale and commercial intensity than service quality given the relatively modest differences in price ($39.91 per night), capacity (2.50 persons) and number of bedrooms (0.64) across segments, whilst the small separation between segments indicates a continuum market rather than hard division or lack of differentiation between segments.

3.2.1. Goodness-of-Fit Tests

As shown in Table 4, ANOVA and Kruskal–Wallis tests confirmed that all features (except for the cancellation policy) differ significantly ($p < 0.001$) between clusters. Two main structural axes are identified via effect size analysis. As such, quality is the key differentiator: higher values of Guest Satisfaction Rating ($\eta^2 = 0.628$) and Host Rating Average ($\eta^2 = 0.639$) correspond to a greater share of between-cluster variance; the stability of these effects indicates that are importantly rooted in service quality differentials as an axis of market segmentation. The second is capacity (y-axis), defined by Number of Bedrooms ($\eta^2 = 0.436$) and Person Capacity ($\eta^2 = 0.205$) as property-scale meaningful distinctions between clusters. Notably, Price per Night has a rather small effect size ($\eta^2 = 0.009$) and implying that partition internal structure is segmented more by differences in quality and capacity than price. These results challenge conventional hedonic interpretations of core–periphery designation. Other specifications — cancellation policy indicators ($\eta^2 = 0.005$–0.007), superhost status ($\eta^2 = 0.028$) and room type ($\eta^2 = 0.019$) also yield $p < 0.001$, but negligible to small effect size so that mere statistical significance mainly results from sample sizes rather than meaningful cluster differentiation based on these variables. Albeit some of these features were kept in the model to ensure completeness, they do not represent core axes for market segmentation.

Table 4: Statistical Comparison Between Core and Periphery Clusters.

Feature	ANOVA F	Kruskal–Wallis H	Effect Size (η^2)	ANOVA p-value	Kruskal p-value
Number of reviews	∞	5326.000	1.0000	<0.001	<0.001
Host rating average	833.182	315.542	0.6385	<0.001	<0.001
Guest satisfaction rating	1121.895	286.800	0.6279	<0.001	<0.001
Number of bedrooms	513.433	2302.341	0.4358	<0.001	<0.001
Person capacity	171.348	1056.794	0.2049	<0.001	<0.001
Superhost status	18.854	146.892	0.0276	<0.001	<0.001
Room type	12.862	101.093	0.0190	<0.001	<0.001
Rating availability	12.129	95.434	0.0179	<0.001	<0.001

Price per night	5.777	62.548	0.0086	<0.001	<0.001
Cancellation policy 1(Flexible)	4.797	38.161	0.0072	<0.001	<0.001
Cancellation policy 2 (Moderate)	4.646	36.968	0.0069	<0.001	<0.001
Cancellation policy 3 (Strict)	3.791	30.203	0.0057	<0.001	<0.001
Cancellation policy 4 (Non-refundable)	1.634	13.062	0.0025	0.110	0.110

Note: η^2 (eta squared) represents effect size; values above 0.14 are considered large, 0.06–0.14 medium, and below 0.06 small. Features with $p < 0.001$ but η^2 below 0.06 — including price per night, all cancellation policy indicators, superhost status, and room type — should be interpreted as statistically significant due to large sample size ($n = 5,657$) rather than substantively meaningful between-cluster differences. The final cancellation policy category was not statistically significant ($p > 0.05$).

As shown in Figure 3, feature distributions are shown across Core (C1) and Periphery clusters (C0). Core median nightly rates (≈$92) are nearly twice as high as the Periphery (≈$45); core assets are larger, more expensive, and can accommodate well over 10 people, versus a tight cluster at about 2 in the Periphery. Bedroom counts are the same. Regarding quality metrics, both clusters cluster close to the 5.0 ceiling for host rating and guest satisfaction. Though the Periphery has a longer lower tail for host rating, indicating greater downside dispersion in service quality among peripheral listings.

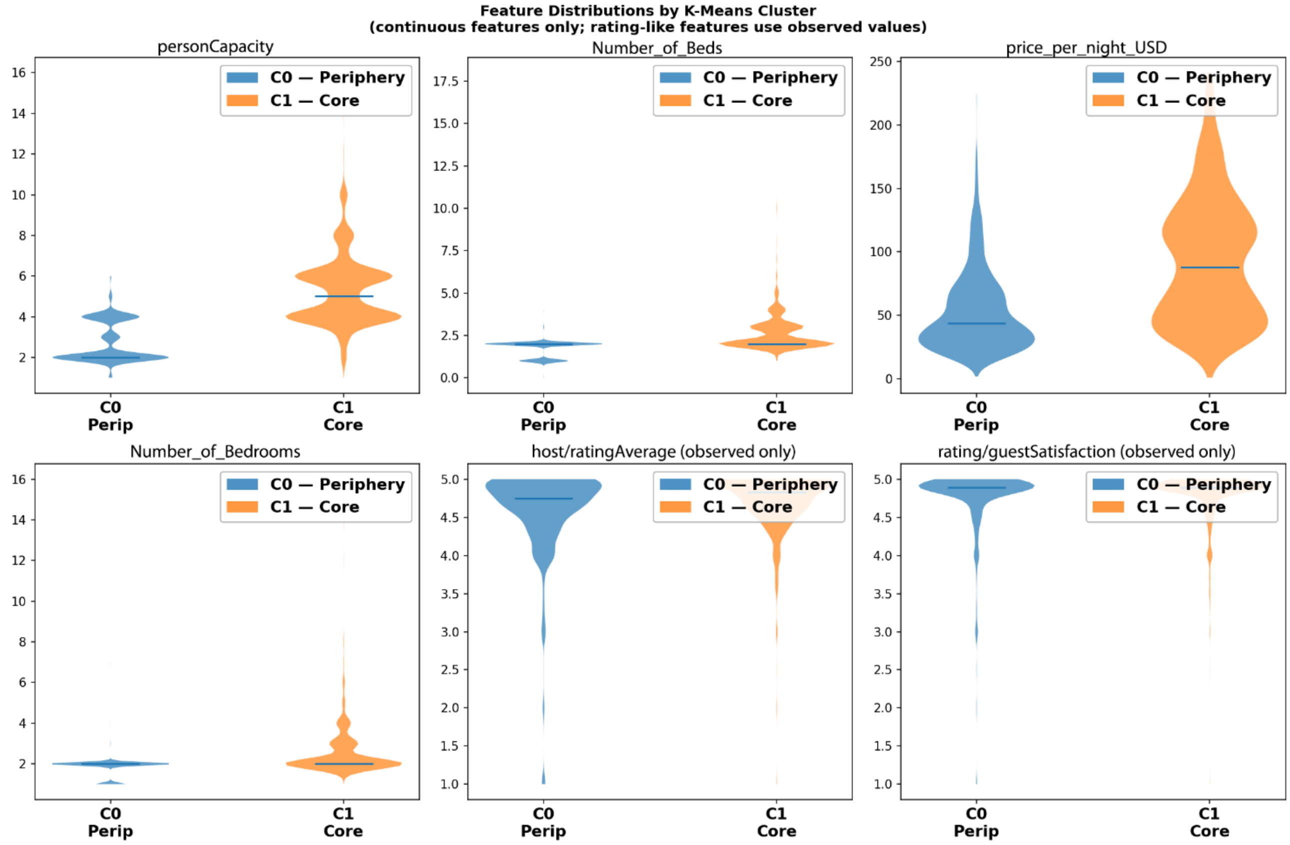

Figure 3. Violin plots for top-6 discriminating features by cluster. Horizontal line = median. Cluster colours: Periphery (C0) = blue, Core (C1) = orange.

3.2.2. Post-hoc Analysis of Price Differences

The post-hoc Tukey's HSD test indicated a statistically significant difference between the Core (Cluster 1) and the Periphery (Cluster 0) for aggregate sales (+40.50 USD, $p < 0.001$, 95% CI [38.34, 42.65]). Core listings tend to register a positive mean, signifying that baseline prices are likely to be greater.

