

Spatial Analysis of Airbnb Properties: A Review of Applied Methods

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Abstract

The phenomenon of short-term house rentals has rapidly developed in recent years. The most well-known platform offering primarily short-term rentals is “Airbnb”. Initially, the platform allows hosts to rent out accommodations (apartments, houses, or even rooms). The platform allows users to filter accommodation options based on several factors, including cost per night, property category, user feedback, and proximity. The factors influencing the demand in terms of location and setting the spatial distribution of Airbnb properties have been the subject of many studies. These factors include, among others, social, economic, and demographic aspects, as well as considerations of accessibility, the location and attractiveness of popular areas, and the characteristics of the available accommodations. This paper provides an overview of the methods used in previous research papers to analyze the spatial distribution of Airbnb properties and compares the findings. By offering a structured comparison, this article aims to provide an integrated understanding of the spatial dynamics that drive Airbnb property distribution.

Keywords

Spatial Analysis, Airbnb, Review, Short-Term Rentals

1. Introduction

The rise of short-term rental platforms has redefined the way people experience travel and accommodation. Among these platforms, Airbnb has appeared as a global leader, bridging the gap between traditional hospitality and peer-to-peer sharing economies. Offering diverse lodging options—from comfortable single

rooms to luxurious villas—Airbnb caters to a broad spectrum of travellers. Its user-friendly interface, combined with customizable search options for price, location, and amenities, has positioned it as a dominant force in the travel industry. However, the rapid expansion of Airbnb has also sparked significant interest in understanding the factors that influence the spatial distribution of its properties. These factors include socioeconomic and demographic variables, the attractiveness of popular areas, and even specific property characteristics. By analysing these aspects, researchers aim to uncover the underlying dynamics shaping Airbnb's spatial footprint and its implications for urban development. The study of Airbnb's spatial distribution is crucial for several reasons. Airbnb has reshaped urban landscapes, influencing housing markets, gentrification, and local economies [1]. Analyzing its spatial footprint enables policymakers to track housing availability and affordability, check rising rental prices, and design effective strategies to balance the interests of local communities and tourists. Also, understanding the spatial factors that influence Airbnb's spread, including accessibility to public transport, major road networks, and airports, as well as the attractiveness of areas with cultural landmarks or scenic views, is crucial as it lays the groundwork for any future studies examining the impact of other variables [2]. At the same time, Airbnb impacts urban planning and governance [3]. Short-term rentals can lead to over-tourism in specific neighbourhoods, putting pressure on local infrastructure and affecting community life. On the other hand, they may increase economic activity, for example by attracting travellers to less. Mapping these patterns aids in uncovering challenges and thus creating sustainable urban policies. The sharing economy through the Airbnb platform, has introduced significant changes as well as several challenges and opportunities, such as:

- Airbnb diverts revenue from traditional market sectors such as the hotel industry to individual property owners. This coupled with a lack of regulatory frameworks, has caused some tax revenue losses for governments in the past. On the other hand, some property owners have managed to survive the economic crisis in Greece by earning a moderate monthly income by renting their houses through the Airbnb platform. Since 2010 and up to 2018 about 126331 properties in total have been registered on the Airbnb platform; however, this number has decreased significantly today because properties of lower quality standards have difficulty finding tenants.
- A new form of gentrification, termed “hotelization”, has appeared especially in tourist or central areas. This transformation, driven by Airbnb, involves turning middle-class neighbourhoods into tourism-focused, exclusive areas. The growth of Airbnb has caused rents to rise, as property owners choose short-term tourist rentals over long-term tenants. This has forced lower-income residents out of city centres, turning entire neighbourhoods into “hotel zones”.
- Fourthly, the transformation of these neighbourhoods affects not just real estate but also the social fabric, leading to conflicts between locals and tourists.

The displacement of economically weaker groups has undermined original urban planning goals, disrupted daily life, and caused tensions within communities.

- Airbnb has contributed to urban renewal, with neglected or abandoned buildings being renovated to accommodate tourists, which improves the city's image but also leads to greater demands on infrastructure [4]. For example, many old and vacant apartments in Athens have been renovated with the purpose of being used for short-term renting as this is the only rental type that may recover the renovation and maintenance expenses fast.
- The rapid growth of short-term rentals needs policy interventions to address issues like noise, congestion, and safety while ensuring urban planning and housing policies are revised for balanced and sustainable development.

By taking into account these elements, a study on Airbnb's spatial distribution not only highlights the transformative effects of Airbnb on cities but also underscores the importance of strategic planning to mitigate the challenges. The primary aim of this review is to consolidate and evaluate the methods and data used in previous studies to analyse the spatial distribution of Airbnb properties. These analytical approaches allow researchers to assess the impact of various spatial, social, and economic factors on Airbnb distribution. By offering a structured comparison of methods and findings, this article aims to provide an integrated understanding of the spatial dynamics driving Airbnb distribution. Ultimately, the insights derived from this review aim to inform urban planning, policymaking, and future academic research, contributing to a more balanced and sustainable approach to managing the growth of short-term rentals. To achieve this, the review systematically compares existing studies on the spatial distribution of Airbnb, focusing on four key aspects examined in previous research:

- Study Area: Analysis of the geographic regions selected in previous studies to show potential spatial distribution patterns of Airbnb in different urban and tourist environments.
- Data: Comparison of the types of data used in the studies, such as Airbnb listings, transportation networks, accessibility to points of interest, rental or property prices, and other relevant variables.
- Methods: Evaluation of the methods applied in the studies, including spatial analysis techniques, statistical methods, and machine learning models.
- Results: Comparison of the main findings of each study to highlight trends, similarities, and differences in the spatial distribution of Airbnb, as well as to show potential research gaps.

