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Spatiotemporal Lock-In of Short-Term Rentals in Dubrovnik's Historic Core

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Abstract

Platform-mediated short-term rental (STR) markets concentrate intensely in heritage urban cores, yet the temporal stability of this concentration remains poorly understood. This study examines spatial dynamics of STR concentration in Dubrovnik's UNESCO-listed historic core across five biennial cross-sections (2017–2025) using complete administrative eVisitor registration data and an H3 hexagonal grid at resolution 11. Global and local spatial autocorrelation (Moran's I, LISA, Getis-Ord Gi*), Emerging Hot Spot Analysis for spatiotemporal typologies, and bivariate LISA to distinguish capacity saturation from fragmentation were applied. Results demonstrate structural persistence: Moran's I remained highly significant ($p < 0.001$) across all periods including COVID-19 disruption (range 0.417–0.467, CV = 4.4%), despite 53% supply growth and only 3.7% spatial expansion. Consecutive hotspots dominated typological classification, indicating active consolidation. Capacity analysis revealed concordant High–High patterns (56.8% of significant cells) with zero High–Low associations, confirming saturation not fragmentation. Findings support spatial lock-in in STR markets: concentration persists because locational advantages are properties of place rather than market volume, requiring spatially differentiated regulation rather than aggregate supply controls.

Keywords: short-term rentals; spatial clustering; heritage tourism; emerging hot spot analysis; overtourism; Dubrovnik

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1. Introduction

In tourist cities, one of the defining urban challenges of the twenty first century is the transformation of residential neighborhoods into zones of tourist accommodation. The tension is most evident in heritage-listed historic cores, where the spatial limits of a protected urban fabric clash with the unbounded logic of growth of platform-mediated short-term rental (STR) markets. The historic core of Dubrovnik, a UNESCO World Heritage Site since 1979, is an extreme example of this dynamic, being less than one square kilometer within the medieval city walls. Today, the population of the internal area has decreased to around 1500, a situation that has been described as a "demographic catastrophe" and is partly linked to the systematic conversion of dwellings into tourist accommodations [1,2]. In this framework, short-term rental platforms have not only responded to the tourist demand, but also re-organized the spatial logic of the historic core itself [3,4].

Yet despite mounting concern over the socio-spatial consequences of STR proliferation in heritage destinations, the spatial dynamics of these markets remain poorly understood at the micro-scale. The overwhelming majority of existing STR research relies on cross-sectional Airbnb data for large metropolitan areas, offering snapshots rather than trajectories, and administrative boundaries rather than fine-grained spatial grids [5–7]. What is missing is a longitudinal, spatially explicit analysis capable of answering a fundamental question: is STR concentration in a heritage urban core a stable, structurally persistent spatial phenomenon, or does it fluctuate with external shocks such as regulatory pressure or the COVID-19 pandemic?

This study addresses that gap by analyzing the spatial dynamics of STR concentration in Dubrovnik's historic core across five biennial cross-sections spanning 2017 to 2025, using administrative eVisitor registration data, a source with complete market coverage unavailable through platform-scraped alternatives. The spatial framework employs an H3 hexagonal grid at resolution 11, enabling micro-scale analysis at a level of granularity that is both theoretically appropriate for a sub-kilometer study area and methodologically immune to the Modifiable Areal Unit Problem that afflicts administrative unit-based approaches [8]. Three research questions guide the analysis:

RQ1: Is spatial clustering of STR units a structurally persistent feature of the Dubrovnik historic core, stable across all five time points including the COVID-19 disruption period?

RQ2: What spatiotemporal patterns characterize the evolution of STR hotspots and coldspots between 2017 and 2025, as revealed by Emerging Hot Spot Analysis?

RQ3: Does the capacity structure of STR clusters reflect saturation; the co-occurrence of high unit density and high beds-per-unit, or fragmentation into smaller, dispersed units?

The paper makes three contributions. Empirically, it provides the first longitudinal micro-spatial analysis of STR market dynamics in a UNESCO-listed historic core using complete administrative registration data. Methodologically, it applies Emerging Hot Spot Analysis (EHSA), a space-time pattern mining technique rarely used in tourism geography and in combination with bivariate Local Indicators of Spatial Association (LISA) to characterize both the persistence and the internal capacity structure of STR clusters. Theoretically, the findings speak to the concept of spatial lock-in in STR markets: the persistence of concentration not merely despite supply growth of 53% over eight years, but apparently reinforced by it.

2. Literature Review

2.1. STR Markets as Spatially Selective Processes

Rapid expansion of platform-mediated short-term rental markets since the mid-2010s has generated a substantial body of urban research, with spatial concentration emerging as one of its most consistent empirical findings. From New York to Barcelona, Seoul to Lisbon, STR listings systematically cluster in culturally desirable, centrally located neighborhoods rather than distributing evenly across metropolitan areas [4,9,10]. At the broader European scale, Adamiak [5] provides comparative evidence of the uneven geography of Airbnb supply across European cities, particularly in relation to differences in city type, tourism intensity, and the structure of accommodation supply.

Wachsmuth and Weisler [4] formalized this observation through the concept of the STR rent gap: because short-term tourist rentals generate higher returns than long-term residential leases precisely in neighborhoods with high symbolic and locational capital, platform activity introduces a geographically uneven revenue logic into urban housing markets. The spatial selectivity of this process is not incidental as it is constitutive. High–demand locations attract STR investment, which raises property values and displaces long-term residents, which in turn reinforces the tourist character of the area and attracts further STR investment [3,11].

This self-reinforcing dynamic has been documented across multiple European contexts. Cocola-Gant and Gago [3] demonstrated through fine-grained fieldwork in Lisbon's Alfama district that STR supply is overwhelmingly provided by buy-to-let investors rather than occasional home-sharers, with 78% of property owners in their sample classified as professional investors. The implication is that STR concentration reflects deliberate capital allocation toward locations of maximum tourist appeal, not spontaneous platform participation. Similar professionalization patterns have been observed in Thessaloniki [12] and across a comparative pan-European sample [13], suggesting that the concentration of STR supply in historic cores is a structural feature of market organization rather than a contingent outcome. Adamiak [5] confirmed the pan-European pattern through systematic mapping of Airbnb listings across 83 cities, finding consistent concentration in city center areas regardless of national context. The entry of smaller, individually managed units alongside professional operators is a process of market atomization observed in several Southern European cities [11,14] which further complicates the spatial picture, as it can sustain or even increase listing counts in saturated zones while reducing average unit capacity, a dynamic empirically visible in this study.

The economic consequences of this concentration have been extensively quantified. García-López et al. [15] estimated that Airbnb expansion in Barcelona increased rental prices in affected neighborhoods by up to 1.9% annually, with effects concentrated in areas of highest STR density. Horn and Merante [16] found comparable rent effects in Boston, while Barron, Kung and Proserpio [17] produced a comprehensive estimate attributing a 0.018% rent increase and a 0.026% house price increase per 1% growth in Airbnb listings across the United States. In Portugal, Franco and Santos [18] documented localized price effects exceeding 3% in high-tourism municipalities, while Deboosere et al. [19] demonstrated through multilevel hedonic modelling that locational premium and degree of professionalization jointly determine STR revenue potential, reinforcing the logic of spatial concentration in high-value zones. For Croatia, one of the most STR-intensive economies in the European Union; Vizek, Stojčić and Mikulić [20] demonstrated significant spatial spillover effects of tourism activity on housing prices, while Stojčić, Vizek and Glaurdić [21] showed that STR-driven displacement in high-tourism Croatian cities creates closed migration circuits that constrain both labor mobility and knowledge exchange, compounding the socio-economic costs of spatial concentration.

The pandemic episode thus functions as an inadvertent longitudinal test of structural lock-in: the rapid reassertion of spatial concentration once mobility restrictions eased implies that the forces reproducing geographic hierarchy are endogenous to market organization rather than dependent on sustained external conditions. Yet this interpretation remains inferential so long as the analytical framework is cross-sectional as a limitation that points directly to the methodological gaps addressed in this study.

The COVID-19 pandemic provided an involuntary natural experiment in STR market resilience. Dolnicar and Zare [22] documented the severity of the initial shock which demonstrated global Airbnb bookings collapsed by over 70% in spring 2020, but also noted the speed of market recovery in tourism-dependent destinations once mobility restrictions eased, suggesting that the structural drivers of STR concentration reassert themselves once external constraints are removed. Llaneza Hesse and Raya Vílchez [23] confirmed asymmetric spatial recovery patterns, finding that high-concentration zones recovered faster and more completely than peripheral areas, effectively reinforcing pre-existing spatial hierarchies rather than redistributing activity. Sigala [24] positioned the pandemic as a potential inflection point for tourism restructuring, though subsequent empirical evidence. That includes the findings of the present study, where Moran's I in 2021 remained highly significant at I = 0.417 despite a 6% decline in total units which suggests that the spatial structure of STR markets proved more resilient than their aggregate volumes.

Despite this growing body of evidence, the literature exhibits two persistent limitations. First, the temporal dimension has been largely neglected: the majority of studies analyze single cross-sections of platform data, making it impossible to determine whether observed

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spatial patterns are stable structural features or transient configurations [6,7,14]. Second, the spatial unit of analysis has typically been the neighborhood or administrative district where units are subject to the Modifiable Areal Unit Problem [8], rather than uniform grids enabling unbiased micro-spatial comparison. Both limitations are particularly acute in heritage cores, where sub-neighborhood variation in STR density carries direct implications for residential displacement and heritage management.

2.2. Overtourism, Touristification, and the Heritage City

The spatial concentration of STR markets does not occur in a vacuum but is both a driver and a symptom of a broader urban transformation process variously described as touristification [25,26], tourism gentrification [11], or overtourism [27–30]. While the precise delineation of these concepts remains contested [27,31], their common analytical core is the progressive displacement of residential functions, local commerce, and everyday urban life by tourism-oriented land uses. That is a process in which STR platforms play an increasingly central structural role [3,13,25].

Koens, Postma and Papp [27] identified overtourism as a multidimensional phenomenon that cannot be reduced to visitor volume alone, emphasizing that its impacts are mediated by the spatial distribution of tourism activity within destinations. This spatial dimension is particularly salient in heritage cities, where the concentration of tourist appeal within a limited and legally protected perimeter creates conditions for an especially intense form of the phenomenon. Russo [32] described this dynamic as the "vicious circle" of heritage tourism development: as a historic core's attractiveness draws increasing visitor flows, the commodification of its built fabric displaces the residential population that gave the space its authentic character, ultimately undermining the very heritage value that made it attractive. Van der Borg, Costa and Gotti [33] documented parallel processes of heritage city museumification across European UNESCO sites, noting that resident population decline and STR-type accommodation expansion tend to co-occur as mutually reinforcing processes. Ashworth and Page [34] further contextualized these dynamics within the broader paradoxes of urban tourism research, arguing that the concentration of tourist infrastructure in historic cores produces spatial conflicts that conventional urban planning frameworks are ill-equipped to resolve. At the Italian provincial scale, Brandano, Faggian and Pinate [35] show that COVID-19 produced a sharp but spatially uneven disruption of tourism flows, particularly affecting international arrivals, while domestic and slow tourism gained relative importance in some destinations.

Cocola-Gant [25] has most recently theorized this process as place-based displacement, arguing that touristification does not merely displace residents physically but dismantles the relational fabric of places, producing feelings of loss and dispossession even among those who remain. In Seville, Jover and Díaz-Parra [26] documented how transnational STR investment accelerated neighborhood transformation beyond what local demand alone could explain, a finding that resonates with the Croatian context where foreign property investors have been identified as key actors in STR market expansion [20,21]. Goodwin [30] and Milano [36] both highlighted that the political and civic responses to overtourism. They go from resident protests to regulatory demands as they tend to emerge precisely in the most spatially concentrated tourist zones, suggesting that spatial concentration is not merely an analytical variable but a governance trigger. Dodds and Butler [37] surveyed regulatory and management responses across multiple heritage destinations, concluding that the most effective interventions are those capable of differentiating spatially between zones of saturation and zones where tourism growth remains compatible with residential life. This conclusion underscores the policy relevance of the spatial typologies generated in this study.