Due to the small effect size for price per night in the cluster solution ($\eta^2 = 0.009$). However, with respect to price per night, this result should be taken with caution, as it may be largely driven by the large sample size (n = 5,657) rather than substantive price discrimination executed by the resulting clustering algorithm. The price level differences are real but do not constitute a primary structural axis of the partition.

3.3. DBSCAN Results and Algorithm Comparison

The k-distance plot shows a steep elbow occurring in the first ~100 points; nearest-neighbor distances drop before tapering off over the remaining listings. This density limit means the GBA STR market contains a central, high-density submarket surrounded by more dispersed, more isolated listings.

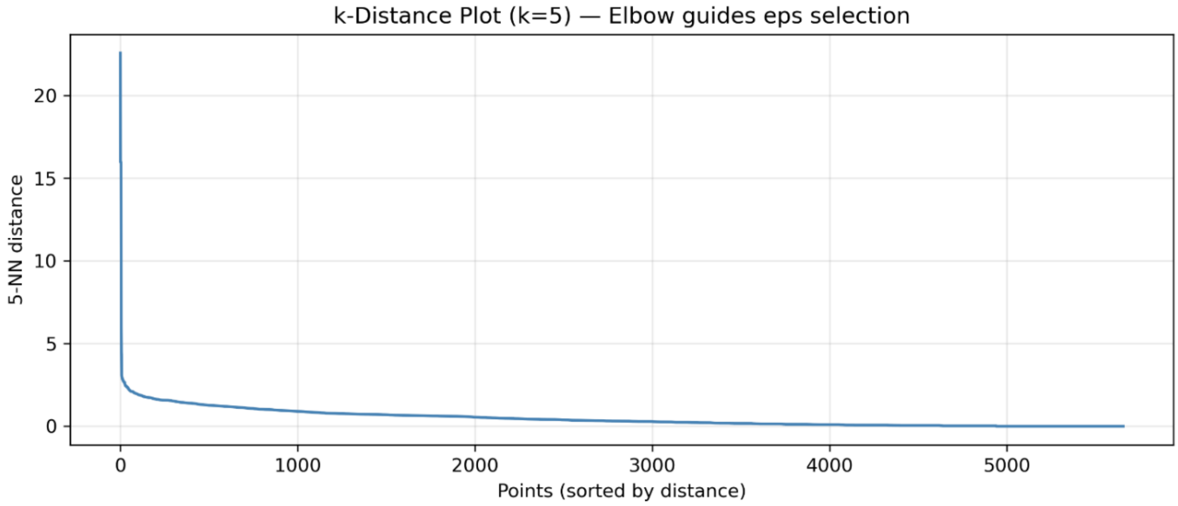

Figure 4. a) k-distance elbow plot (k=5): elbow at 4.73 guides eps selection.

DBSCAN cluster quality is very sensitive to the eps parameter as shown in Figure 5. Very low eps values split the market into many poorly defined partitions with high levels of noise and negative silhouette scores, while too larger eps values merge all listings into a single indistinct group. Positive silhouette scores are obtained for eps=1.5 with min_samples=10, noise decreases to 5.83%, nine clusters are returned which forms the most interpretable partition retrieved. The peak silhouette of 0.145 is still modest and indicates that STR listings do not decompose into crisply delimited natural groups; this solution does, however, provide a layered view of market segments from a compact central element to more diffuse edge regions.

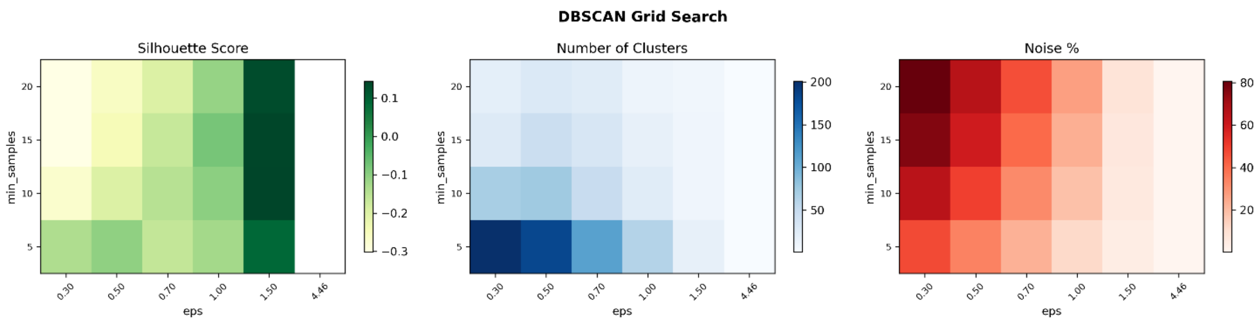

Figure 5. (b) DBSCAN grid search heatmap: silhouette score (left), number of clusters (centre), noise percentage (right).

3.3.1. PCA Projection: K-Means vs DBSCAN Cluster Comparison

Figure 6 presents the K-Means and DBSCAN projections of PCA. The K-Means projection demonstrates that, with respect to capacity and price gradient (i.e., high-value listings group toward one end of the feature space), Core and Periphery separate along PC1. DBSCAN projection suggests that the cluster segments lie on a continuous rather than rational spectrum, as seen in the observation that the DB-Core are at high PC1 Values. In contrast, peripheral and semi-peripheral clusters reside at the lower extremes. The 330 noise points in the outer margins indicate listings whose feature profiles are different enough from dense market segments that they cannot be cleanly assigned to a cluster.

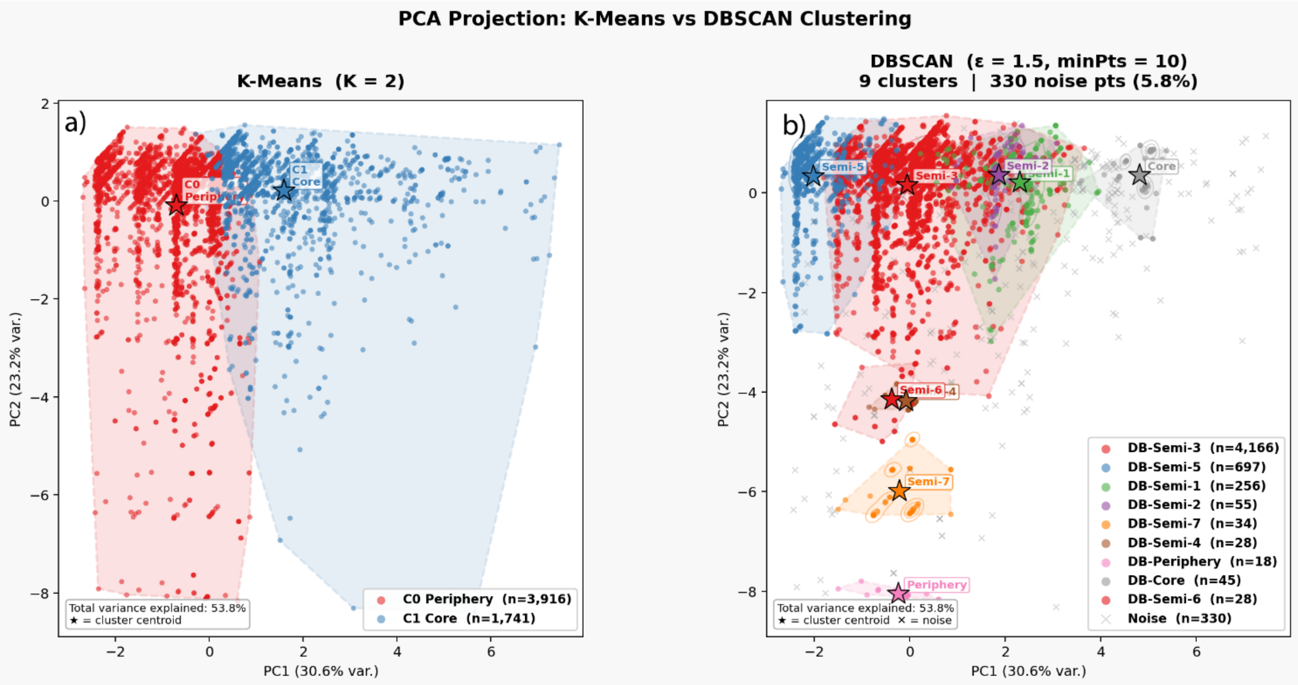

Figure 6. PCA projection (PC1 vs PC2) comparing K-Means clusters (left) and DBSCAN clusters (right). Grey points = noise.