Through this comparative approach, the review aims to highlight the strengths, limitations, and gaps of the methods used in the literature, providing a comprehensive overview of existing research and future directions for studying the spatial dimension of Airbnb. As a methodological approach, this study adopts a systematic literature review in order to identify, compare, and critically assess the data sources and analytical methods applied in previous research on the spatial distri-

bution of Airbnb properties. This review is based on a systematic literature search conducted between 2017 and 2025. Academic articles were identified using the Scopus and Web of Science databases, complemented by targeted searches in Google Scholar to capture recently published or in-press studies. The search strategy combined keywords such as Airbnb, short-term rentals, spatial distribution, spatial analysis, geographically weighted regression, spatial econometrics, and urban tourism. Inclusion criteria required that studies (i) explicitly analysed the spatial distribution of Airbnb listings, (ii) applied quantitative spatial or econometric methods, and (iii) focused on urban or tourist contexts. Exclusion criteria included purely descriptive studies, non-spatial analyses, conference abstracts without full papers, and studies focusing exclusively on demand-side behaviour. Following screening and eligibility checks, a total of seventeen peer-reviewed articles were selected for detailed analysis.

2. Historical Development of Short-Term Rentals and Characteristics

2.1. History of Short-Term Rentals

The history of the short-term rental market, a kind of “private rooms to let” informal and untaxed or organized businesses, is a post-World War type of tourism and low-cost accommodation closely related to vacation in the various popular tourist destinations in Europe and globally. It worked in parallel with the formal travel organizers’ market and hotels, guesthouses, and “bed and breakfasts” industry, mainly as a low-cost accommodation alternative for both local and international tourism for vacation purposes. Its informal operation was tolerated due to its dual benefit. It helped local economies by increasing the income of low- and low-middle-income residents during vacation periods, too. In the second half of the 20th century, there was a rise of mass tourism, with more people having the means and leisure time to travel; many individuals offered rooms in their homes to tourists, creating a diverse range of “personalized” accommodation choices. The current form of short-term rentals is closely linked to the globalization of tourism, the rapid increase of tourist destinations, and the parallel evolution of Internet services and online platforms in the 90s. It began in 1995 with the launch of VRBO (Vacation Rentals by Owner), which operated as digital “advertisements” and focused on vacation rentals in resort destinations, mainly in the U.S. [5]. Booking.com emerged one year later, comparing hotel rates and Craigslist began ads for long- and short-term rentals around the same time [6]. In the mid-2000s, HomeAway appeared from the merger of five rental sites and acquired VRBO in 2006, becoming a dominant player in marketing [7]. The autumn of 2007 marked the beginning of Airbnb, an idea born out of necessity when Brian Chesky and Joe Gebbia sought extra income to pay their rent in San Francisco. They purchased three inflatable mattresses and rented them out nightly, branding their concept “Airbed and Breakfast” and creating a website to advertise. In February 2008, Nathan Blecharczyk, a technical architect and Harvard graduate,

joined Brian and Joe to set up Airbnb officially. By 2012, Airbnb's website featured over 100,000 properties (houses, apartments, and villas) in 192 countries. Today, Airbnb boasts over 8 million listings worldwide. Several other platforms have contributed to the evolution of the short-term rental market, including Couchsurfing (launched in 2004)—a free online hospitality exchange network [8], Onefinestay (founded in 2010), which focuses on luxury accommodations, and Wimdu, established in Berlin in 2011 as an online marketplace for short-term lodging. Nevertheless, this study will concentrate on Airbnb, given its widespread popularity, rapid expansion, and significant impact on the rental property sector.

2.2. Opportunities

Airbnb and similar short-term rental platforms have introduced many benefits to urban environments and travelers alike. Research examining the success of Peer-to-Peer (P2P) rental practices, where individuals rent out properties via online platforms, indicates that this success is driven by several key factors that also influence their spatial distribution. One of the primary reasons is supplemental income and asset use, as P2P rentals allow individuals to generate extra income by monetizing underutilized housing stock, often located within residential neighborhoods. Another major factor is the desire for authentic experiences, with travelers increasingly seeking alternatives to standardized tourism offerings. Many visitors prefer accommodations embedded in everyday urban environments, allowing them to immerse themselves in local culture, daily life, and neighborhood dynamics [9]. Cost-effectiveness also plays a crucial role, as short-term rentals often provide access to centrally located or well-connected areas at more affordable prices than traditional hotels, contributing to a spatial redistribution of tourist accommodation beyond established hotel districts. Additionally, social interaction between hosts and guests reinforces the attractiveness of short-term rentals in residential settings, supporting their expansion outside conventional tourism zones. Another factor contributing to the success of P2P rentals is the availability of unique and non-standardized accommodation options. Unlike conventional hotels, which generally follow standardized designs, short-term rental platforms offer a diverse range of lodging choices, facilitating the emergence of Airbnb listings in areas that traditionally lacked formal tourist infrastructure. Collectively, these elements explain the widespread appeal and rapid expansion of Airbnb, while highlighting its role in reshaping the spatial structure of urban tourism and accommodation markets.

2.3. Challenges

Despite its popularity, Airbnb has raised a series of challenges with significant implications for urban housing markets and community dynamics. From a spatial perspective, these challenges are closely related to the uneven geographical distribution and spatial concentration of short-term rental properties [10]. Airbnb's challenges include issues related to rising housing costs [11] and reduced availa-

bility of long-term rentals, particularly in central, tourist-oriented, and high-demand neighborhoods, as well as neighborhood disruptions and gentrification processes [12]. The spatial concentration of Airbnb listings in specific districts has been associated with increased pressure on local residents, contributing to changes in the social composition of neighbourhoods and alterations in their functional and residential character. Historic centres and well-connected areas are especially affected, as residential units are increasingly converted into short-term rentals, intensifying socio-spatial inequalities. Moreover, spatial clustering of Airbnb properties can amplify localized disturbances, including noise, congestion, and changes in everyday community life. These spatially uneven impacts have led to growing reactions from residents in many cities, who argue that Airbnb exacerbates housing problems and undermines neighbourhood cohesion and sense of community. As a result, many local authorities have introduced regulatory measures aimed at controlling the spatial concentration of short-term rentals and mitigating their effects on housing affordability and urban liveability [13].