The regulatory responses to overtourism pressures have been extensively documented across European cities [38–41]. Nieuwland and van Melik [38] systematically compared STR regulatory approaches across 12 cities, finding that cities with spatially differentiated licensing regimes achieved better outcomes than those applying uniform city-wide rules. Von Briel and Dolnicar [39] traced the evolution of Airbnb regulation globally between 2008 and 2020, identifying a general trajectory from permissiveness toward increasingly restrictive and spatially targeted policies. Dredge et al. [40] analyzed the regulatory experiences of Barcelona, Berlin, Amsterdam and Paris, concluding that effective STR governance requires granular spatial intelligence about concentration patterns are precisely the kind of intelligence that the analytical framework developed in this study is designed to provide. Colomb and Novy [41] framed these regulatory debates as part of the broader politics of the tourist city. They argued that resistance to commodification of tourism is best organized and politically effective in neighborhoods where the concentration of STRs has reached saturation levels. The COVID-19 pandemic added another layer of complexity to STR regulation. Niedziółka et al. [42] recorded the temporary drop in STR activity in Polish destinations during the pandemic and the acceleration of regulatory reform, a common trend across Europe. Croatia is an especially acute case of these dynamics. One of the most tourism-dependent economies in the European Union and the member state with the highest share of STR capacity in total tourist accommodation, Croatia combines regulatory pressures documented in Western European cities with a structural economic dependence on tourism that constrains the political will to impose binding spatial limits.

In the Croatian context, the tourism sector's structural dominance of the coastal economy creates conditions in which STR-related displacement pressures are amplified relative to most comparable European cases [21]. Tourism development across Croatian coastal municipalities has been tracked through composite indices [43], confirming that Dubrovnik consistently ranks among the highest-intensity tourism destinations in the national system. The heritage dimension adds further specificity: Gredičak [44,45] documented the dual role of cultural heritage in Croatian economic development; as both a driver of tourism income and a resource increasingly strained by the tourism it attracts. Also, the UNESCO World Heritage Centre's State of Conservation report for the Old City of Dubrovnik [46] explicitly flagged tourism pressure and STR expansion among the primary threats to Outstanding Universal Value. Dubrovnik specifically has been recognized as an extreme case within this already extreme national context: the European Parliament's overtourism report [29] identified the city among a small number of European destinations where carrying capacity had been effectively exceeded, while qualitative research among local tourism workers [1] documented widespread awareness of displacement, infrastructure strain, and quality-of-life deterioration attributable to STR proliferation. Residents' attitude surveys conducted by Pavlić, Portolan and Benić [47] and by Pavlić, Portolan and Puh [48] across multiple time points document growing ambivalence and increasingly negative assessments of tourism's net impact among permanent residents of the historic core. Mikulić et al. [49] further contextualized destination attractiveness dynamics in competitive multi-destination regions, providing a framework within which Dubrovnik's STR market can be understood as a response to extraordinary locational premium rather than simply to regional tourism trends.

2.3. Spatial Analytical Methods in STR and Urban Tourism Research

The spatial analysis of STR markets has progressively adopted a wider range of geostatistical techniques beyond simple density mapping. Gutiérrez et al. [9] applied spatial analysis to compare distributional patterns of hotels and Airbnb listings in Barcelona, finding systematic differences in clustering intensity and locational preferences. Lestegás, Seixas and Lois-González [50] employed GIS-based density analysis to document extreme STR concentration in six historic parishes of Lisbon. Eugenio-Martin, Cazorla-Artiles and González-Martel [51] modelled the determinants of Airbnb location using spatial econometric techniques, confirming the primacy of proximity to tourist attractions and historic urban fabric as locational predictors. Ki and Lee [10] applied spatial autocorrelation analysis to Airbnb data in Seoul, finding significant positive clustering that varied by neighborhood type and listing category.

The foundational statistical tools for spatial cluster detection; Global Moran's I [52], Local Indicators of Spatial Association (LISA) [53], and the Getis-Ord Gi* statistic [54,55] have been extensively developed and validated in the spatial statistics literature [56,57] and their implementation in R is well established through the spdep and sfdep packages [58–60]. Bivand and Wong [56] provided a comprehensive comparative assessment of global and local spatial autocorrelation implementations, establishing the methodological standards against which the present study's results can be evaluated. Anselin's [61] extension of LISA to the multivariate case through the bivariate Local Geary's C provides the theoretical basis for the bivariate LISA analysis employed in this study to examine the joint spatial distribution of STR unit density and accommodation capacity. Geary's C complements Moran's I as a convergent global autocorrelation statistic: because the two measures respond differently to extreme values and local heterogeneity, their agreement across all time points provides stronger evidence of structural clustering than either statistic alone. These tools enable a nuanced decomposition of spatial structure that goes beyond the global question of whether clustering exists to the local question of where, how intensely, and of what type. Those are distinctions with direct policy relevance for STR governance.

Emerging Hot Spot Analysis (EHSA), which combines iterative Gi* computation across time steps with Mann–Kendall trend testing to classify each spatial unit into spatiotemporal typologies: persistent, consecutive, new, sporadic, and historical hotspots and coldspots. Within this typology, the distinction between persistent and consecutive hotspots carries particular theoretical weight. First is a persistent hotspot; significant in 90% or more of all time steps, indicates entrenched structural concentration, whereas a consecutive hotspot, significant in the most recent time steps but not necessarily throughout the full observation window which signals active consolidation, a market in the process of locking in rather than one already locked in. In contexts of rapid STR growth, consecutive patterns may therefore be more diagnostically informative than persistent ones, as they identify zones where concentration is intensifying rather than merely continuing.

Also, EHSA has seen growing application in environmental and health geography [62], but remains relatively uncommon in urban tourism and STR research; the sfdep package for R [60] provides an open-source implementation that makes the technique accessible outside the ArcGIS Pro (Version 3.1) environment in which it was originally developed."

To the best of the authors' knowledge, its application to the longitudinal dynamics of STR markets in heritage urban contexts has not been previously reported in the peer-reviewed literature, though the technique's capacity to distinguish between structurally entrenched concentration and recently emerging or declining hotspot activity makes it particularly well suited to the research questions addressed here. The Cliff and Ord [57] spatial processes framework and Openshaw's [8] MAUP analysis provide the theoretical foundations for understanding why the choice between administrative boundaries and uniform grids; such as the H3 hexagonal indexing system [63] employed in this study. That carries substantive analytical implications, especially in micro-scale study areas where cell size and boundary alignment can strongly influence autocorrelation statistics. Taken together, these tools constitute a methodologically mature analytical toolkit for longitudinal micro-spatial analysis of STR markets. Yet their combined deployment on administrative registration data for a constrained, UNESCO-listed heritage core has not been previously reported. That is a gap that defines the analytical contribution of the present study.

2.4. Research Gap and Positioning

The literature reviewed above converges on three structural observations that jointly define the space this study occupies. First, the spatial concentration of STR markets is not a contingent or ephemeral feature but reflects durable economic logic: the systematic allocation of short-term rental capital toward locations of maximum tourist appeal and locational premium [3,4,19]. Yet the temporal stability of that concentration; its persistence across supply shocks, regulatory pressure, and external disruptions such as the COVID-19 pandemic has not been examined through longitudinal spatial methods applied to a single, bounded heritage core. Cross-sectional studies, by design, cannot distinguish a structurally locked-in spatial pattern from one that merely appears concentrated at a given moment [6,7,14]. This distinction carries direct consequences for governance: if concentration is structurally persistent, spatially uniform regulatory responses will systematically fail, because the forces reproducing spatial hierarchy reassert themselves once constraints are lifted [22,23].

Second, heritage urban contexts are the most acute sites of STR-driven touristification [32,33,46], yet the micro-spatial dynamics within such cores remain analytically understudied relative to the severity of their documented social and heritage consequences [12,47,48]. The administrative boundaries typically used as spatial units in STR research are usually neighborhoods, census tracts, municipalities. Those are poorly suited to the sub-kilometer scale at which residential displacement and heritage impact actually operate in a historic core enclosed within medieval walls. The MAUP problem [8] is not merely a technical nuisance in this context; it is a substantive source of analytical distortion.

Third, the methodological toolkit appropriate for this type of analysis exists and is technically mature. Longitudinal LISA, EHSA, bivariate spatial association on uniform grids [52–55,61–63], but has not been deployed in combination on STR data for a constrained heritage study area. The application of EHSA in particular represents a methodological contribution in its own right: while the technique has been applied in environmental geography and public health, its use in tourism and STR research remains, to the best of the authors' knowledge, unreported. This is notable because EHSA's capacity to distinguish between structurally entrenched concentration and recently emerging or declining hotspot activity is precisely what is required to answer questions about temporal stability in tourist-driven markets which are the questions that Gi* and LISA alone, applied cross-sectionally, cannot address.

The present study addresses all three gaps simultaneously. Using complete administrative eVisitor registration data. That is a source which is not subject to the undercoverage and listing duplication problems of platform-scraped alternatives. Data spans across five biennial cross-sections spanning 2017 to 2025, and deploying an H3 hexagonal grid at resolution 11 to eliminate MAUP distortion at the micro-scale, this study provides the first longitudinal spatial analysis of STR concentration dynamics in a UNESCO World Heritage historic core. The findings are organized around three research questions that collectively test whether spatial concentration in Dubrovnik's intramural zone constitutes a structurally persistent, spatiotemporally patterned, and capacity-saturated phenomenon, or whether the substantial supply growth observed over the study period has redistributed activity across the grid in ways that existing cross-sectional evidence could not detect.

To make explicit the link between the research questions introduced in Section 1 and the hypotheses derived from the literature review, the hypotheses are formulated as direct analytical expectations corresponding to each research question. H1 corresponds to RQ1 and addresses the structural persistence of spatial clustering across all observation periods. H2 corresponds to RQ2 and concerns the spatiotemporal typology of hotspot and coldspot dynamics. H3 corresponds to RQ3 and tests whether the internal capacity structure of STR clusters reflects saturation rather than fragmentation.

Drawing on the theoretical and empirical foundations reviewed above, three directional hypotheses guide the analysis.

H1. *STR unit density in Dubrovnik's historic core exhibits statistically significant positive spatial autocorrelation across all five observation periods, including the COVID-19 disruption year, indicating structural persistence of clustering rather than transient concentration (corresponding to RQ1).*

H2. *EHSA classification of the study area's H3 cells will be dominated by consecutive and persistent hotspot types concentrated in the central and south zones, with coldspot types prevailing in peripheral cells, reflecting a spatiotemporally structured rather than random distribution of market dynamics (corresponding to RQ2).*

H3. *Bivariate LISA analysis of unit density and beds-per-unit will yield a dominant High–High association pattern among significant cells, indicating capacity saturation rather than fragmentation as the operative logic of STR concentration in the historic core (corresponding to RQ3).*

The novelty of the study operates on four levels. Empirically, the combination of administrative census data with a longitudinal micro-spatial design distinguishes this study from the overwhelming majority of STR research, which relies on platform-scraped snapshots of large metropolitan areas: the use of eVisitor data enables analysis of legal supply rather than platform-visible supply, and the five-period temporal span allows structural persistence to be distinguished from transient concentration. Methodologically, the analytical framework combines H3-based spatial autocorrelation statistics, LISA, Gi*, Emerging Hot Spot Analysis, and bivariate LISA in a single integrated study. That is a combination, to the best of the authors' knowledge, has not been previously applied to STR data in a heritage urban context. EHSA in particular represents a methodological contribution in its own right: while the technique is established in environmental and health geography [63], its application to the spatiotemporal dynamics of STR markets remains, to the authors' knowledge, unreported in the peer-reviewed tourism geography literature. At the level of the individual research questions, the bivariate LISA framework deployed in RQ3 introduces a further analytical dimension largely absent from existing STR spatial research: rather than treating STR units as homogeneous, it distinguishes between capacity saturation. The concordant co-occurrence of high unit density and high per-unit bed capacity and fragmentation, providing a more granular characterization of what spatial concentration actually means for accommodation intensity on the ground. Theoretically, the study advances the concept of spatial lock-in in STR markets, proposing that the persistence of concentration in the historic core reflects a structural property of the market. It means, in one which locational capital reproduces spatial hierarchy regardless of aggregate supply fluctuations, rather than a contingent outcome of any particular period's demand conditions. Taken together, these contributions amount to a study whose novelty lies not in the invention of new methods but in a new combination of data source, spatial scale, temporal design, analytical toolkit, and theoretical framing applied to a case that is both empirically extreme and theoretically generative.

3. Materials and Methods

3.1. Study Area

The Old City of Dubrovnik, surrounded by its medieval defensive walls, is one of the most geographically constrained and tourism-intensive historic cores in the Mediterranean. The historic core, inscribed on the UNESCO World Heritage List, comprises built urban fabric within walls of an approximate perimeter of 1940 m [46]. The area's outstanding universal value is grounded in its exceptional preservation of a late medieval and renaissance urban morphology, characterized by a dense street network, continuous stone building fabric, and the near-total absence of post-industrial urban transformation within the walls (Figure 1).