With respect to the three retained internal validation metrics, K-Means consistently produces a better partition than DBSCAN, with Silhouette scores increasing towards 1 (cohesiveness) and Davies–Bouldin and Calinski–Harabasz scores generally decreasing (better-defined and interpretable partitions, respectively). DBSCAN outputs 9 clusters and 5.8% noise, as it is sensitive to density granularity but also compromises full coverage of the listings. K-Means, on the other hand, would place all 5,657 listings into one of two partitions, which provides greater stability and better analytics visibility in the dataset. The preferred solution, therefore, depends on whether complete coverage or density-sensitive detail is the analytical priority.

Table 5: Comparison of K-Means and DBSCAN clustering performance on internal validation metrics.

Algorithm	Clusters	Noise points	Silhouette (↑)	Davies–Bouldin (↓)	Calinski–Harabasz (↑)	Notes
K-Means	2	0	**0.2334**	**1.8219**	**1,215.95**	Predefined K; all points assigned
DBSCAN	9	330	0.1821	1.0804	390.82	Density-based; noise flagged

3.4. Spatial Distribution: K-Means, DBSCAN & LISA

As illustrated in Figure 7, K-Means reveals a distinct spatial core-periphery division, with Core listings clustered along the northwestern coastline and Periphery rankings extending southward into lower-density inland territories. DBSCAN recovers a similar geography to that observed in K-Means Periphery, with listings labeled as noise extending into the outgoing areas. This is also supported by the LISA significance map, which reveals that HH hotspots and the Core zone align spatially, while

LL coldspots overlap with the Periphery area. The general spatial consistency of these three methods does not provide definitive proof for the presence or absence of hierarchical convergence around the hierarchy we identified. Because of DBSCAN's modest silhouette (0.145), this clustering solution adds only independent confirmatory weight, and both LISA and K-Means use the same input variable, which prevents their full independence as validations. Collectively, these approaches point to a spatially coherent market gradient, corroborating core–periphery expectations. Still, the strength of this convergence warrants caution, given the overlapping methodological bases and the relatively weak internal validity scores for the density-based solution.

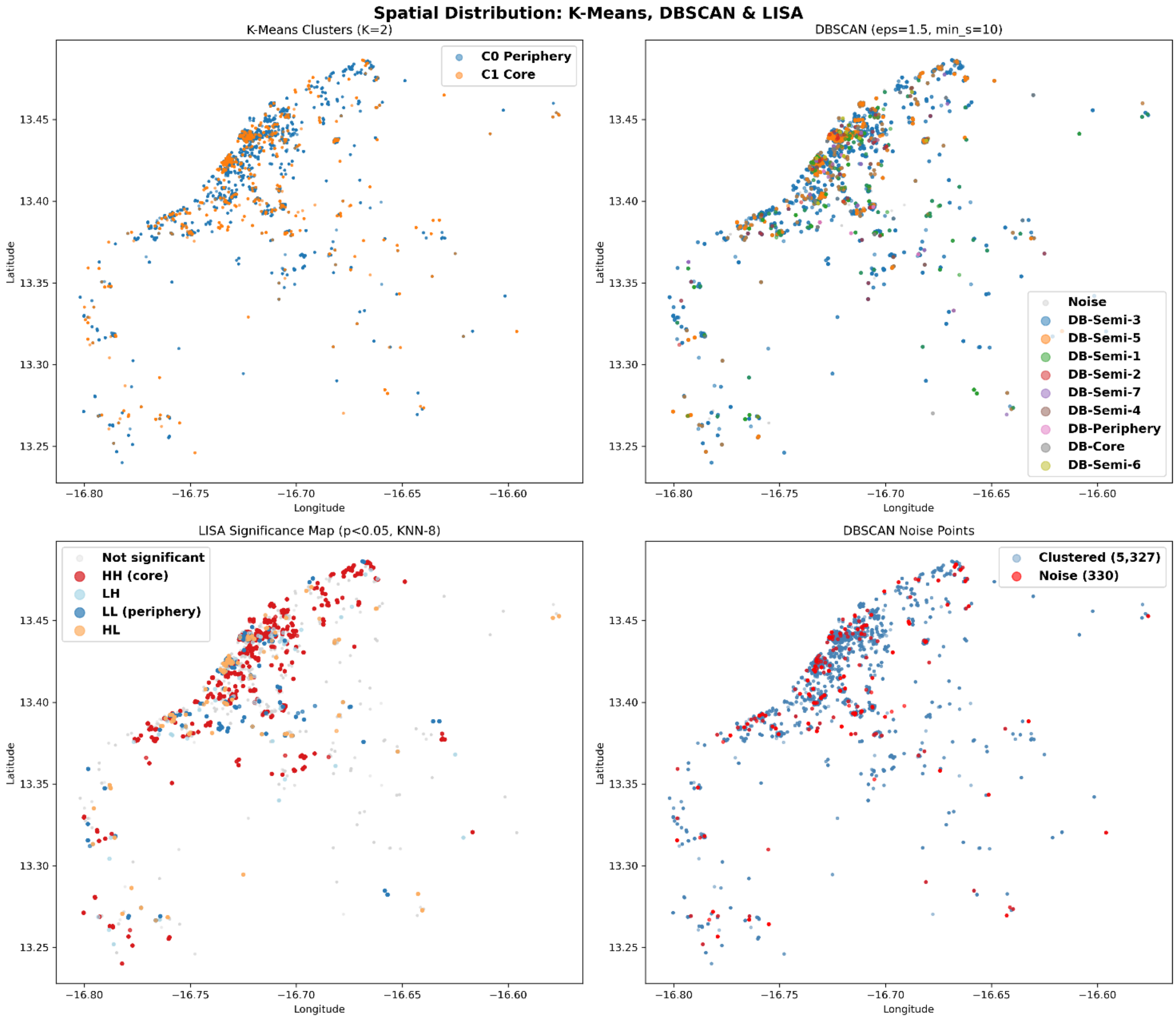

Figure 7. Four-panel spatial distribution: K-Means clusters (top left), DBSCAN (top right), LISA significance map (bottom left), DBSCAN noise (bottom right).

3.4.1. Continuous Core-Periphery Gradient and KDE Density Surface

The core–periphery STR structure across the Greater Banjul Area is mapped in Figure 8. Panel (a) shows a smooth core–periphery gradient where high intensity listings are found within the northwest coastal corridor including Senegambia, Kololi and Fajara with an expansion towards Kanifing and Serrekunda, reflecting this area's established tourism infrastructure. In panel (b), the discrete four-zone classification illustrates that Core (n=1,741) occupies the northwestern coastal belt alongside Far-Periphery (n=3,916), which disperses into southern and interior zones. The suggested spatial agreement of K-Means Core assignments, DBSCAN DB-Core designations and LISA HH hotspots

(Figure 5) in this corridor is a trend and not a definitive cross-method consistency. Overlap is moderate to low across methods, and the confirmatory weight of a DBSCAN when internal validity scores are modest low.