3. International Research: State-of-the-Art

This section presents a comprehensive literature review based on the analysis of recent academic articles that investigate the spatial distribution of Airbnb accommodations. Each article was examined in terms of study area, data sources, applied methods, types of variables used, and key findings. The aim is to find patterns, commonalities, and differences in how researchers approach the spatial analysis of Airbnb. To enhance clarity and enable meaningful comparisons, the studies are categorized by continent (Europe, North America, Asia). This geographical classification is considered necessary to reflect regional particularities in urban structures, housing markets, tourism patterns, and regulatory frameworks, all of which can significantly influence both the choice of methods and the resulting outcomes.

3.1. Europe

The spatial distribution of Airbnb accommodations has been widely studied across various European cities, revealing diverse patterns and determinants influenced by socioeconomic, geographic, and tourism-related factors. A spatial analysis of Airbnb in the wider Athens region, Greece [14] conducted a spatial analysis of Airbnb in the wider Athens region, Greece. Using data obtained from the *airdna.com* and *insideairbnb.com* websites, as well as from the Greek Statistical Authority (ELSTAT), they found that the maximum number of rentals was in the center of Athens, while the highest average price per night occurred in Vouliagmeni. They saw a positive correlation between rents and the price per square meter and a negative correlation between wage earners and unemployment. The study applied both Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) methods; OLS was calculated in SPSS and GWR in ArcGIS. With the number of Airbnb rentals as the dependent variable, the OLS method produced an R^2 coefficient of 85.7%, while GWR yielded 93%. When considering

the average price per night as the dependent variable, OLS had an R^2 of 41.7%, and GWR improved this to 71% [14]. In Barcelona, a study examined the spatial distribution of Airbnb accommodations, focusing on the relationship between Airbnb rental prevalence and socioeconomic characteristics alongside tourism-related indicators [15]. Employing a GWR model, it provided localized insights on how socioeconomic factors influence the ratio of Airbnb accommodations to total households per neighborhood. Independent variables included education levels, family income, immigrant diversity, population density, the percentage of residences below 75 sqm, and proximity to the city center and tourist points of interest. Using R software for data analysis, geospatial processing, and mapping, the GWR model outperformed the OLS model with an R^2 value of 0.84 compared to 0.63. The OLS model revealed a significant positive correlation between the Airbnb-to-household ratio and the presence of non-EU migrants and proximity to tourist attractions, alongside negative correlations with family income, population density, and distance from the city center. These findings highlight the uneven distribution of Airbnb accommodations closely tied to socioeconomic disparities [15]. Spatial patterns of Airbnb and hotels in Barcelona were analyzed by comparing geolocated datasets such as Airbnb listings from Inside Airbnb, hotel locations from the Catalonia Tourism Registry, tourist activity from Panoramio geotagged photos, and demographic and land-use data from the municipal census and Cadastre 2014 [16]. The GIS-based method involved data aggregation by census tracts to create density maps and descriptive statistics. Normalization techniques were used to compare hotel and Airbnb distributions. Spatial autocorrelation analysis using Global Moran's I revealed clustering patterns, with Airbnb showing stronger clustering (0.70, $p < 0.01$) than hotels (0.23, $p < 0.01$), contradicting Airbnb's claim of dispersed distribution. Bivariate spatial autocorrelation confirmed a strong spatial correlation between Airbnb and hotels, with Airbnb benefiting more from proximity to tourist attractions (Airbnb-Panoramio Moran's I: 0.18 vs. Hotels-Panoramio Moran's I: 0.08). OLS regression showed that Airbnb supply is positively associated with the city center, beaches, tourist hotspots, and leisure areas, while hotels displayed more diversified location patterns influenced by business districts and transport infrastructure. The study concluded that Airbnb intensifies tourism-related gentrification and conflicts with residents, leading to regulatory interventions [16]. The spatial distribution of Airbnb rentals and hotels in London and their relationships with demographic, socioeconomic, and environmental factors were explored using spatial econometric models that account for spatial dependence [17]. The study incorporated variables from eight categories—population, tourist flows, transport, employment, environmental quality, safety, well-being, and housing—chosen based on previous literature. Using the local bivariate Moran's I index, the spatial relationship between Airbnb and hotels was analyzed, while spatial lag and error models investigated the influence of socioeconomic and environmental factors. Results revealed a coexistence relationship between Airbnb rentals and hotels in central ar-