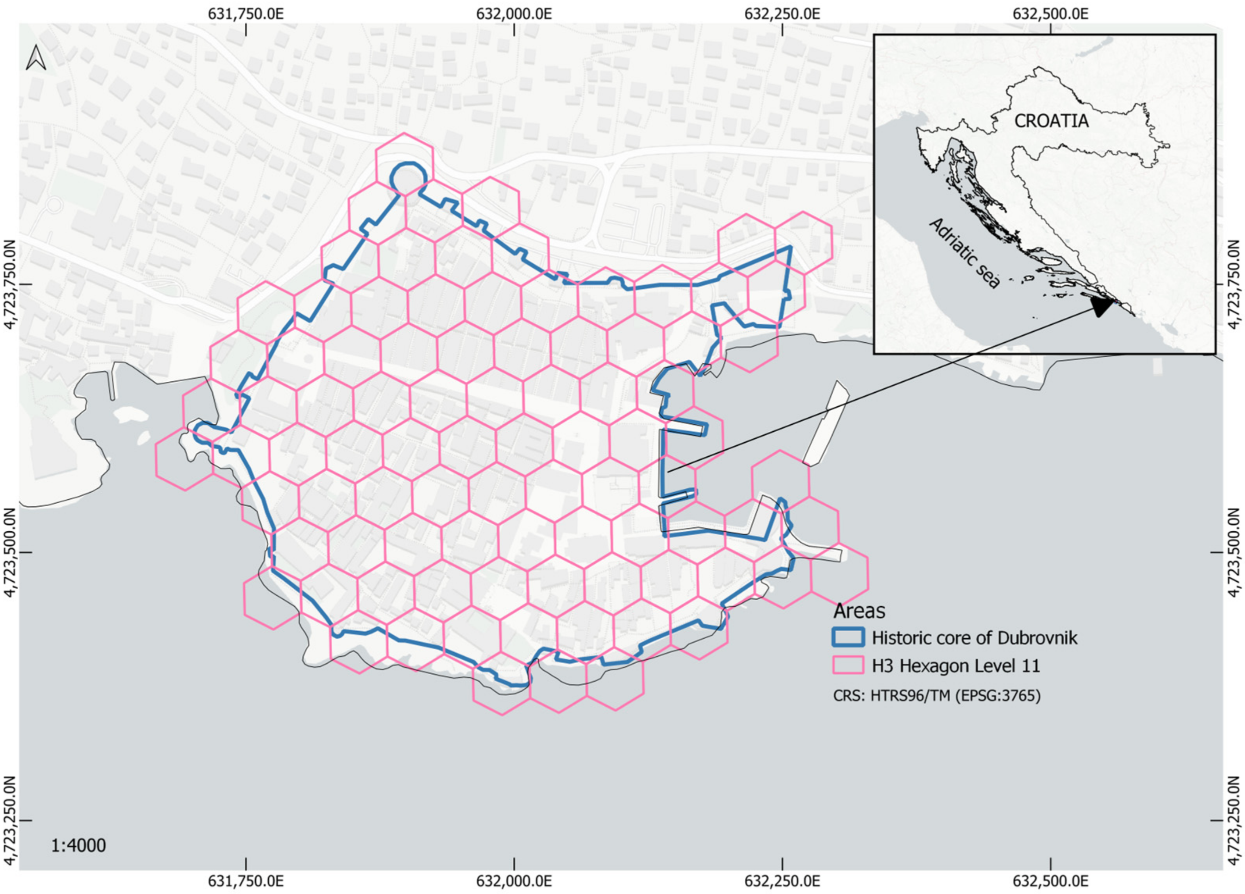

Figure 1. Study area.

Although the walled city is often perceived as an almost continuously built historic fabric, its internal morphology is not spatially homogeneous. The orthogonal street system, the central east–west axis, public squares, religious and institutional complexes, fortification edges, and smaller open or semi-open spaces create local variation in the amount of residential and accommodation-convertible floor space available within individual grid cells. Consequently, H3 cells without registered STR units should not automatically be interpreted as market absence in an otherwise equivalent urban fabric. In several cases, inactive or low-activity cells may reflect the presence of public space, monumental or institutional land uses, edge locations along the walls, or parts of the urban fabric where the stock of potentially convertible residential units is limited. This morphological context is important for interpreting the spatial pattern of STR concentration: the analysis captures the geography of registered STR supply within the historic core, but the opportunity structure for STR conversion is itself conditioned by the inherited urban form.

The socio-demographic trajectory of the intramural zone encapsulates the dynamics this study examines. From a population of approximately 5872 residents in 1961, the permanent population had declined to an estimated 1557 by the most recent systematic enumeration. Demographers are characterizing the process as an accelerating collapse driven by the conversion of residential units to tourist accommodation as well as an ageing population structure in which residents over 65 now outnumber children by a ratio exceeding three to one, and the economic unattractiveness of long-term residential occupancy in a zone where STR income substantially exceeds achievable residential rents [1,2,47,48]. The UNESCO World Heritage Centre's most recent State of Conservation report [46] explicitly identified tourism pressure and STR expansion among the primary threats to outstanding universal value. Within the national context, Croatia holds the highest share of STR capacity in total tourist accommodation among all EU member states [29], and the Old City functions as the gravitational center of this system. Its symbolic capital and walkable compactness making it the primary focus of both visitor activity and STR investment [43].

3.2. Data Sources

The empirical basis of this study is the eVisitor administrative registration dataset maintained by the Croatian Ministry of Tourism and Sport [64]. Unlike platform-scraped STR data, the dominant source in comparative STR research, eVisitor records derive from Croatia's mandatory accommodation registration and guest-reporting framework. Accommodation providers are legally required to register tourist stays through the system, which makes eVisitor the most comprehensive administrative source for legally registered tourist accommodation capacity in Croatia. The database therefore captures official registered STR supply rather than platform-visible listings alone.

This distinction is important for the interpretation of the results. The study does not claim to identify every active Airbnb listing visible online, nor can the eVisitor dataset independently detect possible unregistered or informal rentals operating outside the legal registration system. Instead, the analysis focuses on legally registered STR capacity within the official administrative framework. Compared with platform-scraped sources, this provides a more stable basis for longitudinal analysis because it avoids several well-documented platform-side measurement problems, including undercoverage of non-Airbnb platforms, listing duplication from multi-calendar management, and ghost listings that inflate active supply counts without necessarily corresponding to operationally available units [5–7]. The trade-off is that eVisitor measures registered legal capacity rather than platform visibility, booking activity, or realized occupancy.

Five biennial cross-sections were obtained for the years 2017, 2019, 2021, 2023, and 2025. Each cross-section represents the registered STR supply recorded in eVisitor on 30 June of the respective year, providing comparable early-summer administrative snapshots across the full observation period rather than annual totals, seasonal averages, or booking-based activity measures. The original unit of observation was the registered accommodation record, geocoded to its address location within Dubrovnik's historic core. For each record, the dataset included the number of licensed lodging units at that address and the total licensed bed capacity. These address-level records were then spatially joined to the H3 resolution 11 grid and aggregated by cell for each year, producing comparable cell-level indicators of STR unit density, total bed capacity, and mean beds per unit. Together, these five temporal points capture the main phases of the contemporary STR cycle in Dubrovnik: pre-pandemic expansion, COVID-19 disruption, post-pandemic recovery, and recent consolidation.

First is the pre-regulatory expansion phase (2017). Second is the peak pre-pandemic period (2019). COVID-19 disruption year (2021) follows. Then, the post-pandemic recovery

(2023), and the latest consolidation phase (2025). Across this period, total registered STR units increased from 466 to 713. It is a growth of 53.0%, while spatially active H3 cells expanded only marginally from 54 to 56, a divergence that anticipates the spatial lock-in pattern tested in H1 and H2.

3.3. Spatial Framework

The spatial unit of analysis is the H3 hexagonal grid at resolution 11, implemented using Uber's open-source H3 hierarchical spatial indexing system [62–64]. At resolution 11, H3 hexagons have an average area of approximately 0.00215 km^2. The intramural study area was represented by 89 H3 cells, including both active and inactive STR micro-locations. The choice of a uniform hexagonal grid over administrative sub-units is motivated by three considerations directly relevant to the reliability of the spatial statistics underlying H1, H2, and H3.

First, the Modifiable Areal Unit Problem [8] poses a severe analytical risk in a sub-kilometer study area: cell geometry and boundary placement can substantially alter local autocorrelation statistics, potentially producing spurious clustering or masking genuine concentration patterns. Hexagonal cells of uniform size eliminate the size-bias artefacts that arise with irregular administrative units. Second, the H3 system's hierarchical structure enables consistent cross-resolution comparison and facilitates replication in comparable heritage cores. Third, the queen contiguity spatial weights matrix constructed on the H3 grid yields a mean of 4.97 neighbors per cell provides a stable neighborhood structure that supports local autocorrelation estimation across all five time points. The weights matrix was row-standardized for all global and local computations. All spatial operations were performed in R using the sf [58] and spdep [59] packages, with EHSA implemented via sfdep [60].

3.4. Analytical Framework

3.4.1. Global Spatial Autocorrelation

To test H1, that STR clustering is structurally persistent across all five time points, global spatial autocorrelation in STR unit density was assessed using Moran's I [52] and Geary's C [57] independently for each cross-section. Moran's I measures the overall degree of spatial clustering by comparing the cross-product of deviations from the mean across neighboring pairs, taking values from -1 (perfect dispersion) through 0 (spatial randomness) to +1 (perfect clustering). Geary's C, which compares squared differences between neighboring values rather than deviations from the global mean, is more sensitive to local spatial heterogeneity and provides a strength check: convergence between the two statistic which includes a Pearson correlation of $r = 0.996$ between the Moran and Geary series in this study. That indicates that the clustering signal is not an artefact of global mean sensitivity. Statistical significance was evaluated using a Monte Carlo permutation test with 999 permutations under the null hypothesis of spatial randomness. Sustained significance across all five periods, including 2021, constitutes the primary evidentiary basis for H1.

3.4.2. Local Spatial Autocorrelation

Local spatial structure was characterized using two complementary statistics that decompose the aggregate signal from Section 3.4.1 into cell-level patterns relevant to both H1 (persistence of clustering location) and H2 (spatiotemporal typology of hotspot dynamics). Local Indicators of Spatial Association (LISA) [53] classify each cell into one of four association types: High–High (HH, above-mean density surrounded by above-mean neighbors), Low–Low (LL), High–Low (HL, a positive outlier in a low-density neighborhood), and Low–High (LH). HH cells constitute the spatial core of STR concentration; their consistency across five time points provides local-level evidence for H1 beyond the global Moran's I.

The Getis-Ord Gi* statistic [54,55] quantifies clustering intensity as a standardized z-score, classifying each cell as a hotspot or coldspot at three confidence levels ($p < 0.10, 0.05, 0.01$). Period-by-period stability of both LISA and Gi* classifications is assessed through temporal transition matrices tracking the proportion of cells retaining identical classifications across consecutive periods. That provides a direct empirical measure of spatial persistence.

3.4.3. Emerging Hot Spot Analysis

To directly test H2, that spatiotemporal patterns are dominated by consecutive and persistent hotspot types reflecting structured rather than random dynamics, EHSA was applied to the full five-period space-time cube [60,63]. EHSA extends the Gi* framework into the temporal dimension by computing Gi* for each cell at each time step and applying the Mann–Kendall trend test to the resulting Gi* time series per cell. The Mann–Kendall test is a non-parametric monotonic trend detector appropriate for short, potentially non-normally distributed time series. The combination of Gi* significance profile and trend direction classifies each cell into one of eight spatiotemporal types: persistent hotspot (significant in $\geq$90% of time steps), consecutive hotspot (significant in the most recent uninterrupted time steps), intensifying hotspot (significant with upward trend), new hotspot (significant only in the most recent period), sporadic hotspot (significant in a non-consecutive pattern), historical hotspot (significant in earlier but not recent periods), and coldspot variants thereof, plus oscillating and no-pattern categories. As noted in Section 2.3, the distinction between persistent and consecutive hotspots carries particular theoretical weight for H2: persistent hotspots indicate entrenched long-run concentration. Consecutive hotspots signal active recent consolidation in which a market is in the process of locking in. H2 is supported if the distribution of EHSA types is non-random and dominated by structurally interpretable categories concentrated in theoretically predictable zones, and if consecutive hotspot emerges as the dominant type, this is consistent with a market undergoing active spatial consolidation rather than merely maintaining historical inertia. With n = 5 time points, the Mann–Kendall test has limited statistical power, and EHSA classifications are therefore interpreted as descriptive spatiotemporal typologies rather than formal trend inferences.