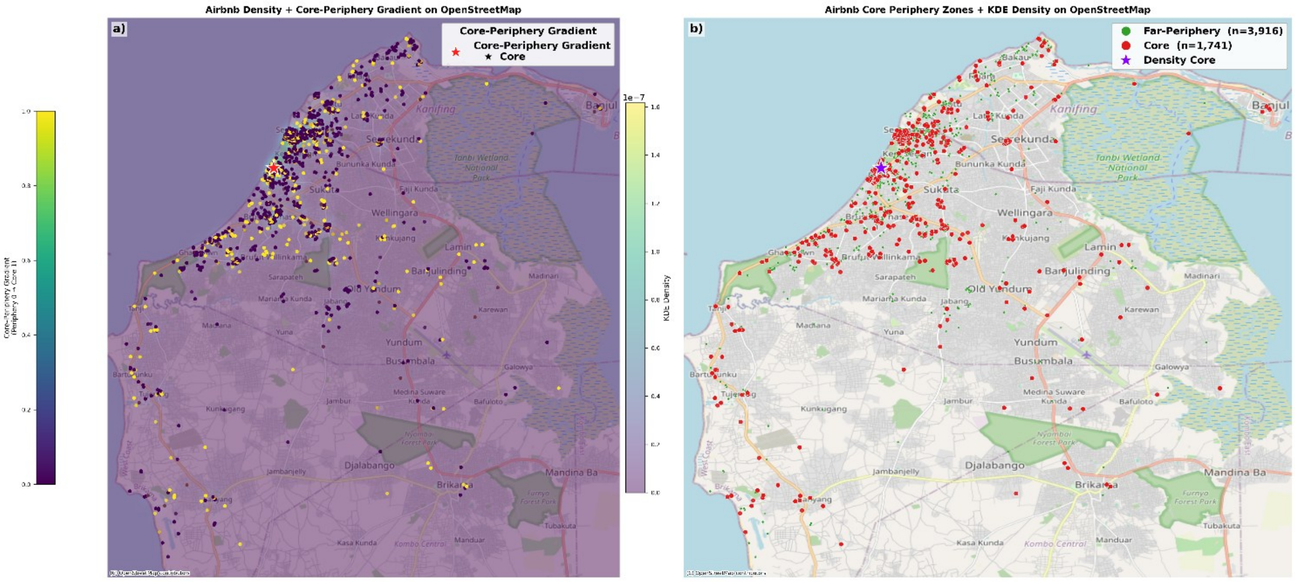

Figure 8. Dual-panel OSM visualisation of Airbnb STR listings across the Greater Banjul Area, The Gambia. (a) Continuous core–periphery gradient (viridis colormap: purple = periphery, yellow = core) overlaid on a KDE density surface; red star (★) marks the density core centroid. (b) Discrete two-zone classification: Core (red, n=1,741) and Far-Periphery (green, n=3,916), with the density core centroid marked by a purple star (★). Basemap: OpenStreetMap contributors.

3.5. Spatial Autocorrelation Robustness

Global Moran's I confirms significant positive spatial autocorrelation (I=0.480, p<0.001) in the GBA STR market, indicating non-random spatial distribution of listing quality and activity – broadly consistent with core–periphery expectations. This correspondence is also confirmed in the Moran scatter plot (Figure 9), where HH concentrations exhibit a spatially coherent core of high-ranking suppliers, succeeded by similar-performing neighbors, whilst LL groupings define a spatially coherent periphery of low-activity zones. Concentric semi-core transitional bands (HL and LH) outliers indicate that core-periphery separation is a gradient rather than a discrete spatial separation, as different areas of the GBA where platforms have penetrated unevenly.

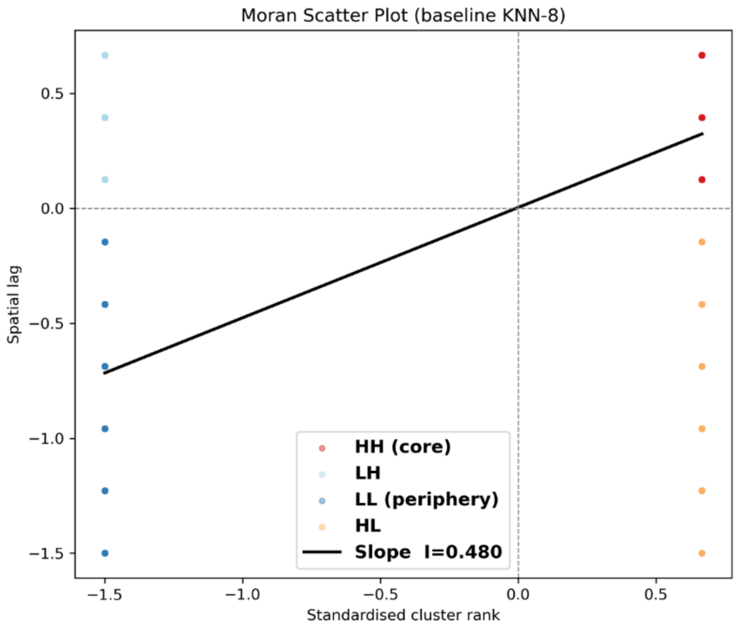

Figure 9. Moran scatter plot: standardized cluster rank vs spatial lag, LISA quadrant colors (HH=red, LH=blue-light, LL=blue, and HL=yellow).

3.5.1. Spatial Weights Sensitivity Analysis: Moran's I Across Nine Weight Specifications

The results of Figure 10 depict the spatial weights sensitivity diagnostic using nine alternative weight matrix specifications. The values of Global Moran's I for cp_rank range from 0.037 to 0.642 across specifications; the magnitude decreases as neighborhood definitions widen — KNN-4 provides the highest I, while distance-band (500m–2km) specifications produce lower values reflecting their fixed-radii constraints. Importantly, we find that all nine specifications produce statistically significant positive autocorrelation ($p<0.05$), and the predominance of LL clusters across specifications shows that low-activity zones are a spatially coherent estate feature of the GBA STR market. In contrast, core concentrations remain stable but geographically restricted to higher-order zones. Sensitivity in direction (cp_rank) appears not to be applicable for interpreting magnitude; thus, the coefficient of variation of 0.69 and 95% CI [0.30] warrants caution in interpreting magnitude estimates, while the directional conclusion that positive spatial clustering is a consistently significant characteristic across all specifications remains.