areas and a substitution relationship in popular tourist areas. Accessibility was identified as a key determinant for accommodation supply, with hotels influenced mainly by agglomeration effects, whereas Airbnb locations were shaped by environmental factors, the presence of hotels, and rental housing availability. The study emphasized the importance of spatial dependence in understanding accommodation dynamics and highlighted differing spatial drivers for Airbnb and hotels [17]. The spatial distribution of Airbnb in Barcelona and Lisbon was examined, analyzing penetration degree, spatial clustering using the Local Indicator of Spatial Association (LISA), and the determinants of clustering [18]. Data from Inside Airbnb (2019-2020), the 2011 Census, municipal registers (2011-2019), and OpenStreetMap were used. Explanatory variables included distance to the city centre, points of interest, public transport access, population density, average rent, and cultural characteristics such as the proportion of native residents and university education. LISA analysis revealed significant spatial clustering of Airbnb listings in central neighborhoods of both cities, with Barcelona showing the highest concentration in historic areas such as Barri Gòtic and El Raval, while peripheral neighborhoods exhibited low penetration. Moran's I values were 0.79 for Barcelona and 0.55 for Lisbon. Negative binomial regression models indicated that proximity to the city centre was negatively related to Airbnb penetration in both cities, with a stronger effect observed in Barcelona. Points of interest had a positive impact on Airbnb listings, while public transport access facilitated Airbnb expansion in Lisbon but was not significant in Barcelona. High average rent increased Airbnb listings in Barcelona, whereas vacant apartments played a key role in Lisbon. Demographic factors exhibited contrasting effects, with population density negatively affecting Airbnb in Barcelona but positively in Lisbon. The COVID-19 pandemic resulted in a 3.7% reduction in listings in Barcelona and a 21.6% reduction in Lisbon between September 2019 and December 2020, particularly in central neighborhoods. The pandemic also shifted listing typology towards a higher share of entire apartments in Barcelona. The study concluded that Airbnb exacerbates spatial inequalities, benefiting affluent central neighborhoods while providing limited benefits to peripheral areas, thereby underscoring the need for effective regulation to promote fairer urban space distribution [18]. Airbnb listings across Spain were analyzed, focusing on spatial variation, density, and influencing factors [19]. The dataset of 247,456 listings (October 2018) was collected through web scraping and classified into entire homes (81.7%), private rooms (17.7%), and shared rooms (0.6%). The study covered 8,124 municipalities and 79 tourist areas, using the Hoover Index and Moran's I to measure spatial concentration and autocorrelation. A Hoover Index value of 0.802 indicated a high concentration of Airbnb listings in coastal and urban areas. Moran's I was 0.314 ($p < 0.001$), confirming strong spatial autocorrelation. Regression analysis showed that proximity to the coastline significantly increased Airbnb availability by 51.5%, while the number of non-primary dwellings per square kilometer positively affected listings (coefficient 0.133, $p < 0.001$). Coastal areas such as Costa del Sol and Costa Blanca

recorded over 500 listings per 1000 hotel rooms, whereas inland cities such as Madrid exhibited lower densities (323.6 listings per 1000 hotel rooms). Private rooms were mainly concentrated in large cities, where they nearly equaled entire homes in Barcelona and Madrid. Moran's I values for private rooms were 0.276 in Barcelona, while entire homes exhibited a value of 0.327. The study concluded that peer-to-peer platforms enhance tourism dynamics, particularly in tourist areas; however, concentration in already developed locations may exacerbate spatial imbalances, highlighting the need for targeted regulation [19]. Airbnb's spatial penetration was examined in seven major Spanish tourist cities—Madrid, Barcelona, Valencia, Seville, Malaga, Palma de Mallorca, and Bilbao [20]. Using Inside Airbnb data, the 2011 census, municipal registers, and OpenStreetMap, spatial clustering was analyzed via LISA, while determinants of spatial spread were identified through negative binomial regression. Airbnb listings were found to cluster in city centers and tourist areas, challenging claims that the platform benefits peripheral neighborhoods. Key determinants included proximity to tourist attractions, population density, house rent, household income, education level, and migration patterns. R^2 values for the LISA analysis ranged from 0.49 in Bilbao to 0.83 in Madrid, indicating strong spatial clustering. A high proportion of multi-hosts suggested a significant degree of Airbnb commercialization. The findings highlighted Airbnb's role in intensifying spatial inequalities and housing pressures, leading to calls for regulation, rental quotas, and targeted policy interventions to mitigate negative urban impacts [20]. Airbnb's spatial distribution and its determinants were explored in the Canary Islands, a region characterized by urban, sun-and-beach, and nature-based tourism [21]. Using 25,987 georeferenced Airbnb listings, 1792 hotels, and 819,039 geotagged tourist photos as a proxy for demand, modified Pearson's r , Global Bivariate Moran's I, and Local Bivariate LISA were applied to measure spatial correlation. The spatial analysis employed a 1-km grid and an eighty nearest neighbors spatial weight matrix. High spatial correlation was identified, particularly in urban areas (Pearson's $r = 0.910$ in Gran Canaria and 0.809 in Tenerife). Airbnb supply was more spatially dispersed than hotels, with peak spatial autocorrelation at 4.7 km compared to 3.7 km for hotels. Local Bivariate LISA detected High-High clusters in coastal areas of Tenerife, Gran Canaria, and Lanzarote, as well as in urban centers, while protected areas exhibited limited supply. Elasticity analysis indicated that Airbnb price was the most significant determinant (elasticity = 4.456), with tourist demand and population size also exerting a positive influence. In sun-and-beach destinations, Airbnb location was primarily driven by proximity to tourist resources, whereas nature-based destinations displayed greater spatial dispersion, contributing to spatial equity. The study concluded that Airbnb distribution varies by destination type, with stronger competition in urban areas and greater spatial equity in nature-based destinations, supporting the need for differentiated regulatory approaches [21]. Airbnb's spatial distribution in Switzerland was examined using data from 32,761 listings (January 2018) obtained via the Airbnb API, alongside