3.4.4. Bivariate LISA

To directly test H3; that capacity saturation rather than fragmentation characterizes the internal structure of STR clusters, bivariate LISA was applied to examine the joint spatial distribution of STR unit density per cell and mean accommodation capacity per unit (total licensed beds divided by unit count). The bivariate LISA statistic computes the spatial lag of one variable against the local value of another, identifying cells where high unit density co-occurs with spatially associated high capacity per unit (High–High: saturation), high unit density co-occurs with spatially associated low capacity (High–Low: fragmentation), and low-density variants. H3 is supported if High–High significantly dominates among statistically significant cells and High–Low associations are absent or negligible which suggests a pattern consistent with professional buy-to-let investment logic in which large-capacity units accumulate in already-dense zones. Temporal stability of the bivariate classification was assessed through a transition matrix tracking cell-level changes across consecutive periods, providing a measure of capacity structure persistence that complements the unit-density persistence assessed in Sections 3.4.1 and 3.4.2. All analyses were conducted in R (version 4.3.2). Spatial data management and grid construction used the sf package [58]; global and local autocorrelation statistics were computed using spdep [59]; EHSA and bivariate LISA were implemented using sfdep [60]. Visualizations were produced using ggplot2.

4. Results

4.1. Descriptive Trends in STR Market Development

Before examining spatial autocorrelation and cluster dynamics, a descriptive overview of market-level trends establishes the empirical context for the subsequent spatial analysis. Across the five biennial cross-sections, the total number of registered STR units in Dubrovnik's historic core increased from 466 in 2017 to 713 in 2025, representing cumulative growth of 53.0% over eight years (Table 1). This growth, however, was distributed very unevenly in spatial terms.

Table 1. Descriptive statistics of STR units per H3 cell by year.

Year	n Cells	n Active	% Active	Total Units	Mean Units	Median Units	SD Units	CV Units	Max Units	Gini Units	Total Beds	Mean Beds	Mean BPU
2017	89	54	60.7	466	5.24	2	6.56	125.3	28	0.641	1657	18.62	3.55
2019	89	55	61.8	554	6.22	3	7.72	124.1	33	0.636	1885	21.18	3.39
2021	89	55	61.8	522	5.87	2	7.47	127.3	33	0.643	1725	19.38	3.27
2023	89	56	62.9	600	6.74	3	8.53	126.5	37	0.642	1952	21.93	3.27
2025	89	56	62.9	713	8.01	3	9.94	124.1	41	0.636	2267	24.74	3.21

The number of active H3 cells, defined as cells containing at least one registered STR unit, increased only marginally, from 54 to 56 out of 89 total cells. This limited expansion should be interpreted in relation to the urbanistic structure of the walled city. Not all H3 cells contain an equivalent amount of accommodation-convertible built fabric: some inactive or weakly active cells correspond to public spaces, larger religious or institutional complexes, fortification edges, or other parts of the historic fabric where the available residential stock is limited. The finding of spatial lock-in therefore does not imply that every inactive cell represents an equally suitable but unused STR location. Rather, it indicates that market growth occurred primarily within the subset of cells where the inherited urban morphology and existing building stock provide realistic opportunities for STR conversion.

The contrast between aggregate growth and limited spatial expansion is nevertheless substantial. The additional 247 units that entered the market over eight years were overwhelmingly absorbed by cells already active in 2017 rather than by the activation of new micro-locations. A 53.0% increase in units against a 3.7% increase in active cells is therefore a first descriptive indication of the spatial lock-in dynamic examined in the following sections.

Total licensed bed capacity increased from 1657 to 2267 beds over the study period, while mean beds per unit declined from 3.55 in 2017 to 3.21 in 2025, a reduction of approximately 9.6% (Figure 2). This suggests a gradual compositional shift toward smaller-capacity units despite continued aggregate capacity growth. At the same time, the Gini coefficient of unit distribution across H3 cells remained virtually unchanged, ranging from 0.636 to 0.643, while the coefficient of variation remained similarly stable, between 124.1% and 127.3%. These measures confirm that the entry of smaller units did not reduce spatial concentration. Instead, new units entered in proportion to existing density patterns rather than redistributing activity toward less-saturated cells.

4.2. RQ1—Structural Persistence of Spatial Clustering

4.2.1. The Aggregate Level

Global Moran's I was computed independently for each of the five cross-sections using a row-standardized queen contiguity spatial weights matrix (n = 89 cells, mean 4.97 neighbors). The results are presented in Table 2 and visualized in Figure 3. H1, which examines whether spatial clustering constitutes a structurally persistent feature of the STR market, received unambiguous support. Moran's I was positive and statistically significant at $p < 0.001$ in every year, with values ranging from I = 0.417 in 2021 to I = 0.467 in 2025. The mean value was I = 0.446, and the coefficient of variation across the five periods was only 4.4%. The magnitude of clustering was therefore consistently well above the expected value under spatial randomness (E[I] = −0.011), with z-scores ranging from 6.41 to 7.11.

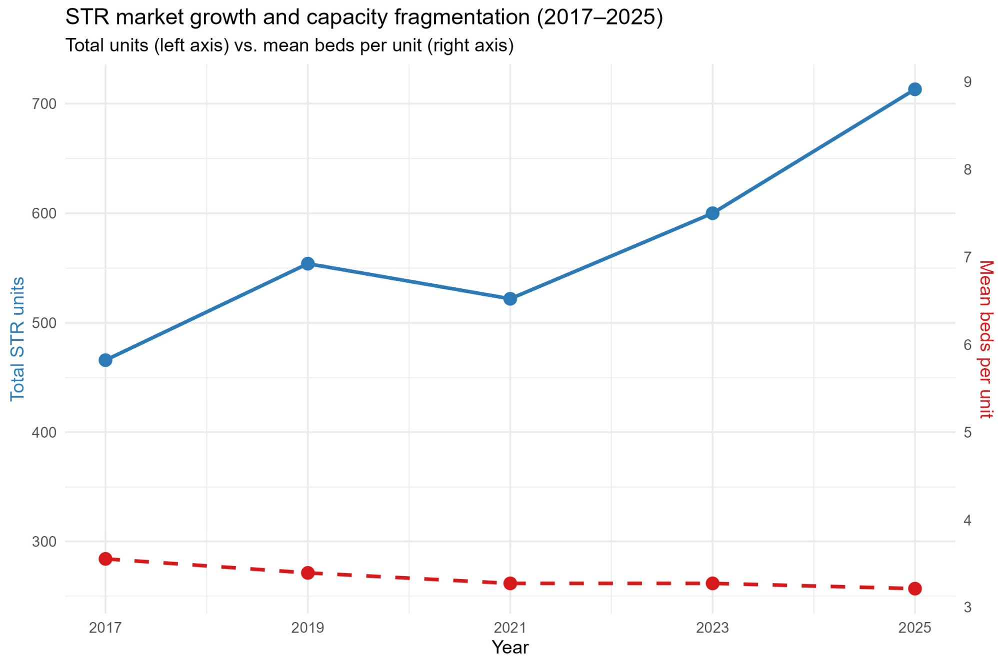

Figure 2. Total STR units and mean beds per unit, 2017–2025.

Table 2. Global Moran's I by year: I value, expected I under randomness, variance, z-score, analytical *p*-value, Monte Carlo *p*-value (999 permutations).

Year	Moran's I	Expected I	Variance	z-Score	*p*-Value (Analytic)	*p*-Value (MC)
2017	0.462	−0.011	0.0045	7.034	1.01×10^{-12}	0.001
2019	0.442	−0.011	0.0045	6.738	8.03×10^{-12}	0.001
2021	0.417	−0.011	0.0045	6.409	7.34×10^{-11}	0.001
2023	0.441	−0.011	0.0045	6.734	8.23×10^{-12}	0.001
2025	0.467	−0.011	0.0045	7.115	5.61×10^{-13}	0.001

The trajectory shown in Figure 3 is particularly relevant in relation to the COVID-19 disruption. Between 2019 and 2021, total STR units declined by 5.8%, from 554 to 522, representing the only contraction in the observation window. Yet Moran's I declined by only 0.024 points, from 0.442 to 0.417, and remained highly significant. The subsequent recovery saw Moran's I return to pre-pandemic levels by 2023 (I = 0.441) and reach its series maximum in 2025 (I = 0.467). This indicates that the spatial structure of STR concentration was not meaningfully altered by the pandemic shock.

Association was confirmed through Geary's C, which provides a complementary measure more responsive to local spatial dissimilarity than global covariance. All five Geary's C values were significantly below 1.0, the value expected under spatial randomness, ranging from C = 0.543 in 2025 to C = 0.597 in 2021, with *p*-values between 3.9×10^{-11} and 6.5×10^{-9}. The Pearson correlation between the Moran's I series and the (1 − Geary's C) series was r = 0.996, indicating near-perfect convergence between the two statistics. As visible in Figure 3, both statistics trace parallel trajectories across all five time points, with the 2021 trough and 2025 peak replicated in both series.

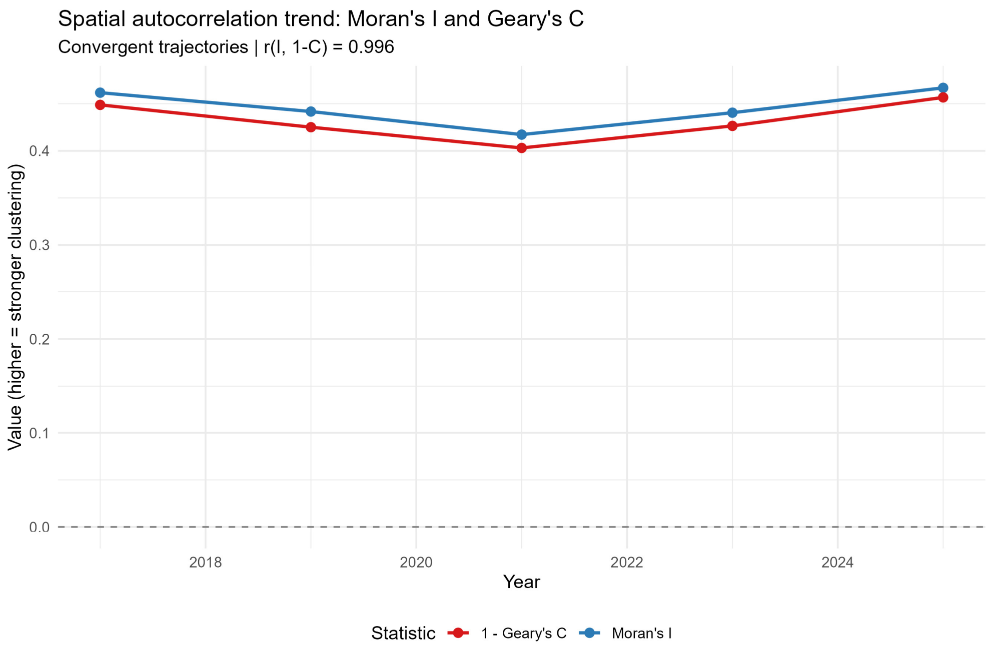

Figure 3. Convergent trend of Moran's I (blue) and 1 − Geary's C (red) across five time points, 2017–2025.

4.2.2. Mapping the Structure of Clustering

Decomposition of the global signal through LISA and Getis-Ord Gi* reveals the cell-level geography of STR concentration. LISA results, mapped in Figure 4, identify between 10 and 14 High–High cells per year, representing micro-locations where above-average unit density co-occurs with spatially adjacent above-average neighbors. The complete absence of statistically significant Low–Low or High–Low clusters in any year is analytically informative. It indicates that no part of the historic core exhibits stable low-density co-clustering, and that no isolated high-density outlier cells exist outside the main concentration zone. The only non-High–High significant cluster type observed across all years was Low–High, numbering 1 to 2 cells per year and representing spatial gaps within the broader concentration zone rather than evidence of dispersal.

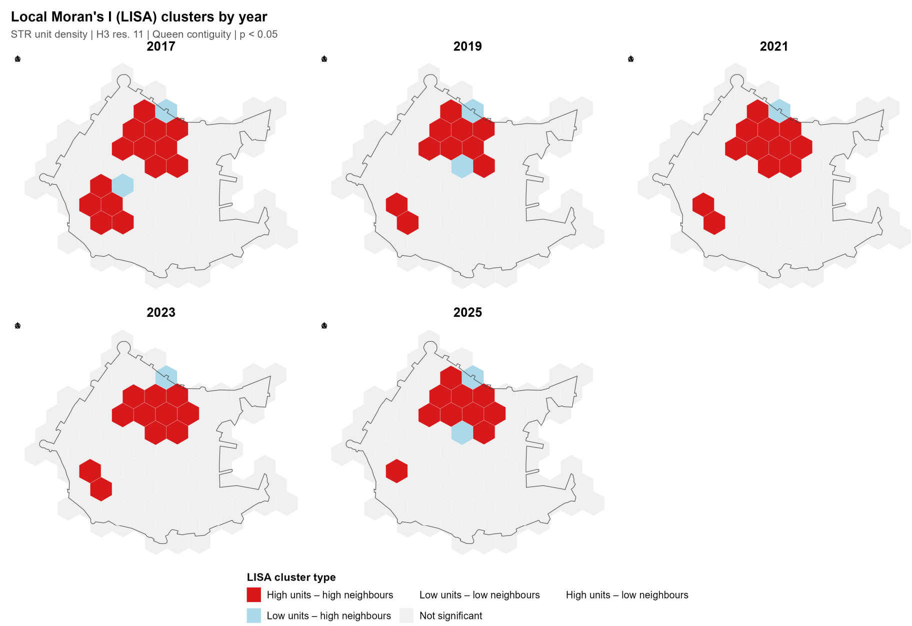

Figure 4. Local Moran's I (LISA) cluster maps for 2017, 2019, 2021, 2023, and 2025.