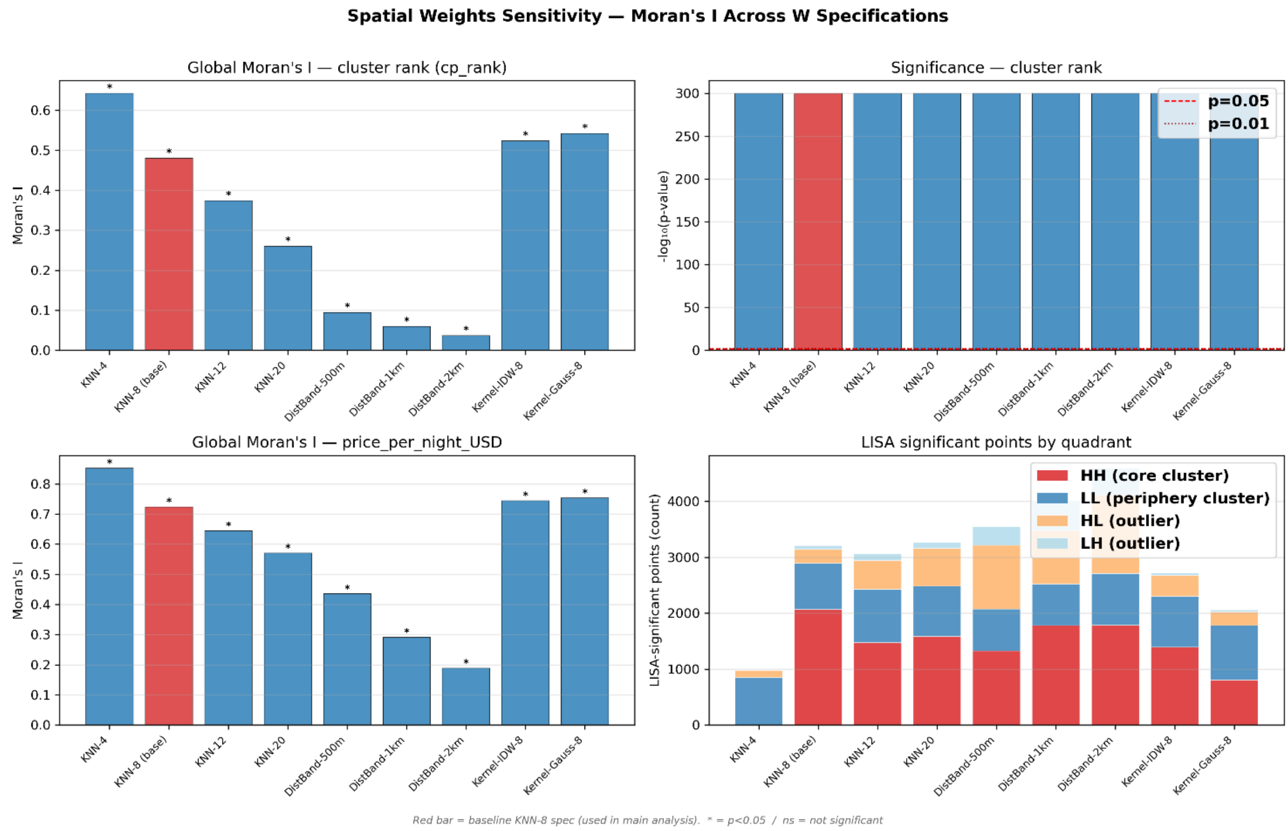

Figure 10. Spatial Weights Matrix Sensitivity Analysis — Global Moran's I and LISA Quadrant Counts Across Nine Weight Specifications.

Table 6: Sensitivity analysis of clustering performance under different feature-weighting schemes.

Weight	Silhouette	Top Feature	Top η^2	No. of Features with $\eta^2 > 0.5$	Dominated
1.0	0.2301	cancellationPolicies_Moderate	1.0000	2	True
0.5	0.2191	rating/guest Satisfaction	0.5827	1	False
0.3	0.3110	rating/guest Satisfaction	0.6057	2	False
0.1	0.3468	rating/guest Satisfaction	0.6036	2	False

As per the sensitivity sweep, at full weight (1.0), there was a 1-D cluster solution on a single categorical feature (cancellationPolicies_Moderate, η^2=1.000), indicating that our partition is trivially separating on one binary variable rather than anything resembling meaningful multi-feature structure. By reducing the weight to 0.5, this avoids domination, but the silhouette performance remains poor (0.219). Improvements in silhouette scores (specifically 0.311 and 0.347) are recognized at weights of 0.3 and 0.1; guest satisfaction is the leading discriminating aspect across a reasonable impact size (η^2≈0.60). As evidenced from 0.3 to 0.1, the marginal shape gain at higher weights is near zero, verifying that weight 0.3 provides a sufficient partition that is stable and informative.

3.6. Rank-Size Rule and Urban Hierarchy

As seen in Figure 11, the rank-size distributions for price and stay length follow distinctly different patterns. The nightly price follows a sub-Zipfian power law (α = 0.571), indicative of a moderately compressed relative pricing hierarchy, where high-end listings may still attract higher premiums, but without the extreme concentration as predicted for pure Zipfian structure. Stay length, alternatively, showed virtually no rank-size hierarchy (α = 0.044) and hovered tightly around 5–7 nights irrespective of listing rank. This difference suggests that price (not booking duration) is the main way in which STR market hierarchy manifests in the GBA.

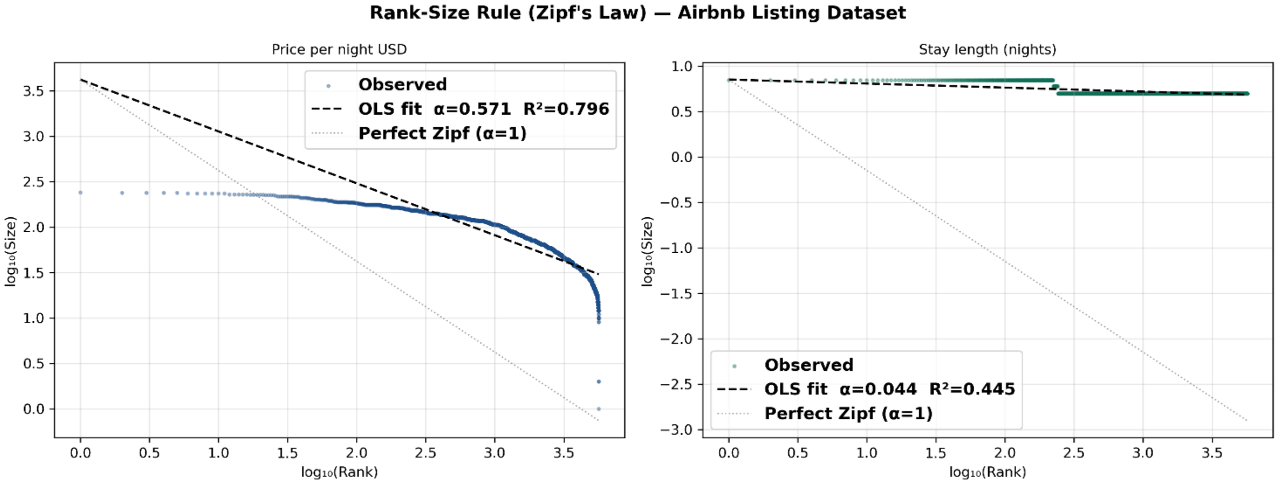

Figure 11. Rank-Size Rule log-log plots. (a) Price per night USD and (b) stay length at listing level with OLS fit and perfect Zipf (alpha=1) reference line.

At the per-cluster level illustrated in Figure 12, both clusters yield near-identical Zipf exponents: Periphery (α=0.517, R^2=0.814) and Core (α=0.506, R^2=0.682). The slopes are both significantly lower than the ideal Zipf (α=1), indicating moderate internal hierarchy compression at each level. The fitted lines are vertically displaced, with Core always above across all points, indicating differences in absolute price levels rather than the nature of the hierarchy. The exponents in such sites are almost identical, indicating that price hierarchy operates within each spatial tier but not across them. Core and Periphery listings are distinguishable by absolute price levels rather than by contrasts in intra-tier distribution. In particular, this implies that the Core–Periphery divide revealed by K-Means reflects topological variations in the price per square meter rather than an unequal concentration of premium listings within an area.