official statistics from Swiss authorities on second homes, population density, hotel density, employment sectors, and proximity to ski resorts [22]. Spatial clustering was confirmed by a global Moran's I value of 0.34, revealing high-density Airbnb clusters in Geneva, Lausanne, and other major tourist hubs. Bivariate Moran's I analysis indicated positive spatial autocorrelation between Airbnb listings and second homes ($I = 0.26$) as well as ski resorts ($I = 0.24$). Spatial regression models, including the Spatial Error Model and Spatial Lag Model, demonstrated that the prevalence of second homes significantly and positively influenced Airbnb density (coefficients ranging from 0.17 to 0.22), together with proximity to ski resorts and urban amenities. The study concluded that Airbnb listings follow traditional second home patterns and are concentrated in both urban centers and tourist mountain areas, with notable implications for regional tourism management and housing markets [22]. The geographical dimensions of Airbnb in mountain areas were examined through an in-depth spatial analysis of Andorra, a small Pyrenean country highly dependent on tourism [23]. The study focused on the spatial distribution of Airbnb listings and their correlation with traditional tourist accommodations and urban settlement types. The dataset was compiled through web scraping from DataHippo and included 819 active Airbnb listings recorded between April and September 2018. In addition, data on 325 officially registered tourist accommodations—comprising hotels, apartments, and other lodging types—was collected from the Tourism Department of Andorra. The analysis employed spatial correlation techniques, including Bivariate Moran's I and Pearson's R, to assess the degree of clustering between Airbnb and traditional accommodation. Furthermore, K-means clustering analysis was used to classify Andorran urban settlements based on the intensity of tourist accommodation supply. The findings revealed a significant concentration of Airbnb activity in the municipality of Canillo, with 113.3 listings per 1,000 inhabitants, strongly associated with proximity to Grandvalira, the most visited ski resort in the region. In contrast, the capital city, Andorra la Vella, recorded only 64 listings (representing 7% of the total and just 2.9 listings per 1,000 inhabitants), indicating that Airbnb distribution follows a profit-maximization logic rather than population density. Both Pearson's R (0.505, $p < 0.01$) and Bivariate Moran's I (0.215, $p < 0.01$) demonstrated a statistically significant positive spatial relationship between Airbnb listings and tourist housing, suggesting overlap between Airbnb and the official accommodation market. However, the discrepancy between the number of Airbnb listings and officially registered tourist homes raises concerns regarding the potential presence of unlicensed short-term rentals. The clustering analysis identified four distinct types of urban settlements, with those closest to ski resorts hosting the highest Airbnb densities—up to 70% of listings operated by multi-hosts in certain areas. Overall, the study indicates that Airbnb operates primarily as an extension of Andorra's established tourism industry rather than as a disruptive force, although regulatory challenges and the control of illegal listings remain [23].

The spatial dynamics of Airbnb in London were investigated by analyzing how five categories of locational factors—accessibility and convenience, spatial competition, land use, neighborhood environment, and socioeconomic attributes—shape the static distribution, birth, and survival of listings between 2019 and 2022 [24]. Using a dataset of 85,043 Airbnb listings from Inside Airbnb, matched across years to identify 37,160 new listings (“births”) and 34,778 continuing listings (“survivals”), all information was aggregated to Middle-Layer Super Output Areas (MSOAs). Additional spatial data were sourced from OpenStreetMap (points of interest, transport infrastructure, hotels), GOV.UK (land-use ratios and house prices), and the CaBA Data Hub (population and demographic indicators). Spatial visualization, Local Moran’s I, and Global Moran’s I revealed strong spatial autocorrelation and a persistent center-periphery pattern, justifying the use of Spatial Lag Models (SLM) instead of OLS, as confirmed by LM and robust LM tests. The models demonstrated strong explanatory power (e.g., Model 1: $R^2 = 0.906$; Adj. $R^2 = 0.861$), indicating that high housing prices, population density, a higher proportion of young residents, shopping, sightseeing and catering POIs, hotel density, and railway and waterway accessibility significantly promoted Airbnb concentration. In contrast, road density, religious diversity, and recreational land use constrained spatial distribution. Listing birth processes were particularly driven by railway and waterway accessibility and by sightseeing, shopping, and catering POIs, whereas survival was more strongly associated with house prices, population density, racial diversity, shopping POIs, and green land use. Ratio-based models revealed asymmetric effects, whereby shopping POIs, residential land use, and waterways encouraged listing births but hindered survival, while green land use and higher house prices supported survival but discouraged new market entry. Overall, the study demonstrates that locational factors assume shifting roles as facilitators, constraints, or neutral elements across different stages of Airbnb development, offering new insights into spatial heterogeneity and the ecological evolution of the platform within a major global city [24].

3.2. North America

In the context of North America, several studies have explored the spatiotemporal patterns and socioeconomic determinants of Airbnb participation, offering valuable insights into how short-term rentals evolve within major urban areas. An in-depth examination of the spatiotemporal dynamics of host participation in the shared accommodation economy in Los Angeles during the period 2015-2017 was conducted [25]. The conceptual framework linked host behavior to demographic, socioeconomic, occupational, and social capital characteristics, with particular emphasis on factors such as trust and attitudes toward green consumption. Drawing on data from Inside Airbnb and applying GIS techniques, OLS regression, and spatial autocorrelation tools including Moran’s I and LISA, the analysis covered 291 ZIP codes and 17 independent variables. The absence of a mortgage emerged as the strongest predictor of Airbnb density, while other significant relationships in-

cluded a negative association with median household income and youth dependency ratio, and positive correlations with the male-to-female ratio and employment in the FIRE (finance, insurance, and real estate) sectors. Temporal variation was also observed: in 2016, educational attainment was positively associated with shared room listings, whereas in 2017 a negative relationship with Asian households was identified. Environmentally conscious motivations appeared to influence hosts offering private rooms. High Airbnb density was concentrated in economically dynamic and tourist-intensive areas such as Downtown, Santa Monica, and Venice. Overall, the findings underscore the non-random nature of Airbnb participation, shaped by a complex interplay of demographic and socioeconomic factors [25]. Building on this line of inquiry, Airbnb penetration was analyzed and predicted across eight U.S. cities—Austin, Los Angeles, Manhattan, New Orleans, Oakland, San Diego, San Francisco, and Seattle—[26]. Using data from Inside Airbnb (May 2016) and the 2010 U.S. Census, OLS regression was applied to examine spatial relationships, while machine learning models—including Support Vector Machines (SVM), Random Forest, and Logistic Regression—were employed for predictive analysis. The results showed that distance from the city center was negatively correlated with Airbnb presence in five cities, whereas Point-Of-Interest (POI) density exhibited a positive correlation. Bus stop density was also positively associated with Airbnb presence in cities such as Austin, Oakland, and San Francisco. Among social indicators, the Bohemian Index—defined following Richard Florida as the proportion of residents engaged in artistic, creative, or culturally oriented occupations relative to the total population and normalized to the national average—was positively related to Airbnb density, reaching its highest value in Manhattan (0.51). Similarly, the Talent Index—measuring educational attainment as the proportion of residents holding a bachelor’s degree or higher per thousand inhabitants, derived from U.S. Census data—showed a strong positive association, particularly in Oakland (0.70). A higher share of young adults aged 20 - 34 was also positively correlated with Airbnb presence. Racial diversity produced mixed effects, with a negative association observed in Austin and a positive one in New Orleans, while income diversity showed no statistically significant influence. Economic variables such as median household value were positively associated with Airbnb density in five cities, whereas median income displayed a negative correlation in Manhattan and Oakland. Model performance yielded R^2 values ranging from 0.47 in Austin to 0.75 in San Diego, with prediction accuracy reaching 0.725. The most influential predictors were distance from the city center, POI density, and the Bohemian and Talent indices. Overall, the findings demonstrate that spatial and socioeconomic variables can effectively forecast Airbnb growth, offering valuable insights for urban planning and regulatory strategies [26]. In a more localized study, the spatial and socioeconomic drivers of Airbnb host participation in New York City were examined using InsideAirbnb data (2015-2017), U.S. Census data, Esri Demographics, and OpenStreetMap [27]. The analysis, employing OLS regression, k-means clustering, and LISA, revealed a