The Gi* maps shown in Figure 5 confirm the same spatial structure while adding information on clustering intensity. Between 16 and 19 hotspot cells were identified per year across all confidence levels combined, with most classified at the highest threshold. Between 8 and 10 cells per year received 99% confidence hotspot designation, indicating that the concentration of STR activity is not only statistically significant but also spatially intensive. Coldspot cells, representing peripheral areas of consistently low STR presence, numbered between 8 and 10 per year. The 2025 cross-section shows a modest increase in 90% confidence coldspots alongside a stable core of 99% hotspots, suggesting a slight strengthening of the contrast between the concentration core and the peripheral parts of the walled city.

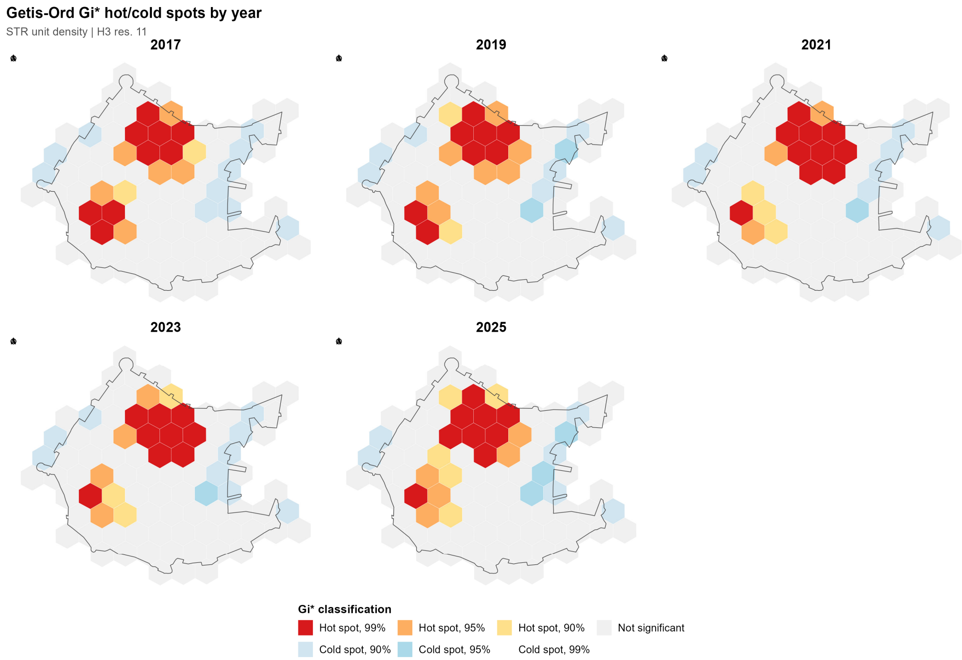

Figure 5. Getis-Ord Gi* hotspot and coldspot maps for all five cross-sections, with colour-graded confidence levels.

4.3. RQ2—Spatiotemporal Dynamics of STR Concentration

Emerging Hot Spot Analysis applied to the full five-period space-time cube provides the temporal dimension missing from the cross-sectional LISA and Gi* results. Table 3 presents the complete EHSA classification, while Figure 6 visualizes the frequency distribution across categories. Of the 89 H3 cells, 52 (58.4%) were assigned a statistically detectable spatiotemporal pattern, either as a hotspot or coldspot classification, while 37 cells (41.6%) showed no detectable pattern. Since H2 requires the structured share to exceed 50%, it is supported. The result confirms that the STR market in the historic core operates as a spatially organized system at the micro-scale, rather than as a randomly distributed phenomenon producing only transient clustering in global statistics.

The typological composition of the 28 hotspot cells is particularly informative. Consecutive hotspots constitute the largest category (n = 10, 11.2% of total cells), followed by new hotspots (n = 9, 10.1%), persistent hotspots (n = 7, 7.9%), and sporadic hotspots (n = 2). The dominance of consecutive over persistent hotspots indicates active ongoing concentration, consistent with a market still in the process of spatial consolidation. The complete absence of intensifying hotspots (n = 0) indicates that no cell exhibited a statistically confirmed monotonic upward trend in Gi* z-scores across all five periods, which is also consistent with the stable global Moran's I trajectory.

Table 3. EHSA classification of all 89 H3 cells.

Classification	n	%
No pattern detected	37	41.6
Consecutive hotspot	10	11.2
Persistent coldspot	10	11.2
New hotspot	9	10.1
Consecutive coldspot	8	9.0
Persistent hotspot	7	7.9
Sporadic coldspot	6	6.7
Sporadic hotspot	2	2.2

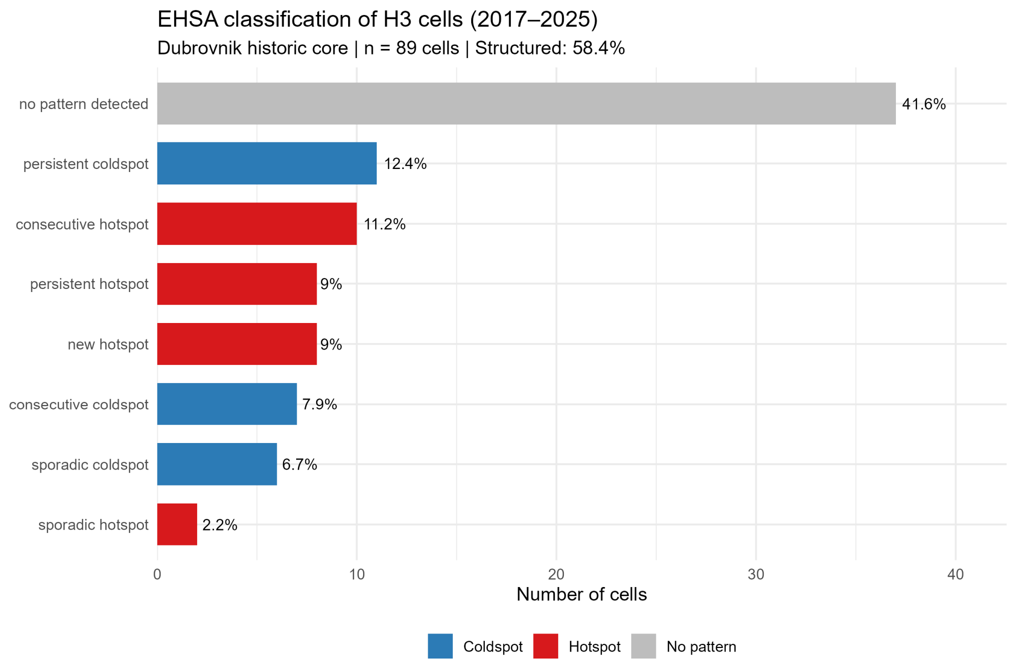

Figure 6. Horizontal bar chart of EHSA classification frequencies, color-coded by broad class.

New hotspots represent cells achieving statistically significant hotspot status only in the most recent cross-section. Their spatial distribution, visible in Figure 7, is predominantly located at the edges of the established consecutive and persistent hotspot core. This pattern is consistent with outward diffusion from the established concentration zone rather than the emergence of new independent clusters. Among the 24 coldspot-classified cells, persistent coldspots were the dominant type (n = 10, 11.2%), followed by consecutive coldspots (n = 8, 9.0%) and sporadic coldspots (n = 6, 6.7%). The persistence of both hotspot and coldspot structures reflects the enclosed geography of the study area, where concentration in the central zone is accompanied by stable low-activity peripheral cells.

Figure 7 shows the full EHSA typology mapped onto the H3 grid. Persistent and consecutive hotspots occupy the central and south-facing areas, new hotspots form a transitional ring at the hotspot margins, and persistent coldspots cluster in the northern and western peripheral zones of the walled city. The Mann–Kendall τ distribution provides supplementary descriptive context: the mean τ across all cells was -0.204 and the median -0.40, with 59 cells showing a negative trend direction and 25 a positive one. No cell achieved statistical significance at $p < 0.05$ in the trend test, reflecting the limited statistical power of the Mann–Kendall test with only five time points. EHSA classifications should therefore be interpreted as spatiotemporal typological characterizations rather than confirmed monotonic trend inferences.

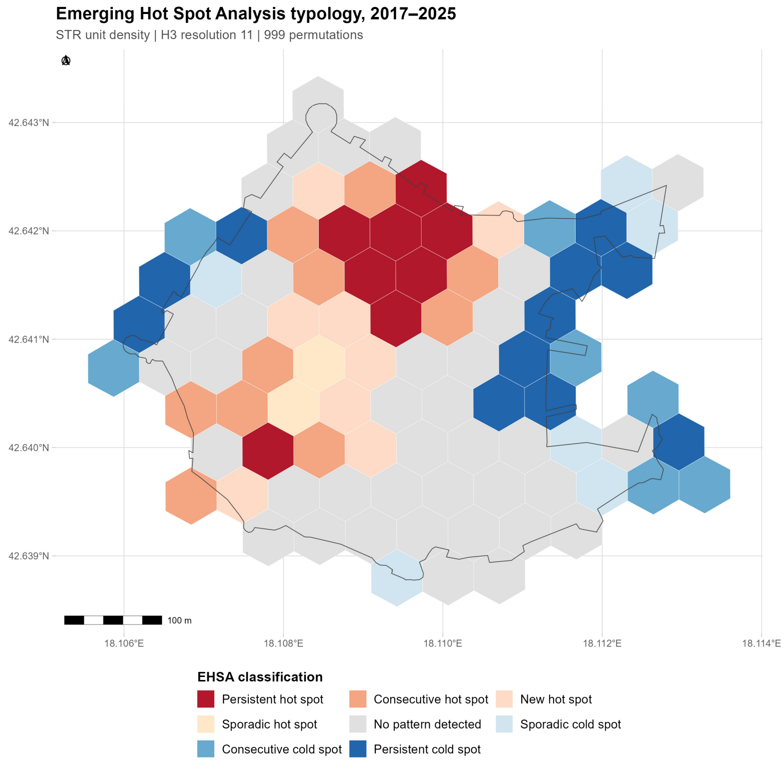

Figure 7. Full EHSA classification map of Dubrovnik's historic core: all eight spatiotemporal types color-coded.

4.4. RQ3—Capacity Structure of STR Clusters

Bivariate LISA analysis of the joint spatial distribution of STR unit density and mean beds per unit assesses whether spatial concentration of units is concordant with spatial concentration of accommodation capacity, or whether a structural mismatch characterizes the historic core market. Results are presented in Table 4 and mapped in Figure 8. Across all five cross-sections combined, 88 cell-year observations reached statistical significance at $p < 0.05$ under the conditional permutation procedure (999 simulations). Of these, 50 (56.8%) were classified as High–High, indicating micro-locations where above-average unit density co-occurs with spatially adjacent above-average beds-per-unit values. This is the saturation pattern predicted by H3.

Table 4. Bivariate LISA cluster counts by year.

Year	High–High	Low–High	Low–Low
2017	13	3	4
2019	8	4	7
2021	12	3	4
2023	8	2	5
2025	9	2	4

Critically, High–Low associations, indicating fragmentation where high unit density is paired with low surrounding capacity, recorded zero significant instances across all five years. H3 is therefore fully supported: capacity saturation, not fragmentation, is the operative structural logic of STR concentration in the historic core. The zero High–Low count rules out the market atomization scenario in which STR growth is driven primarily by small, low-capacity units that increase listing counts without increasing accommodation intensity at the neighborhood level.