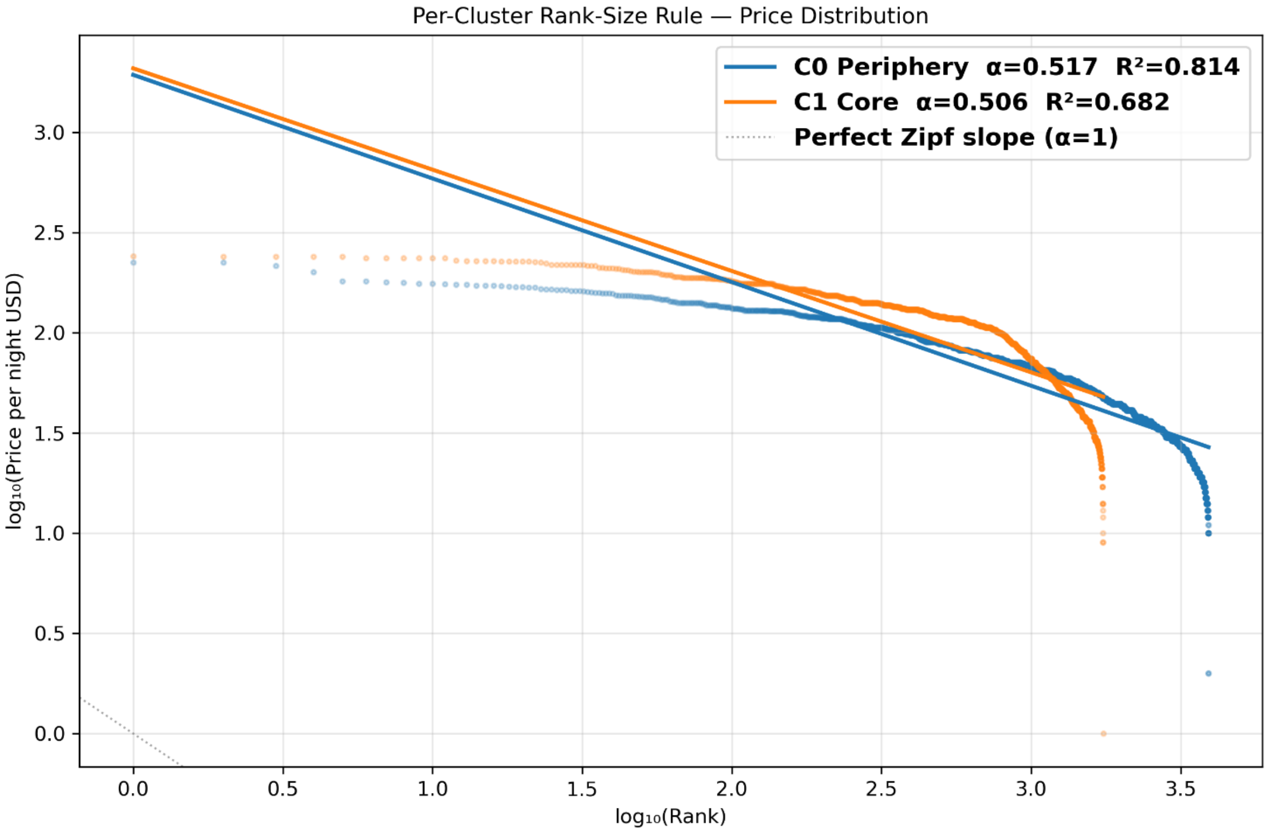

Figure 12. Per-cluster rank-size comparison: all three clusters overlaid, each with fitted slope and R^2.

In Figure 12, we present three separated hierarchical regimes through the STR market dimensions. Spatial listing supply ($\alpha = 1.144$) shows the steepest concentration, consistent with the Zipf benchmark, in which only a small number of grid cells attract a disproportionate share of listings in the GBA. Cross-tabulating the first high-density grid cells (top quartile by listing count) on the y-axis and the K-Means partition of each cell in the x-axis confirms that most of these supply-concentrated cells are located in the Core zone, supporting our conclusion as a Core-side Zipfian phenomenon over the market-wide Zipfian pattern. Nightly prices adhere to a sub-Zipfian shape ($\alpha = 0.571$) with exponents that are nearly identical across the Core ($\alpha = 0.506$) and Periphery ($\alpha = 0.517$) segments, suggesting that price concentration follows a similar, relatively flat distributional logic within each market tier. Stay length records the lowest exponent ($\alpha = 0.044$), indicating an almost uniform distribution in which booking duration varies little across listing ranks, implying that guests adjust price expectations across market tiers but not the length of their stays. The flat distribution means stay length provides no basis for distinguishing Core from Periphery listings, and is therefore treated as a null finding with respect to the spatial classification.

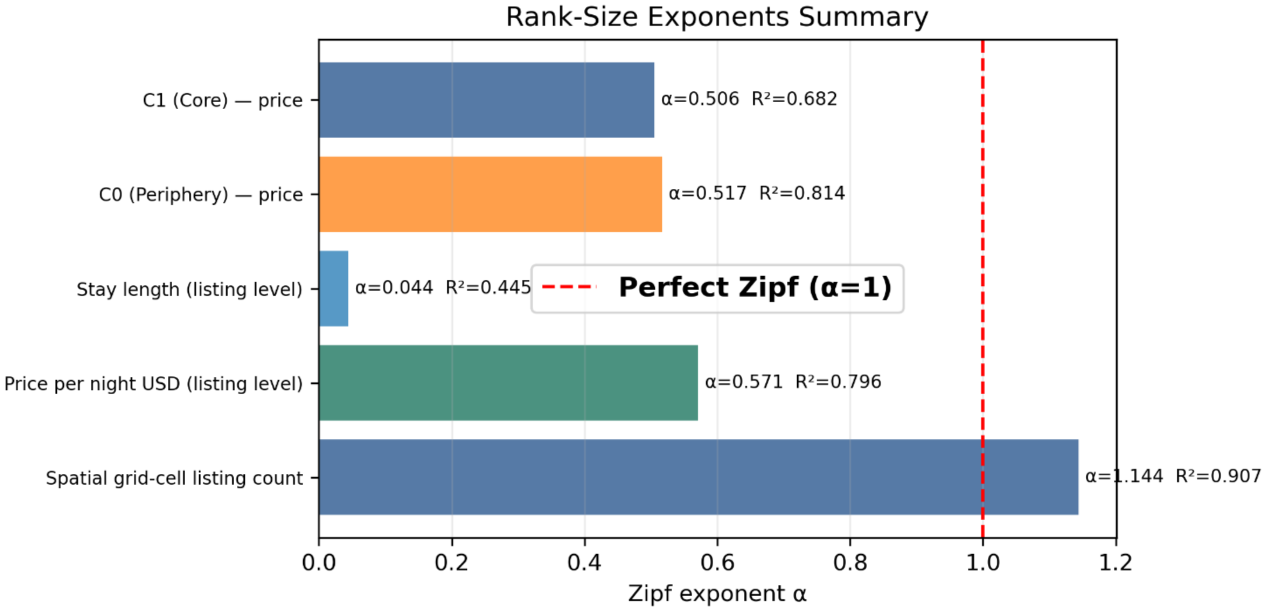

Figure 13. Zipf alpha exponents summary with 95% CI error bars. Red dashed line = perfect Zipf (alpha=1).

3.6.1. Rank-Size Rule Price Zones

In panel a) of Figure 14, we provide an OpenStreetMap basemap on which the listings are plotted. In the same way, we present what is shown in panel (b) also using an Esri WorldImagery satellite basemap. Q1 Core (red, n = 1395) shows an apparent concentration along the northwestern coastal strip in accordance with geographic primacy observed in our cluster-based analyses along the Kololi–Senegambia–Fajara corridor. Here, zone Q1 represents the spatial co-location of peak price and peak listing density, with the density core centroid (purple star) lying within it. Q2 Near-Core (orange, n = 1,362) fully encloses this Coastal concentration in a transition zone; Q3 Mid-Periphery (yellow, n = 1,477) and Q4 Far-Periphery (green, n = 1,423), in turn, are gradually more interior to Yundum, Brusubi, Brikama, and Jambanjelly. The Q1–Q4 quartile zones are a price-ranked spatial classification and are distinct from, though broadly consistent with, the binary K-Means partition. Q1 and Q2 together (n = 2,757) approximate the geographic footprint of the K-Means Core zone (n = 1,741), though the quartile boundary is drawn on price rank alone, whereas K-Means incorporates the full 16-feature profile. It implies that the overlap is only partial. Also, not all K-Means Core listings are landing in Q1, and in between, both clusters' listings spill into Q2. These two classifications should not be thought of as equivalent representations of the same spatial order, but rather as a set of commands to each other.