strong concentration of Airbnb listings in Lower Manhattan and Northern Brooklyn, with a sparse presence in peripheral areas. Key determinants included gender ratio, Black population percentage, professional and technical employment, and median household income. Notably, there was a significant inverse relationship between income and host participation, reinforcing the notion that Airbnb functions as an economic strategy for middle- and lower-income households. Regression models showed strong explanatory power ($R^2 = 0.56 - 0.68$), and spatial clustering analysis confirmed that Airbnb penetration follows discernible geographic patterns. The study's policy implications are significant, touching on housing affordability, neighborhood displacement, and the necessity for targeted regulation to ensure a balance between economic benefits and social equity [27]. Continuing this line of research within the North American context, the understanding of Airbnb dynamics was further advanced through an examination of the spatiotemporal patterns and socioeconomic determinants of host participation in San Francisco during the period 2019-2022 [28]. Drawing on listings from InsideAirbnb, demographic and socioeconomic data from Esri and GfK, and Point-Of-Interest (POI) data from SafeGraph, the analysis was conducted at the census tract level. The results revealed significant spatial clustering (Moran's $I = 0.176$, $p < 0.001$), with Airbnb listings concentrated in north-eastern neighborhoods near major tourist attractions and hotels. OLS regression identified strong positive associations between Airbnb density and employment in professional, scientific, and technical services, employment in hotels and lodging, and proximity to POIs, while the proportion of Asian residents was negatively associated. The model exhibited high explanatory power (adjusted $R^2 = 0.596$), demonstrating that occupational structures, tourism intensity, and socioeconomic inequalities play a central role in shaping Airbnb participation. The study concludes that regulatory strategies must address these spatial inequalities to ensure a balance between tourism development and residential stability [28].

3.3. Asia

Recent studies across major Asian cities have highlighted how the spatial distribution of Airbnb listings is closely tied to local urban structures, cultural assets, and market dynamics. These findings provide critical insights for urban planners aiming to balance tourism growth with housing affordability and neighborhood preservation. In Seoul, the spatial characteristics and influencing factors of Airbnb distribution were examined using geolocated data from 2016 to 2017 [29]. Applying a negative binomial regression model, the study assessed how housing characteristics (e.g., housing prices, size, and type), land use, household composition, and accessibility to urban amenities and transport infrastructure shaped Airbnb's spatial footprint. The findings revealed a concentration of Airbnb units near tourist attractions, with gradual expansion into peripheral residential areas. Key location factors included higher housing prices, proximity to metro stations, and access to universities and grocery stores, while accessibility to bus stops was not sig-

nificant. The study also accounted for spatial autocorrelation, confirming the clustering tendency of Airbnb listings. Importantly, the high percentage of commercial Airbnb hosts in Seoul—surpassing levels observed in comparable global cities—raised concerns about housing affordability and the availability of residential properties. The study stressed the need for regulatory interventions to manage the tension between Airbnb’s expansion and housing policy goals [29]. In the context of China’s rapid urbanization, the spatial distribution of Airbnb listings in Nanjing from 2016 to 2019 was explored [30]. Utilizing data from AirDNA and employing Poisson Regression, Zero-Inflated Negative Binomial Regression (ZINB) models, and Negative Binomial Regression, the analysis identified the ZINB model as the most suitable due to the high variance of the dependent variable, which reached 35,066.28 compared to a mean value of 70.75, as well as the significant presence of zero values in the dataset. The study area covers the central part of the city, where most Airbnb listings are concentrated. The results showed that the main factors affecting the spatial distribution of Airbnb listings were proximity to subway access points, cultural sites, shopping complexes, and universities, which had a negative correlation, while the presence of business apartments and bus stops showed a positive correlation. This highlights a strong relationship between Airbnb distribution and the urban structure of the city, with most listings concentrated in central areas and regions with good public transport accessibility. Moreover, the rent gap phenomenon appeared as a key factor encouraging landlords to convert long-term rentals into short-term ones due to the significant income difference between the two categories. The increasing presence of professional hosts further emphasizes the growing commercialization of the Airbnb market in the city. Professional hosts tend to prefer business apartments near shopping centers and major scenic spots, reinforcing the clustering of listings in specific areas [30]. In Suzhou, a historical and culturally rich tourist city, Airbnb distribution was analyzed using AirDNA and AMap POI data, applying the Spatial Durbin Model (SDM) to examine influences such as tourism, commercial activity, transportation, and the residential environment [31]. The analysis showed that Airbnb units were highly clustered in Suzhou’s old city and near the railway station. Statistically significant positive associations were observed for the presence of traditional folk dwellings (1.097, $p < 0.01$), shopping malls (1.630, $p < 0.01$), tourist attractions (0.606, $p < 0.01$), and catering services (0.042, $p < 0.01$). However, public transportation accessibility (both subway and bus stations) did not significantly affect listing density. The results underscore the importance of cultural heritage in shaping Airbnb’s spatial footprint, while also cautioning against over-commercialization and the transformation of traditional neighborhoods. Regulatory measures were advocated to protect heritage sites while accommodating the platform’s growth [31]. In Hong Kong, the influence of built environment factors on Airbnb’s spatial distribution was explored using Multiscale Geographically Weighted Regression (MGWR) [32]. The dataset included over 11,000 listings (April 2021), land use data, and POIs from Baidu Maps, analyzed across 154 spatial units (TPUs). The