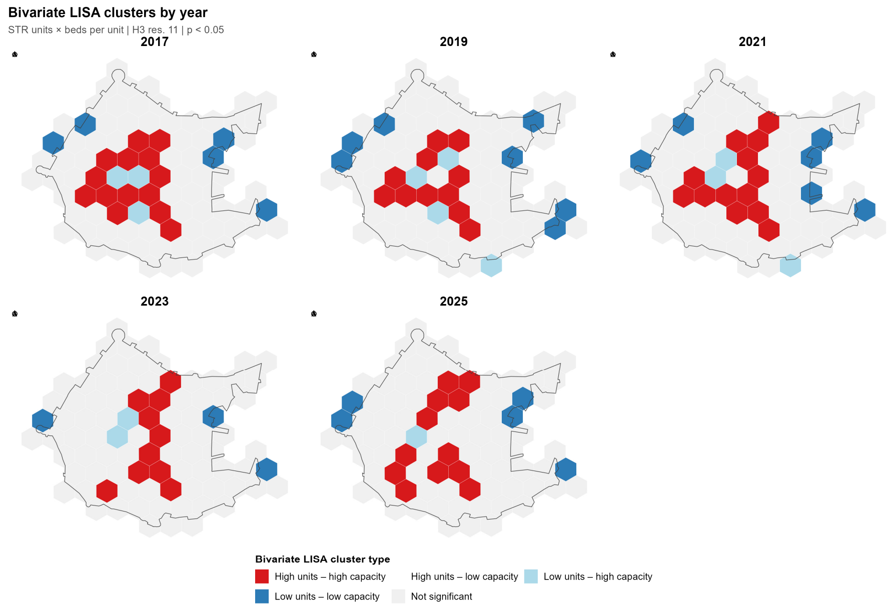

Figure 8. Bivariate LISA cluster maps for all five cross-sections.

The 14 Low–High cell-year observations (15.9% of significant observations) represent a complementary pattern: peripheral cells with below-average unit counts but above-average neighborhood capacity. This is consistent with the presence of a small number of larger-capacity units in zones that have not yet reached high unit density but are adjacent to those that have. Period-by-period transition matrices confirm that these patterns are structurally entrenched rather than transient. Mean classification stability across the four consecutive transitions was 89.9%, ranging from 88.8% in three transitions to 93.3% in the 2021–2023 period (Table 5).

Table 5. Temporal stability of bivariate LISA clusters across four consecutive period transitions.

Period	Total	Stable	Changed	% Stable
2017 → 2019	89	79	10	88.8
2019 → 2021	89	79	10	88.8
2021 → 2023	89	83	6	93.3
2023 → 2025	89	79	10	88.8

In the full 2017-to-2025 transition matrix, 65 of 89 cells remained non-significant throughout, 6 cells maintained continuous High–High classification across the entire eight-year span, and 7 cells that were High–High in 2017 had lost that classification by 2025.

The bivariate LISA cluster maps in Figure 8 provide a spatial synthesis of these results. Across all five cross-sections, High–High capacity-saturation cells correspond closely to the main STR concentration core identified in the preceding Local Moran's I, Gi*, and EHSA analyses. This confirms cross-methodological convergence across all three analytical components: the areas of highest STR unit density are also the areas where accommodation capacity remains spatially concentrated.

5. Discussion

The results of this study provide convergent evidence that the spatial concentration of short-term rental activity in Dubrovnik's historic core is a structurally persistent, spatio-temporally patterned, and capacity-saturated phenomenon. All three hypotheses received empirical support: clustering was statistically significant at every observation point, including the COVID-19 disruption year (H1); the majority of H3 cells exhibited a detectable spatiotemporal pattern rather than random variation (H2); and the dominant capacity structure was one of saturation rather than fragmentation (H3). This section interprets these findings in relation to the theoretical frameworks and empirical precedents reviewed in Section 2 and considers their implications for heritage governance and STR regulation.

5.1. Spatial Lock-In and the Structural Persistence of Clustering

The most consequential finding of this study is the stability of the spatial autocorrelation signal across a period of substantial market change. Total STR units grew by 53% between 2017 and 2025, yet Global Moran's I varied within a narrow band, from I = 0.417 to I = 0.467. This stability was confirmed by Geary's C, which closely tracked the Moran trajectory, and by the near constancy of the Gini coefficient and the coefficient of variation in unit distribution across all five periods. These results do not merely demonstrate that clustering exists, which would be expected from any single cross-section of STR data in a tourism-intensive city [5,9,10]. Rather, they show that clustering intensity remained structurally stable despite a major increase in aggregate supply, a pandemic-induced contraction, and the subsequent recovery. The spatial structure of the market is, in effect, self-reproducing: new units enter in proportion to existing density rather than redistributing activity across the grid.

This finding provides direct longitudinal evidence for the spatial lock-in mechanism theorized in the STR literature but previously inferred mainly from cross-sectional patterns. Wachsmuth and Weisler's [4] rent gap framework predicts that STR investment will systematically target locations where the differential between short-term tourist revenue and long-term residential rent is largest; a differential that is itself spatially concentrated in heritage cores with high symbolic and locational capital. The results presented here demonstrate that this targeting is not a one-time allocation but a continuously reinforced process. The cells that were hotspots in 2017 remained central to the STR market in 2025, while the additional units that entered the market over eight years were absorbed overwhelmingly by cells already active at the start of the observation window. This mechanism is consistent with the professionalized investment logic documented by Cocola-Gant and Gago [3] in Lisbon and Katsinas [3,12] in Thessaloniki, where established STR zones reduce investment risk through tourist footfall, proximity to attractions, complementary tourism services, and accumulated market familiarity.

The pandemic episode provides the most analytically informative test of the lock-in thesis. Between 2019 and 2021, total units declined, yet Moran's I remained highly significant and the spatial structure of clustering did not collapse. This resilience is consistent with the asymmetric recovery patterns documented by Llaneza Hesse and Raya Vilchez [23], who found that high-concentration STR zones recovered faster and more completely than peripheral areas following the pandemic. The Dubrovnik case extends this finding by demonstrating that the spatial structure did not merely recover; it emerged stronger, with Moran's I reaching its series maximum in 2025. The implication is that external shocks to the tourism system are absorbed by aggregate volume rather than by spatial redistribution, because the locational advantages that produce concentration; heritage value, walkability, established tourist infrastructure and proximity to major attractions, are properties of place rather than properties of short-term market conditions.

The V-shaped Moran's I trajectory, from 0.462 in 2017 through a trough of 0.417 in 2021 to 0.467 in 2025, also speaks to a broader theoretical debate about the nature of spatial concentration in urban tourism systems. Russo's [32] vicious circle model predicts cumulative and self-reinforcing concentration in heritage destinations, driven by the progressive displacement of residential functions and their replacement by tourism-oriented land uses. The present results are broadly consistent with this model, but with an important qualification: the system appears to have reached a structural steady state in terms of spatial distribution. The number of active cells changed only marginally, from 54 to 56 out of 89, suggesting that the geographic boundary of the STR market within the walled city has stabilized even as its internal intensity continues to increase. This pattern is better characterized as spatial saturation than as ongoing diffusion. The heritage core has effectively reached a spatial carrying capacity for STR activity, not in terms of total units, which continue to grow, but in terms of the geographic extent of the market within the enclosed urban fabric.

5.2. Spatiotemporal Consolidation and Emerging Hotspot Dynamics

The EHSA results add temporal dimensionality to the cross-sectional picture by classifying each cell into a spatiotemporal typology. The finding that 58.4% of cells exhibit a detectable pattern, narrowly but substantively exceeding the 50% threshold of H2, confirms that the STR market is spatially organized rather than randomly distributed at the microscale. However, the composition of the structured cells is more theoretically informative than the aggregate share. Among the 28 hotspot cells, consecutive hotspots constituted the largest category (n = 10), followed by new hotspots (n = 9), persistent hotspots (n = 7), and sporadic hotspots (n = 2). The dominance of consecutive over persistent hotspots is a key finding. It indicates that the most common spatiotemporal trajectory in the concentration core is one of active, ongoing consolidation rather than inert persistence. This is consistent with a market that is still in the process of locking in its spatial structure, rather than one that locked in long ago and has simply maintained it.

This consolidation interpretation is reinforced by the spatial distribution of new hotspots. The 9 cells classified as new hotspots, achieving significant hotspot status only in the most recent cross-section, are located predominantly at the periphery of the established consecutive and persistent hotspot core. This pattern is consistent with outward diffusion from the concentration center rather than the spontaneous emergence of new independent clusters. It suggests that the lock-in mechanism documented in the global statistics operates through a spatial contagion process, in which cells adjacent to established hotspots progressively attract STR investment as the market matures. The absence of intensifying hotspots (n = 0), defined as cells with a statistically confirmed monotonic upward trend, is consistent with the stable global clustering trajectory: the system is consolidating without accelerating, a pattern of structural maturation rather than runaway growth.

Among the 24 coldspot cells, the near-symmetry between persistent coldspots (n = 10) and consecutive coldspots (n = 8) reflects the bounded geography of the study area. The persistence of these coldspots is itself informative. It indicates that peripheral cells have not been drawn into the STR market despite eight years of aggregate growth, suggesting that the locational factors driving concentration, including proximity to major attractions and position on established tourist walking routes, create hard spatial boundaries to market expansion within the walled city. This finding resonates with Van der Borg, Costa and Gotti's [33] observation that heritage tourism creates sharp internal spatial gradients within historic cores. It also complicates simplistic narratives of wholesale touristification: even within a sub-kilometer heritage core, the transformation is spatially selective and geographically bounded.

The limited statistical power of the Mann–Kendall trend test with five time points remains an important methodological constraint. With only five observations per cell, the test has limited capacity to confirm monotonic trends, which explains why no cell achieved statistical significance at $p < 0.05$. The EHSA classifications should therefore be interpreted primarily as spatiotemporal typological characterizations describing the temporal profile of each cell's Gi* trajectory, rather than as strong monotonic trend inferences. This limitation is inherent to any longitudinal study with biennial spacing and a finite observation window, and it argues for replication at higher temporal frequency as eVisitor data accumulates in subsequent years. Importantly, the limited power of the Mann–Kendall test does not affect the validity of the Gi*-based component of EHSA, which is computed independently at each time step and provides the input data for the typological classification.

5.3. Capacity Saturation and the Absence of Fragmentation

The bivariate LISA results introduce a dimension of STR market analysis largely absent from existing literature: the distinction between unit-density concentration and accommodation-capacity concentration, and the question of whether these two dimensions are spatially concordant or discordant. The finding that High–High associations dominated all five cross-sections (50 significant cell-year observations, 56.8% of all significant cells), while High–Low associations were entirely absent, carries substantial theoretical and policy implications.

The zero High–Low count is the single most analytically decisive result in the capacity analysis. It rules out the market atomization scenario in which STR growth is driven by an influx of small, low-capacity units that increase listing counts without reproducing accommodation intensity at the neighborhood level. This is particularly noteworthy given that mean beds per unit declined monotonically from 3.55 to 3.21 over the study period, a 9.6% reduction that might naively be interpreted as evidence of fragmentation. The bivariate LISA results demonstrate that this compositional shift operates at the aggregate level but not at the spatial level. While the market as a whole is incorporating smaller units, the cells with the highest unit density are surrounded by cells with high per-unit capacity. In other words, smaller units are entering already-dense zones that retain their neighborhood-level capacity intensity, rather than peripheral cells that would represent a new, dispersed, low-capacity market segment. The declining mean beds per unit is thus a market-level compositional shift that coexists with, rather than undermines, the spatial logic of capacity saturation.

This finding speaks directly to debates about the nature of STR professionalization in European heritage cities. Cocola-Gant, Hof, Smigiel and Yrigoy [13] characterized STR expansion as a new urban frontier in which professional investors and individual participants coexist within the same market, but potentially with different spatial behaviors. The present results suggest that, in a constrained heritage core, the spatial behavior of both segments converges toward the same locations. Even as individual participants enter with smaller units, they do so in zones already characterized by high unit density and high accommodation capacity. This suggests that locational capital, the heritage, aesthetic, and infrastructural advantages of specific micro-locations within the walled city, is a more powerful determinant of STR location than either operator type or unit size. The 14 Low–High cell-year observations (15.9% of significant cells) represent a complementary pattern: peripheral cells with below-average unit counts but above-average neighborhood capacity, indicating the presence of fewer but larger units in transitional zones at the edge of the concentration core. This apartmentisation pattern may represent an early stage of the spatial contagion process identified in the EHSA results, where large-capacity operators establish footholds in cells adjacent to the saturation core before smaller operators follow. The high temporal stability of these assignments suggests that both the saturation core and the apartmentisation periphery are structurally entrenched rather than fluctuating, which is consistent with the broader lock-in thesis.

The transition matrix between 2017 and 2025 reveals that the most common trajectory for significant cells was High–High to Not significant (n = 7), while 6 cells maintained continuous High–High status across the full eight-year span. The loss of statistical significance among formerly High–High cells does not necessarily indicate de-intensification of STR activity in those locations. It may reflect the sensitivity of local spatial statistics to neighborhood composition effects, where the significance of a given cell depends not only on its own value but also on the values of its contiguous neighbors. As surrounding cells also increase in density, the local contrast that produces statistical significance can diminish even as absolute density continues to rise. This interpretation is consistent with the observed increase in Moran's I from 2017 to 2025: rising global clustering coupled with a modest reduction in statistically significant local clusters suggests that the spatial distribution is becoming more uniformly concentrated rather than more spatially polarized.