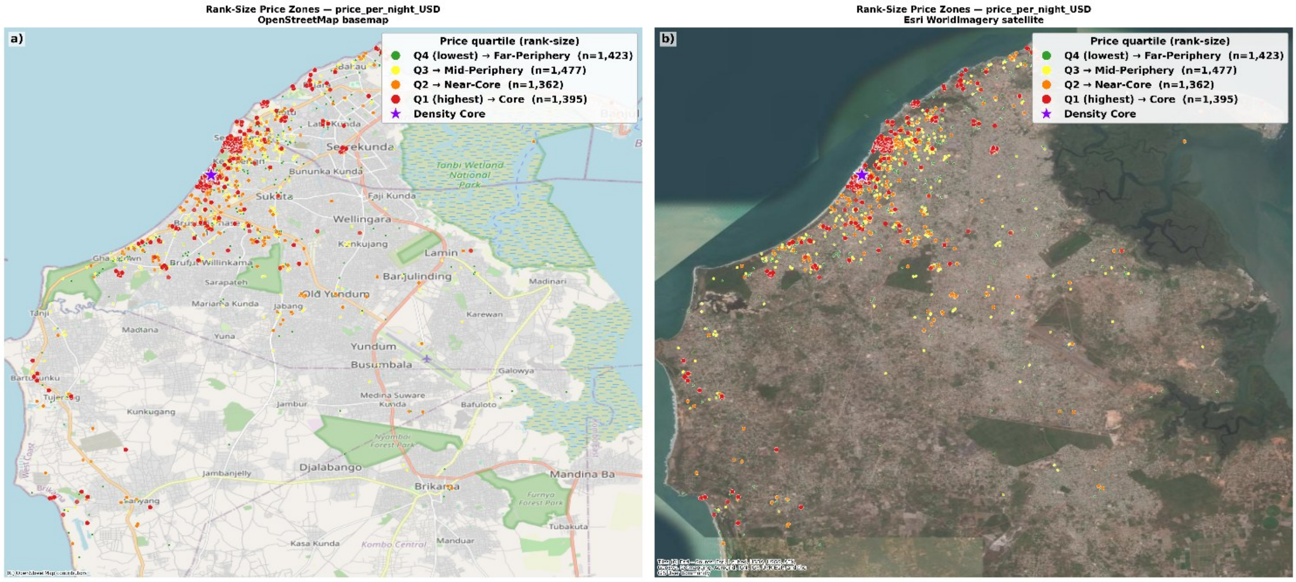

Figure 14. Rank-Size price quartile zones for Airbnb STR listings, Greater Banjul Area. Quartiles: Q4 Far-Periphery (green, n = 1,423), Q3 Mid-Periphery (yellow, n = 1,477), Q2 Near-Core (orange, n = 1,362), Q1 Core (red, n = 1,395). Purple star (★) = KDE density core centroid. (a) OpenStreetMap; (b) Esri WorldImagery satellite. CRS: EPSG:3857.

Panel (b) further reinforces physical land-cover context: the dark built environment along the Q1 coast has lower density peri-urban and rural land use across the Q4 Far-Periphery, providing a visual demonstration that space, not random assortative dispersal, disposes a power-law price distribution.

3.6.2. Rank-Size Rule Summary: α and R² for All Fits

The Zipf exponent of 1.143 shows that listings are relatively steeply concentrated into a small number of locations and indicates that the listing supply is the most hierarchical dimension underlying the GBA STR market (rank–size analysis) among the three dimensions in this study. We observe that our Nightly price follows a sub-Zipfian distribution with a compression factor $\alpha = 0.571$. The sub-Zipfians structure reflects moderate yet flattened hierarchy for its relatively high, but not rank-scale extreme price concentration. Conversely, stay length shows almost no hierarchy ($\alpha = 0.044$) and is tightly clustered across listing ranks. In particular, Core and Periphery clusters yield nearly identical price exponents ($\alpha = 0.506$–0.517), providing compelling evidence that the principle of price hierarchy operates equally across zones rather than solely through core dominance. Spatial supply concentration approaches Zipfian expectations, but pricing and booking duration do not.

Table 7: Rank-Size Rule Summary: α and R² for All Fits.

Variable	Zipf Exponent (α)	R²	n	Interpretation Relative to Perfect Zipf (α = 1)
Spatial grid-cell listing count	1.143	0.907	310	Approximately Zipfian (slightly steeper than Zipf)
Price per night (USD, listing level)	0.571	0.796	5,657	Below Zipf
Stay length (listing level)	0.044	0.445	5,657	Well below Zipf
C0 (Periphery) – Price	0.517	0.814	3,916	Below Zipf
C1 (Core) – Price	0.506	0.682	1,741	Below Zipf

Note. α = Zipf exponent from OLS regression of log(size) on log(rank); α = 1 denotes perfect Zipfian distribution. R^2 indicates goodness-of-fit. Spatial grid-cell fit uses a 0.005° (~500m) grid aggregation (n = 310 cells). Listing-level fits use all listings with valid values. "Below Zipf" indicates a flatter-than-expected price hierarchy; "≈ Zipfian" indicates close conformity to the rank-size benchmark.

3.6.3. Bootstrap Cluster Stability

Bootstrap confidence intervals for the price-scaling exponent overlap extensively between the Core (mean $\alpha = 0.187$, 95% CI: −0.037 to 0.445) and Periphery (mean $\alpha = 0.223$, 95% CI: −0.032 to 0.452) clusters, preventing any statistical distinction of their intra-price hierarchies via bootstrap analysis. However, both estimates have wide intervals (negative to positive values). Therefore, the overlap itself does not imply that a difference is identified with precision, so it should not be taken as support for the idea that two clusters of wealth holders share a price structure. Even though average prices for Core and Periphery listings differ significantly, the scaling behavior of their returns is statistically indistinguishable given our sample.

Table 8: Bootstrap mean and 95% confidence intervals for the Zipf exponent α across K-Means clusters.

Cluster	Label	Bootstrap mean α	95% CI (lower)	95% CI (upper)
0	Periphery	0.2228	-0.0316	0.4523
1	Core	0.1871	-0.0370	0.4452

4. Discussion

4.1. Interpretation of Key Findings

This study applies a multi-method spatial analytical framework, combining K-Means clustering, DBSCAN, spatial autocorrelation analysis, and Zipf rank-size modelling, to examine the spatial organization of the Airbnb short-term rental market across the Greater Banjul Area. By mapping the core–periphery structure of STR listings, identifying which listing-level features drive market segmentation, and testing whether the resulting spatial hierarchy conforms to predictions of urban hierarchy theory, the analysis yields four principal findings.

The short-term rental market in GBA follows structurally significant core–periphery spatial patterns, with Core listings concentrated in the northwestern coastal corridor and Periphery listings more dispersed across the southern and interior zones of the study area. We find that clusters show far more differentiation along the two structural axes of guest satisfaction and host rating rather than by price. That host quality and property capacity emerge as primary drivers of upward mobility, independent of cluster type. Nonetheless, the average price difference between clusters is negligibly significant, indicating that the Core–Periphery divide is evidence of locational rent differentials rather than rigid price stratification.

Importantly, Zipf rank-size analysis shows three hierarchical regimes. The supply of listings in space has a general shape governed by Zipfian predictions; the Core zone is spatially concentrated, but price is consistent with a tightly grouped sub-Zipfian distribution. More surprisingly, though, it reveals the same exponent per clustering, lending further weight to the claim that they not only have an absolute locational rent differential, but also a differential internal price concentration across the Core–Periphery divide. The third was the absence of a hierarchy in stay length, which was interpreted as an absence of effect. These sub-Zipfian price patterns are consistent with theoretical expectations for small, tourism-dependent urban economies in the Global South, where market fragmentation and compressed demand seasonality constrain cumulative agglomeration (Gabaix, 1999; Krugman, 1991). These findings reflect the co-existence of a small number of high-value coastal nodes alongside a large base of loosely competitive peripheral listings lacking the locational rent gradient needed to produce sharper price stratification (Gössling and Hall, 2019; Rogerson, 2015).