MGWR model ($R^2 = 0.906$, Adj. $R^2 = 0.861$) outperformed traditional models in capturing spatial heterogeneity. Globally, Airbnb presence was positively associated with proximity to hotels ($\beta = 0.288$, $p < 0.01$) and cultural facilities ($\beta = 0.386$, $p < 0.01$), while negatively correlated with residential land ($\beta = -0.128$, $p < 0.05$) and high median rents ($\beta = -0.187$, $p < 0.01$). Tourist attractions and open spaces showed localized effects, increasing Airbnb's presence in tourism zones but decreasing it in residential areas. In contrast to other Asian cities, accessibility to public transport and proximity to city centers did not significantly influence Airbnb density. The study highlights the co-location of Airbnb with hotels and cultural hubs and calls for localized regulatory policies to mitigate impacts on residential stability [32].

By categorizing these studies based on their geographic focus, it becomes clear that while common factors such as proximity to tourist attractions and transport hubs influence Airbnb distribution across regions, local socio-economic and regulatory contexts also play a crucial role in shaping these patterns. Subsequently, **Table 1** presents a concise summary of the results from the previous literature review.

Table 1. Summary table of reviewed literature.

Study	Method	Dependent Variable	Independent Variables	Key Findings
[14]	OLS, GWR	Number of Airbnb listings, Average price per night	Price per sqm, salaried workers, unemployment	R^2 OLS: 0.86 (listings) & 0.42 (price), GWR: 0.93 & 0.71
[15]	GWR	The ratio of Airbnb to total households	Education level, income, migrants, population density, distance from city center	R^2 GWR: 0.84, OLS: 0.63, Airbnb concentrated in tourist areas
[16]	Moran's I, OLS	Airbnb density	Distance from city center, tourist attractions, and housing characteristics	Airbnb is clustered in central areas, with a high correlation with tourist zones
[17]	Spatial Econometric Models	Number of Airbnb & Hotels	Transport, tourist flow, population, employment	Coexistence in central areas, substitution in tourist zones
[18]	LISA, NBM	Airbnb clustering	Distance to center, POIs, transport, and rent	Strong Airbnb clustering in central areas
[19]	Hoover Index, Moran's I, OLS	Airbnb per hotel	Distance from the coastline, vacant housing units	Hoover Index: 0.802, Moran's I: 0.314, the highest concentration in coastal cities
[20]	LISA, NBM	Airbnb density	Distance from center, GDP, public transport access	R^2 (LISA: Madrid 0.83, Barcelona 0.79, Valencia 0.70, Seville 0.79, Malaga 0.76, Palma de Mallorca 0.51, Bilbao 0.49), Airbnb clustering in central districts
[21]	Bivariate Moran's I, LISA	Airbnb & Hotel Beds	Tourist demand, population, distance from coast	High concentration in tourist zones, price elasticity 4.456
[22]	Moran's I, NBM	Airbnb listings per	Second homes, hotel density,	Airbnb clustering in Alpine

		municipality	tourism employment	regions, linked to second-home density
[23]	Bivariate Moran's I, Pearson's R, K-means	Airbnb density	Proximity to ski resorts, housing for tourist use	High Airbnb concentration in ski resort areas, competition with official tourist accommodations
[24]	Spatial Lag Model	Airbnb density in 2022, Density of new listings 2019-2022, Density of surviving listings 2019-2022, Birth ratio (new listings/total listings in 2022), Survival ratio (surviving listings/total listings in 2022)	Accessibility, Competition, Land Use, Neighbourhood, Socioeconomic	Multi-factor effects; strong spatial clustering
[25]	OLS, Moran's I, LISA	Airbnb density per area	Income, unemployment, and age structure	R ² OLS: 0.40 - 0.42, higher density in tourist zones
[26]	Moran's I, LISA, K-means clustering, OLS	Airbnb host participation (density of listings at census tract level)	Socioeconomic indicators (employment in professional/technical services, hotel employment, proportion of Asian residents), proximity to POIs	R ² = 0.596, positive associations with professional/technical and hotel employment, proximity to POIs, and a negative association with Asian population
[27]	OLS, SVM, Random Forest	Airbnb per Census Tract	Distance from center, population, Bohemian Index	R ² : 0.47 - 0.75, higher presence near POIs
[28]	OLS, K-means clustering, LISA	Airbnb host participation	Gender ratio, racial composition, professional & technical employment, median household income	R ² : 0.56 - 0.68, Airbnb is highly concentrated in Lower Manhattan & Northern Brooklyn, inverse relationship with a median income
[29]	Negative Binomial Regression	Airbnb concentration	Housing prices, metro stations, and universities	Concentration near tourist areas, and high property prices linked to more Airbnb
[30]	Poisson, ZINB	Number of Airbnb listings	Metro stations, universities, and shopping malls	Airbnb grows in central areas with good public transport
[31]	Spatial Durbin Model (SDM)	Airbnb density	Traditional folk dwellings, shopping malls, tourist attractions, catering services, and public transport accessibility	Airbnb is concentrated in Suzhou's old city and around the railway station, a strong influence on historical & commercial areas, and transport is not a significant factor.
[32]	MGWR	Airbnb density	Hotels, cultural facilities, residential land use	Airbnb co-agglomerates with hotels and cultural hubs, not significantly impacted by transport.