5.4. Theoretical Contributions and Conceptual Implications

The findings of this study advance three theoretical propositions that extend beyond the specific empirical context of Dubrovnik's historic core. First, the concept of spatial lock-in in STR markets can be grounded in longitudinal evidence rather than cross-sectional inference. The present results provide a more precise characterization of lock-in as a market condition in which the spatial distribution of supply remains stable despite substantial changes in aggregate volume, because the locational advantages that produce concentration are properties of place, including heritage value, tourist accessibility and symbolic capital, rather than properties of short-term supply conditions. The COVID-19 episode provides the critical test: the temporary decline in total units produced only a limited reduction in Moran's I, while the subsequent recovery restored and exceeded the pre-pandemic level. Lock-in, in this formulation, is therefore not merely the absence of spatial change, but the active reproduction of spatial hierarchy through continued investment in locations of established advantage.

Second, the EHSA results demonstrate the analytical value of temporal typology for STR research. The distinction between persistent, consecutive and new hotspots maps onto substantively different market dynamics: entrenched concentration, active consolidation and the leading edge of spatial diffusion. The dominance of consecutive hotspots over persistent ones in Dubrovnik suggests that the market, despite its apparent stability in global statistics, is still consolidating at the cell level. This finding would be invisible to cross-sectional analysis and carries different governance implications than a fully locked-in system. Markets still in the process of consolidation may be more responsive to spatially targeted intervention than those that have already reached structural equilibrium.

Third, the bivariate LISA framework demonstrates that spatial concentration and capacity saturation can be empirically distinguished as separate but concordant phenomena. The absence of High–Low clusters indicates that Dubrovnik's historic core has not followed a fragmentation pathway in which market growth is driven primarily by the proliferation of small, individually managed units that increase listing counts without increasing accommodation intensity. Instead, the saturation pathway prevails: high unit density and high per-unit capacity co-occur and reinforce each other spatially, producing zones of maximal accommodation pressure. This distinction has direct relevance for the debate on whether the sharing economy diversifies or concentrates accommodation supply [14], and for the design of regulatory instruments. A fragmented market might respond primarily to listing caps, while a saturated one may require capacity-based regulation, including bed limits or floor-area restrictions, to achieve meaningful spatial impact.

5.5. Policy Implications for Heritage Governance

The spatial intelligence generated by this study carries direct implications for STR governance in Dubrovnik and for comparable UNESCO-listed heritage cores facing similar dynamics. The fundamental policy-relevant finding is that spatial concentration is not a contingent feature of the current market configuration but a structural property likely to reproduce itself under aggregate-level regulation that does not incorporate spatial differentiation. Citywide listing caps, uniform licensing requirements and blanket tourist tax regimes, among the most commonly deployed regulatory instruments across European cities [38–40], operate primarily on aggregate supply volume. However, this study shows that aggregate volume is precisely the dimension along which the market adjusts while leaving its spatial structure largely intact. The 53% increase in units between 2017 and 2025 did not alter the geographic distribution of concentration; by implication, a proportional reduction in units would not necessarily redistribute STR pressure unless it were spatially targeted.

Spatially differentiated regulation, advocated by Nieuwland and van Melik [38] and implemented in various forms in Barcelona, Amsterdam and Paris [40], is therefore the governance framework most consistent with the patterns documented here. The EHSA classification map provides a spatial zoning input: persistent and consecutive hotspot cells constitute the saturation core where regulatory pressure should be most stringent, while no-pattern and coldspot cells may represent areas where limited STR activity remains more compatible with residential function. The bivariate LISA results add a further dimension. Because the saturation core is characterized by the co-occurrence of high unit density and high per-unit capacity, regulation targeting only unit counts without addressing bed capacity would leave part of the saturation mechanism intact. Effective governance in this context therefore requires instruments that operate on both dimensions simultaneously: the number of licensed units and the maximum accommodation capacity within designated saturation zones.

The UNESCO heritage management dimension adds further urgency to these considerations. The State of Conservation report for the Old City of Dubrovnik [46] identified tourism pressure and STR expansion among the primary threats to Outstanding Universal Value. The present study provides an empirical basis for that assessment by showing that STR concentration is not a transient phenomenon likely to self-correct through market dynamics, but a structurally persistent condition requiring active policy intervention. The transition from 54 to 56 active cells over eight years, against a background of 53–unit growth, suggests that the geographic extent of STR penetration within the walled city has effectively plateaued, while intensity within the established footprint continues to increase. Heritage management strategies that focus only on visitor flows at city-wall entry points, without addressing the internal spatial logic of STR concentration, therefore risk treating a symptom rather than the structural driver of tourism pressure within the heritage site.

5.6. Limitations

Several limitations qualify the scope and generalizability of the findings. First, the study area is a sub-kilometer historic core containing 89 H3 cells, a spatial sample size that, while adequate for global autocorrelation detection and EHSA typological classification, constrains the statistical power of cell-level trend tests and limits the number of independent spatial observations available for local statistics. The small n amplifies the influence of individual cells on global measures and reduces the discriminatory power of local statistics, potentially producing conservative significance estimates in the LISA and bivariate LISA analyses. Studies at larger spatial extents would provide stronger local-level inference, though at the cost of the micro-spatial granularity that is this study's principal analytical advantage.

Second, the five biennial time points provide meaningful coverage of the 2017–2025 arc but limit the Mann–Kendall trend test to a maximum of five observations per cell. No cell achieved significance in the trend test, meaning that EHSA classifications rest primarily on the Gi*-based typological component rather than on confirmed monotonic trends. Annual or quarterly temporal resolution would substantially strengthen the EHSA findings, and the continued accumulation of eVisitor data offers a natural pathway for replication at higher temporal frequency.

Third, the eVisitor data capture legally registered capacity rather than realized operational activity or the full universe of platform-visible STR listings. A registered unit that is legally licensed but operationally inactive, listed on no platform, or hosting no guests is indistinguishable in these data from one operating at full occupancy. Conversely, any unregistered or informal rental activity operating outside the eVisitor system cannot be observed. The analysis therefore characterizes the spatial structure of official registered STR capacity, not realized occupancy, revenue, or the full platform-visible Airbnb market. Future work integrating administrative records with platform-scraped data, occupancy indicators, or revenue data would enable analysis of operational intensity alongside spatial capacity.

Fourth, the study is a single-case analysis of an extreme heritage tourism context. Dubrovnik's historic core is a spatially bounded, UNESCO-listed, sub-kilometer enclave with extraordinary tourism intensity, conditions that are theoretically generative but empirically unusual. The lock-in dynamics recorded here may be heightened by the physical enclosure of the walled city, which constrains the spatial extent of the STR market as well as the residential alternatives available to displaced households. The analysis is also spatial-statistical and does not directly measure qualitative dimensions of residential displacement, heritage fabric degradation, or resident wellbeing, which remain central to the normative evaluation of STR impacts. The spatial patterns documented here provide the geographic structure within which these processes operate, but they do not measure them directly.

Finally, the analysis does not explicitly model intra-urban morphological variables such as building footprint density, public-space share, institutional land use, or the amount of accommodation-convertible residential floor space within each H3 cell. These features are discussed qualitatively as part of the study-area interpretation, but future research could integrate cadastral building data or land-use information to distinguish market-driven STR absence from morphologically constrained absence. Such integration would further strengthen the interpretation of spatial lock-in by linking STR concentration not only to market dynamics, but also to the inherited urban form of the historic core.

6. Conclusions

This study set out to answer a question that the existing STR literature, dominated by cross-sectional snapshots of large metropolitan areas, has rarely been able to address: is the spatial concentration of short-term rental activity in a heritage urban core a structurally persistent phenomenon, or does it fluctuate with the market conditions that produce it? Using administrative eVisitor registration data across five biennial cross-sections from 2017 to 2025, and applying an H3 resolution 11 spatial framework, the analysis provided clear answers to all three research questions.

First, spatial clustering of STR units in Dubrovnik's historic core is structurally persistent. Global Moran's I was positive and highly significant at every time point, including the COVID-19 disruption period, while the number of active H3 cells changed only marginally. The spatial structure of the market absorbed pandemic contraction, post-pandemic recovery, and sustained aggregate growth without meaningful redistribution. This pattern is characterized here as spatial lock-in: a condition in which the geographic distribution of STR supply remains stable because it is anchored to properties of place rather than to short-term market volume.

Second, the spatiotemporal typology of STR concentration reflects active consolidation rather than inert persistence. Emerging Hot Spot Analysis classified most cells as spatio-temporally structured, with consecutive hotspots outnumbering persistent ones and new hotspots forming at the edge of the established concentration core. This indicates a market still consolidating its spatial structure through incremental extension from already established zones, rather than one that has simply maintained a fixed geography from the beginning of the observation period. Persistent coldspots further confirm that even within a sub-kilometer heritage core, STR transformation is geographically selective and internally bounded.

Third, the capacity structure of STR concentration is one of saturation rather than fragmentation. Bivariate LISA analysis showed that High–High associations between unit density and beds per unit dominated the significant results, while High–Low associations were entirely absent. This finding rules out a fragmentation pathway in which STR growth is driven primarily by small, low-capacity units dispersing into new areas. Instead, smaller and larger units are entering the same established concentration zones, producing micro-locations where high unit density and high accommodation capacity reinforce one another spatially.

The convergence of these findings across global autocorrelation statistics, local cluster indicators, space-time pattern mining, and bivariate spatial association constitutes the principal empirical contribution of the study. The STR market in Dubrovnik's historic core operates as a spatially self-reproducing system in which locational capital, including heritage value, tourist accessibility, symbolic centrality, and position on established visitor routes, channels new investment into already concentrated areas. This is not a market likely to spatially self-correct through growth, contraction, or compositional change; it is a market whose spatial logic is structural.

The methodological contribution lies in the integrated use of H3-based spatial autocorrelation, Emerging Hot Spot Analysis, and bivariate LISA on administrative registration data for a constrained heritage site. The framework distinguishes not only where STR concentration occurs, but also whether it persists, consolidates, diffuses, or saturates over time. This provides a replicable approach for analyzing STR markets in other heritage cities where administrative accommodation registers are available.

The policy implication is direct: aggregate-level regulatory instruments that do not incorporate spatial differentiation are unlikely to alter the geography of STR pressure in Dubrovnik's historic core. If the spatial structure of the market is resistant to changes in aggregate volume, then effective governance must operate spatially and by capacity. Persistent and consecutive hotspot cells identified through EHSA provide a potential basis for targeted zoning, while the bivariate LISA results show that regulation should address both the number of licensed units and accommodation capacity within saturation zones. For the UNESCO heritage management framework, the findings provide empirical support for the concern that STR pressure is not a transient market effect, but a structural condition of the heritage site.

Future research should pursue four directions. First, higher-frequency temporal data would strengthen the trend component of EHSA and enable more precise detection of consolidation dynamics. Second, comparative application of the same framework to other UNESCO-listed heritage cores would test the generalizability of spatial lock-in beyond Dubrovnik. Third, integration of operational indicators such as occupancy, revenue, or platform visibility would allow analysis of realized rather than registered STR intensity. Fourth, coupling the spatial-statistical framework with qualitative fieldwork on residential displacement, heritage fabric condition, and everyday livability would connect the spatial patterns documented here to the social and material consequences they produce. The spatial lock-in of STR markets in heritage cores is ultimately a governance problem; this study provides spatial intelligence on which more effective governance can be built.