Positive spatial autocorrelation was established across nine alternative spatial weight matrix specifications, indicating that similar listings cluster spatially rather than randomly and that this conclusion is robust to alternative neighborhood definitions. Density-based clustering recovers a broadly similar geographic structure to K-Means but with modest internal validity, providing suggestive rather than conclusive cross-method convergence around the identified spatial hierarchy.

4.2. Comparison with Previous Studies

The hierarchical core–periphery pattern identified here echoes Xiaoqian et al. (2023), who reported a similar structure in the Yangtze River Delta Urban Agglomeration, yet diverges from their account of weakening spatial inequality, as the STR hierarchy observed in this study remains sharply concentrated and near-Zipfian, sustained by host-quality and capacity differentials rather than land-based dynamics. The spatial dependence is also consistent with Sarkaret al. (2024), whose Moran's I, K-Means, and LISA analyses revealed similar clustering of Airbnb in San Francisco, with their hotspots located outside of the urban core rather than along the centrally skimming hierarchy we identified here on our Senegambia–Kololi–Fajara coastal corridor. Broader STR scholarship reinforces this picture: Garcia-López et al. (2020) document strong central concentration of Airbnb listings, Barron et al. (2021) show that location, more than price, drives clustering, and Gutiérrez et al. (2017) reveal pronounced hotspot dominance in Madrid. The combined results of these studies enable STR markets to be characterized by consistently non-random, hierarchical spatial structures, and our results expand upon this existing body of work in demonstrating that, in a less-represented coastal African context, host quality and property capacity outrank price as structural axes.

4.3. Strengths and Limitations

This study makes several methodological and empirical contributions. Analytically, it is among the first to apply an integrated multi-method pipeline, combining K-Means, DBSCAN, Global and Local Moran's I, and Zipf rank-size modelling, to STR market analysis, with bootstrap validation to ensure reproducibility. The spatial weights sensitivity analysis across nine alternative specifications strengthens confidence in the reliability of spatial autocorrelation findings beyond what single-specification studies typically provide. Empirically, the study breaks new ground by applying core–periphery and urban hierarchy theory to a sub-Saharan African STR market, filling a significant geographical gap in the global STR literature and demonstrating the transferability of these frameworks to lower-income urban contexts.

Several limitations need to be considered when interpreting these findings. First, it relies on the primary labeling criterion of nightly price, a spatial-economic proxy that, however, less directly integrates with core-periphery classification theory, especially since no detailed accessibility, land-value, or footfall data are available in GBA. Second, K-Means imposes a hard partition by construction, whereby each listing belongs to exactly one cluster, and even a violation of that requirement is not challenged: while bootstrap stability analysis and DBSCAN comparison partly address this issue, the sensitivity to feature scaling choices remains. Third, we calculated the distance-band spatial weights in EPSG:3857 (Transverse Mercator). This projection has limited geometric distortion at this analysis scale, although a local UTM projection would be preferable for higher precision. Fourth, the mapping of Moran's I decreases with wider neighborhoods, and thus, for absolute values of I, comparability between studies is limited. Finally, despite the relatively large sample ($n = 5{,}657$), many measures approach statistical significance at $p < 0.001$ whilst having small effect sizes ($\eta^2 < 0.06$); thus, findings need to be interpreted in terms of effect size rather than statistical thresholds. Lastly, the dataset records snapshots scraped from September 2024 to July 2025 rather than a continuous panel, which limits temporal inference and could plausibly mask seasonal demand variation in a charter-tourism-dependent market like GBA.

4.4. Implications and Future Directions

The results have theoretical, practical, and policy relevance. Still, they need to be interpreted within the limitations of the study methods, on the one hand, and the specificities of the GBA context, on the other. Theoretically, the results show that core–periphery and urban hierarchy frameworks apply to Sub-Saharan African cities for STR markets, which adds to an under-researched branch of platform urbanism literature and suggests that these frameworks may travel across urban contexts beyond the Global North settings.

In terms of policy, the association between the spatial concentration of high-intensity listings and the Senegambia–Kololi–Fajara coastal corridor indicates that area-based rather than market-wide regulations would be empirically justified. Measures in core zones with high listing density can support the health of the housing stock and manage overtourism pressures (e.g., by imposing licensing requirements or monitoring density). At the same time, enabling frameworks may be needed in peripheral areas to encourage healthy market development. Our finding that price is driven more by host quality and property capacity than by price indicates that cost-based regulatory instruments, such as taxation, are likely insufficient, and future research may benefit from identifying other means by which place-based governance measures could respond to emerging threats, including those related to listing density or host standards. Transitional zone fields should be monitored regularly, as early intervention may prevent unchecked scale-up (or intensification of market forces) before it becomes entrenched. Given its reliance on listing-level data and lack of direct evidence on housing (dis)placement, resident welfare, or regulatory capacity in the GBA, these implications are suggestive rather than prescriptive. In light of GBA-specific institutional capacity, land tenure arrangements, and tourism dependency, town planners must proactively identify potential STR concentration issues as they emerge and modify regulatory strategies to local contexts, as governance tools that may be effective in other jurisdictions are only likely to work here with substantial modification (Sharma and Roy, 2024). Further research should comparatively use this multi-method framework across African and global coastal cities; examine temporally fluctuating dynamics of cluster membership (for example, how hosts transition to new clusters with a cumulative increase in ratings); and incorporate guest-side data on booking patterns and review behavior alongside the host- and listing-level perspectives taken here.

5. Conclusion

This study examined the spatial organization of the Airbnb short-term rental market across the Greater Banjul Area, The Gambia, applying a multi-method framework combining K-Means clustering, DBSCAN, spatial autocorrelation analysis, and Zipf rank-size modelling to 5,657 listings. The findings confirm a statistically significant core–periphery spatial structure, with Core listings concentrated along the northwestern coastal corridor and Periphery listings dispersed across southern and interior zones. The effects of price and guest quality on market segmentation are minimal, suggesting a structural axis of differentiation primarily driven by host quality and property capacity (guest satisfaction and host rating were the most important axes, η^2=0.628, η^2=0.639, respectively). In contrast, the price per night was negligible ($\eta^2 = 0.009$). Zipf rank-size analysis shows that spatial listing supply broadly follows Zipfian expectations, and is more of a Core-side phenomenon. In contrast, price follows near-identical exponent's sub-Zipfian distributions with near-equivalent exponents across both clusters, confirming the Core-Periphery divide determined by absolute locational rent differentials rather than internal price concentration. Positive spatial autocorrelation ($I = 0.480$, $p < 0.001$) holds consistently across nine alternative weight matrix specifications, reinforcing the robustness of the identified hierarchy.

These findings carry several implications. They illustrate, in theory, the transferability of core–periphery and urban hierarchy models to a Sub-Saharan African STR context, adding to an understudied strand within global platform urbanism. In terms of policy, the regional clustering of high-intensity listings along a narrow coastal corridor would indicate that spatially differentiated regulation might be required, with tighter controls in the core and enabling frameworks in peripheral areas to support balanced market development.

Several limitations warrant consideration. The nightly price was used as a proxy for locational advantage due to the lack of fine-grained accessibility data, which in turn determined core–periphery labeling. K-Means derives cluster listings and generates strong boundaries that might mask borderline listings. Given the large sample size, results should be interpreted with reference to effect size rather than significance thresholds alone, and the discrete scraping intervals constrain temporal inference and may underrepresent off-peak market conditions.

Future research should apply this multi-method framework comparatively across African and global coastal cities, explore the temporal dynamics of cluster membership, including how hosts progress as they accumulate ratings, and integrate guest-side data on booking patterns and review behavior alongside the host- and listing-level perspective adopted here.

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Conflicts of Interest

The author(s) declare(s) no conflicts of interest.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

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