4. Conclusions and Findings

The literature review on the spatial distribution of Airbnb accommodations has highlighted several critical findings on the factors influencing their geographical

dispersion. The main conclusions are summarized as follows:

- Entrepreneurship and economic activity: Areas with increased commercial activity are more attractive to both visitors and property owners looking to use short-term rental platforms. At the same time, it is worth noting that the diversity of land uses is a key factor in defining the city center.
- Cafes, bars, and restaurants: The presence of dining establishments, cafes, bars, and retail stores is positively correlated with the concentration of Airbnb accommodations.
- Proximity to landmarks: Most studies confirm that Airbnb accommodations are primarily concentrated in areas often visited by tourists, such as historical centers, archaeological sites, and cultural landmarks. In cities that attract more tourists, proximity to points of interest is a crucial factor in figuring out the spatial distribution of short-term rental properties.
- Transportation networks and accessibility: The presence of metro stations, bus stops, and well-developed public transportation networks plays a significant role in attracting investments in Airbnb properties. Studies show that areas with easy access to public transport show a higher concentration of listings.
- Population Density and Demographic Characteristics: Airbnb listings are more common in areas with higher education and income levels, which offer better infrastructure and are seen as safer and more attractive. In contrast, neighborhoods with high immigrant populations or greater density tend to have fewer listings. Lower-income and high-unemployment areas show increased participation, as residents seek extra income, while wealthier areas take part less. Additionally, areas with more children and adolescents typically have lower Airbnb activity.

Frequent use of specific spatial analysis methods in the investigation of Airbnb distribution. More specifically, there is extensive application of Ordinary Least Squares (OLS), Local Indicators of Spatial Association (LISA), and Geographically Weighted Regression (GWR). Additionally, spatial autocorrelation indices such as Moran's I and Pearson's correlation coefficient are widely used in various data analysis software. OLS regression is commonly employed as a baseline model due to its simplicity and interpretability; however, its global nature often limits its ability to capture spatial non-stationarity. In contrast, Geographically Weighted Regression (GWR) consistently demonstrates superior explanatory power, as evidenced by higher R^2 values in empirical studies conducted in cities such as Athens, Barcelona, and Hong Kong. By allowing model coefficients to vary spatially, GWR reveals localized relationships between Airbnb density and explanatory variables, including proximity to tourist attractions and socioeconomic characteristics. Furthermore, spatial econometric models, such as spatial lag and spatial error models, have been shown to further improve model performance by explicitly accounting for spatial dependence. This is particularly evident in large metropolitan areas, including London and Switzerland, where strong spatial autocorrelation characterizes Airbnb distribution patterns. These methodological findings indicate that

while OLS remains a useful benchmark, spatially explicit models are more appropriate for capturing the heterogeneous spatial dynamics of Airbnb accommodations. Despite their widespread application, traditional methods such as OLS and GWR exhibit important limitations. OLS assumes spatial stationarity and independence of observations—assumptions that are frequently violated in urban spatial data—leading to biased or inefficient estimates. Although GWR addresses spatial non-stationarity, it remains sensitive to bandwidth selection, multicollinearity among local variables, and edge effects, which can complicate interpretation and reproducibility. Moreover, both OLS and GWR are limited in their ability to model complex, non-linear relationships and high-dimensional interactions among variables. These methodological constraints reduce their capacity to fully capture the evolving, multi-scalar nature of Airbnb spatial dynamics. This trend reflects the establishment of consistent methods for studying the spatial dynamics of short-term rentals. Additionally, in most of the reviewed studies, the results obtained from these methods, such as R-squared values and other statistical measures, were quite satisfactory. This confirms their suitability for analyzing the spatial distribution of Airbnb accommodations and explains their widespread use in the relevant literature. Nevertheless, the frequent use of traditional statistical methods in the reviewed literature may limit the ability to fully capture the complexity of spatial patterns. These approaches, while useful, can be restrictive in certain contexts. This highlights the need for more flexible and advanced techniques, such as those offered by artificial intelligence, which can provide deeper and more correct insights.

Despite the extensive body of literature on the spatial distribution of Airbnb accommodations, several aspects remain underexplored, revealing key areas for future research. Most studies focus on major urban centers, leaving the expansion of Airbnb in suburban, rural, and island areas relatively unexplored. Additionally, few studies have explored the effects of different regulatory frameworks on Airbnb's geographical distribution, despite the significant influence of legal restrictions on spatial patterns. Comparative research between areas with strict regulations and those with more flexible policies could offer a clearer understanding of the role of regulations in shaping Airbnb's distribution. As mentioned above, researchers have traditionally relied on statistical methods such as Ordinary Least Squares (OLS), Geographically Weighted Regression (GWR), and Moran's I to analyze Airbnb's spatial distribution. While these methods have offered useful insights, advancements in data science and geospatial analysis offer new opportunities for more flexible and advanced studies. Integrating Artificial Intelligence (AI) methods and techniques is a very promising approach to discovering the complex spatial relationships that traditional models might overlook. Notably, AI-based approaches related to OLS and GWR can extend and enhance the capabilities of these traditional models, allowing for more nuanced spatial analysis. Finally, the application of Artificial Intelligence (AI) methods and techniques for regression analysis and the adoption of more automated prediction methods could enhance

the accuracy of spatial distribution models for Airbnb. Optimizing machine learning algorithms could improve predictive accuracy and offer more detailed insights into the spatial patterns of Airbnb listings. This research follows this direction, aiming to use Artificial Intelligence (AI) methods and techniques to examine the spatial relationships that influence Airbnb's distribution. Future studies will focus on developing AI-driven models to analyze how factors such as proximity to landmarks, transport networks, and economic activity shape Airbnb's spatial patterns. By adopting these innovative methods, this approach aims to contribute to a more accurate and detailed understanding of Airbnb's role in transforming urban and tourism spaces.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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