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Abbreviations

The following abbreviations are used in this manuscript:

STR	Short-Term Rentals
LISA	Local Indicators of Spatial Association

References

1. Abbasian, S.; Fredman, P. Overtourism in Dubrovnik in the Eyes of Local Tourism Employees: A Qualitative Study. *Cogent Soc. Sci.* **2020**, *6*, 1775944. [CrossRef]
2. Pavlić, I.; Portolan, A.; Puh, B. Segmenting Local Residents by Perceptions of Tourism Impacts in an Urban World Heritage Site: The Case of Dubrovnik. *J. Herit. Tour.* **2020**, *15*, 398–409. [CrossRef]
3. Cocola-Gant, A.; Gago, A. Airbnb, Buy-to-Let Investment and Tourism-Driven Displacement: A Case Study in Lisbon. *Environ. Plan. A* **2021**, *53*, 1671–1688. [CrossRef]
4. Wachsmuth, D.; Weisler, A. Airbnb and the Rent Gap: Gentrification Through the Sharing Economy. *Environ. Plan. A* **2018**, *50*, 1147–1170. [CrossRef]
5. Adamiak, C. Mapping Airbnb Supply in European Cities. *Ann. Tour. Res.* **2018**, *71*, 67–71. [CrossRef]
6. Gurran, N.; Phibbs, P. When Tourists Move In: How Should Urban Planners Respond to Airbnb? *J. Am. Plan. Assoc.* **2017**, *83*, 80–92. [CrossRef]
7. Ferreri, M.; Sanyal, R. Platform Economies and Urban Planning: Airbnb and Regulated Deregulation in London. *Urban Stud.* **2018**, *55*, 3353–3368. [CrossRef]
8. Openshaw, S. *The Modifiable Areal Unit Problem*; CATMOG 38; Geo Books: Norwich, UK, 1984.
9. Gutiérrez, J.; García-Palomares, J.C.; Romanillos, G.; Salas-Olmedo, M.H. The Eruption of Airbnb in Tourist Cities: Comparing Spatial Patterns of Hotels and Peer-to-Peer Accommodation in Barcelona. *Tour. Manag.* **2017**, *62*, 278–291. [CrossRef]
10. Ki, D.; Lee, S. Spatial Distribution and Location Characteristics of Airbnb in Seoul, Korea. *Sustainability* **2019**, *11*, 4108. [CrossRef]
11. Cocola-Gant, A. Holiday Rentals: The New Gentrification Battlefront. *Sociol. Res. Online* **2016**, *21*, 112–120. [CrossRef]
12. Katsinas, P. Professionalisation of Short-Term Rentals and Emergent Tourism Gentrification in Post-Crisis Thessaloniki. *Environ. Plan. A* **2021**, *53*, 1652–1670. [CrossRef]
13. Cocola-Gant, A.; Hof, A.; Smigiel, C.; Yrigoy, I. Short-Term Rentals as a New Urban Frontier: Evidence from European Cities. *Environ. Plan. A* **2021**, *53*, 1601–1608. [CrossRef]
14. Guttentag, D. Airbnb: Disruptive Innovation and the Rise of an Informal Tourism Accommodation Sector. *Curr. Issues Tour.* **2015**, *18*, 1192–1217. [CrossRef]
15. García-López, M.A.; Jofre-Monseny, J.; Martínez-Mazza, R.; Segú, M. Do Short-Term Rental Platforms Affect Housing Markets? Evidence from Airbnb in Barcelona. *J. Urban Econ.* **2020**, *119*, 103278. [CrossRef]
16. Horn, K.; Merante, M. Is Home Sharing Driving Up Rents? Evidence from Airbnb in Boston. *J. Hous. Econ.* **2017**, *38*, 14–24. [CrossRef]

17. Barron, K.; Kung, E.; Proserpio, D. The Effect of Home-Sharing on House Prices and Rents: Evidence from Airbnb. *Mark. Sci.* **2021**, *40*, 23–47. [CrossRef]
18. Franco, S.F.; Santos, C.D. The Impact of Airbnb on Residential Property Values and Rents: Evidence from Portugal. *Reg. Sci. Urban Econ.* **2021**, *88*, 103667. [CrossRef]
19. Deboosere, R.; Kerrigan, D.J.; Wachsmuth, D.; El-Geneidy, A. Location, Location and Professionalization: A Multilevel Hedonic Analysis of Airbnb Listing Prices and Revenue. *Reg. Stud. Reg. Sci.* **2019**, *6*, 143–156. [CrossRef]
20. Vizek, M.; Stojčić, N.; Mikulić, J. Spatial Spillovers of Tourism Activity on Housing Prices: The Case of Croatia. *Tour. Econ.* **2023**, *29*, 1376–1390. [CrossRef]
21. Stojčić, N.; Vizek, M.; Glaurdić, J. Short-Term Rental Expansion and Residential Displacement in Tourism Communities: Evidence from Croatia. *Reg. Stud.* **2024**, *58*, 2115–2128. [CrossRef]
22. Dolnicar, S.; Zare, S. COVID19 and Airbnb—Disrupting the Disruptor. *Ann. Tour. Res.* **2020**, *83*, 102961. [CrossRef] [PubMed]
23. Llaneza Hesse, C.; Raya Vílchez, J.M. The Effect of COVID-19 on the Peer-to-Peer Rental Market. *Tour. Econ.* **2022**, *28*, 222–247. [CrossRef]
24. Sigala, M. Tourism and COVID-19: Impacts and Implications for Advancing and Resetting Industry and Research. *J. Bus. Res.* **2020**, *117*, 312–321. [CrossRef] [PubMed]
25. Cocola-Gant, A. Place-Based Displacement: Touristification and Neighbourhood Change. *Geoforum* **2023**, *138*, 103665. [CrossRef]
26. Jover, J.; Díaz-Parra, I. Gentrification, Transnational Gentrification and Touristification in Seville, Spain. *Urban Stud.* **2020**, *57*, 3044–3059. [CrossRef]
27. Koens, K.; Postma, A.; Papp, B. Is Overtourism Overused? Understanding the Impact of Tourism in a City Context. *Sustainability* **2018**, *10*, 4384. [CrossRef]
28. Milano, C.; Cheer, J.M.; Novelli, M. (Eds.) *Overtourism: Excesses, Discontents and Measures in Travel and Tourism*; CABI: Wallingford, UK, 2019.
29. Peeters, P.; Gössling, S.; Klijs, J.; Milano, C.; Novelli, M.; Dijkmans, C.; Eijgelaar, E.; Hartman, S.; Heslinga, J.; Isaac, R.; et al. *Research for TRAN Committee: Overtourism: Impact and Possible Policy Responses*; European Parliament: Brussels, Belgium, 2018. [CrossRef] [PubMed]
30. Goodwin, H. The Challenge of Overtourism; Responsible Tourism Partnership Working Paper 4. 2017. Available online: https://haroldgoodwin.info/wp-content/uploads/2020/08/rtpwp4overtourism012017.pdf (accessed on 30 March 2026).
31. Capocchi, A.; Vallone, C.; Pierotti, M.; Amaduzzi, A. Overtourism: A Literature Review to Assess Implications and Future Perspectives. *Sustainability* **2019**, *11*, 3303. [CrossRef]
32. Russo, A.P. The "Vicious Circle" of Tourism Development in Heritage Cities. *Ann. Tour. Res.* **2002**, *29*, 165–182. [CrossRef]
33. Van der Borg, J.; Costa, P.; Gotti, G. Tourism in European Heritage Cities. *Ann. Tour. Res.* **1996**, *23*, 306–321. [CrossRef]
34. Ashworth, G.; Page, S.J. Urban Tourism Research: Recent Progress and Current Paradoxes. *Tour. Manag.* **2011**, *32*, 1–15. [CrossRef]
35. Brandano, M.; Faggian, A.; Pinate, A.C. *The Impact of COVID-19 on the Tourism Sector in Italy: A Regional Spatial Perspective*; Working Paper CRENoS 202309; Centre for North South Economic Research, University of Cagliari and Sassari: Sardinia, Italy, 2023. Available online: https://ideas.repec.org/p/cns/cnscwp/202309.html (accessed on 30 March 2026).
36. Milano, C. Overtourism, Social Unrest and Tourismphobia: A Controversial Debate. *PASOS* **2018**, *16*, 551–564. [CrossRef]
37. Dodds, R.; Butler, R. (Eds.) *Overtourism: Issues, Realities and Solutions*; De Gruyter: Berlin, Germany, 2019.
38. Nieuwland, S.; van Melik, R. Regulating Airbnb: How Cities Deal with Perceived Negative Externalities of Short-Term Rentals. *Curr. Issues Tour.* **2020**, *23*, 811–825. [CrossRef]
39. von Briel, D.; Dolnicar, S. The Evolution of Airbnb Regulation—An International Longitudinal Investigation 2008–2020. *Ann. Tour. Res.* **2021**, *87*, 102983. [CrossRef]
40. Dredge, D.; Gyimóthy, S.; Birkbak, A.; Jensen, T.E.; Madsen, A.K. *The Impact of Regulatory Approaches Targeting Collaborative Economy in the Tourism Accommodation Sector: Barcelona, Berlin, Amsterdam and Paris*; Impulse Paper No. 9; European Commission: Brussels, Belgium, 2016.
41. Colomb, C.; Novy, J. (Eds.) *Protest and Resistance in the Tourist City*; Routledge: London, UK, 2016.
42. Niedziółka, A.; Tucki, A.; Świeca, A.; Skowronek, E. Impact of COVID-19 on Short-Term Rental Market in Poland. *Land* **2021**, *10*, 862. [CrossRef]
43. Opačić, V.T.; Klarić, Z.; Beroš, I.; Boranić Živoder, S. Tourism Development Index of Local Self-Government Units: The Example of Croatia. *Acta Geogr. Slov.* **2022**, *62*, 77–87. [CrossRef]
44. Gredičak, T. Kulturna baština u funkciji turizma. *Acta Tur. Nova* **2008**, *2*, 205–234.
45. Gredičak, T. Kulturna baština i gospodarski razvitak Republike Hrvatske. *Ekon. Pregl.* **2009**, *60*, 196–218.
46. UNESCO World Heritage Centre. State of Conservation (SOC 2023)—Old City of Dubrovnik (Croatia). 2023. Available online: https://whc.unesco.org/en/soc/4440 (accessed on 30 March 2026).
47. Pavlic, I.; Portolan, A.; Benić, Ð. Residents' Attitudes towards Tourism Development: The Case of Dubrovnik. *Int. J. Tour. Res.* **2013**, *15*, 407–416. [CrossRef]

48. Pavlić, I.; Portolan, A.; Puh, B. (Un)supported Current Tourism Development in UNESCO Protected Site: The Case of Old City of Dubrovnik. *Economies* **2017**, *5*, 9. [CrossRef]
49. Mikulić, J.; Krešić, D.; Prebežac, D.; Miličević, K.; Šerić, M. Identifying Drivers of Destination Attractiveness in a Competitive Environment: A Comparison of Approaches. *J. Destin. Mark. Manag.* **2016**, *5*, 163–174. [CrossRef]
50. Lestegás, I.; Seixas, J.; Lois-González, R.C. Commodifying Lisbon: A Study on the Spatial Concentration of Short-Term Rentals. *Soc. Sci.* **2019**, *8*, 33. [CrossRef]
51. Eugenio-Martin, J.L.; Cazorla-Artiles, J.M.; González-Martel, C. On the Determinants of Airbnb Location and Its Spatial Distribution. *Tour. Econ.* **2019**, *25*, 1224–1244. [CrossRef]
52. Moran, P.A.P. Notes on Continuous Stochastic Phenomena. *Biometrika* **1950**, *37*, 17–23. [CrossRef]
53. Anselin, L. Local Indicators of Spatial Association—LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [CrossRef]
54. Getis, A.; Ord, J.K. The Analysis of Spatial Association by Use of Distance Statistics. *Geogr. Anal.* **1992**, *24*, 189–206. [CrossRef]
55. Ord, J.K.; Getis, A. Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geogr. Anal.* **1995**, *27*, 286–306. [CrossRef]
56. Bivand, R.S.; Wong, D.W.S. Comparing Implementations of Global and Local Indicators of Spatial Association. *TEST* **2018**, *27*, 716–748. [CrossRef]
57. Cliff, A.D.; Ord, J.K. *Spatial Processes: Models and Applications*; Pion: London, UK, 1981.
58. Pebesma, E. Simple Features for R: Standardized Support for Spatial Vector Data. *R J.* **2018**, *10*, 439–446. [CrossRef]
59. Bivand, R.S.; Pebesma, E.; Gómez-Rubio, V. *Applied Spatial Data Analysis with R*, 2nd ed.; Springer: New York, NY, USA, 2013. [CrossRef]
60. Parry, J.; Locke, D. *sfdep: Spatial Dependence for Simple Features*, R package version 0.2.8; Comprehensive R Archive Network (CRAN): Vienna, Austria, 2023. [CrossRef]
61. Anselin, L. A Local Indicator of Multivariate Spatial Association: Extending Geary's C. *Geogr. Anal.* **2019**, *51*, 133–150. [CrossRef]
62. Roshan, G.; Ghanghermeh, A.; Asadi, K.; Attia, S. Spatiotemporal Analysis of Urban Heat Islands and Vegetation Cover Using Emerging Hotspot Analysis in a Humid Subtropical Climate. *Atmosphere* **2024**, *15*, 161. [CrossRef]
63. Uber Technologies. H3: Uber's Hexagonal Hierarchical Spatial Index. 2018. Available online: https://h3geo.org (accessed on 1 April 2026).
64. Hrvatska turistička zajednica. Statistički Podaci iz Sustava EVisitor. 2026. Available online: https://www.htz.hr/ (accessed on 1 April 2026).