



A Digital ‘Smiley’ Analysis of the Appreciation for Tourist Amenities by Visitors to London

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Abstract

Digital wellbeing research is on a rising edge. It is also increasingly applied in the hospitality sector to measure the satisfaction of visitors (metaphorically called here ‘*smileys*’); understanding and enhancing visitor satisfaction are pivotal for the success of tourism destinations. This study seeks to identify critical factors influencing the visitors’ appreciation for London, a city renowned for its allure, by harnessing available user data from Airbnb listings and hotels, using online reviews, with a particular view to the spatial pattern of visitors’ choices in corona times. Advanced statistical techniques, including sentiment analysis, digital text analysis, multi-level analysis, and geographically weighted regression, are employed to discover geographical patterns as well as statistical correlations between land use, density, geographic location, and visitor contentment. The findings reveal that proximity to parks, accessibility to public transportation, and the presence of natural amenities exert substantial influence on visitor satisfaction in London. Especially, the proximity to a park enhances visitor satisfaction, predominantly in western London. Efficient access to public transportation in central areas of the city positively impacts visitor contentment levels as well. Furthermore, the availability of and accessibility to natural attractions in the southern and southwest areas of London appear to elevate visitor satisfaction. These novel insights empower destination managers, policymakers, and tourism stakeholders to make informed decisions, formulate targeted strategies, and enhance visitor experiences in specific London locales. The research highlights the importance of considering location-specific factors and customizing approaches to optimize the visitor appreciations for a city. By understanding the complex dynamics between land use, density, location, and visitor satisfaction, stakeholders can foster sustainable tourism growth and create a more appealing environment for visitors.

Keywords Sentiment analysis · Text analysis · Airbnb · Appreciation · Smileys · Visitor satisfaction · Spatial patterns · Land use · Proximity to parks · Public transportation · Cultural amenities

Setting the Scene

In recent years a wide array of quantitative spatial modeling approaches has been developed and applied to map out complex urban systems (see e.g. Batty, 2013; Lai, 2021). Examples can inter alia be found in urbanometric analyses (see e.g. Kourtit et al., 2022b), complex interactive urban models (see e.g. Concha, 2018) and morphometric studies (see e.g. Dibble et al., 2019; Venerandi et al., 2023). The application fields of such quantitative tools are diverse and range from urban labour or housing markets to urban transportation or tourism domains. Especially the tourism, recreation and leisure sector appear to exert a significant influence nowadays on the evolution of cities. The present study addresses the intra-urban volatile mechanism of diverse spatial choices of urban visitors in corona times, taking London as a case study.

Visitors to tourist and entertainment amenities aspire to enjoy new and attractive experiences that leave a lasting impression. These attractions serve as hot-spots of attractiveness and personal satisfaction, evoking genuine "big smiles" from tourists and recreationists. Metaphorically, the frequency and intensity of these smiles can be seen as a measure of the level of contentment experienced by visitors spending their leisure time in various captivating destinations. In the past, measuring such subjective feelings of personal satisfaction and happiness posed significant research challenges. Fortunately, in today's digital age, social media platforms and online reviews provide a wealth of data that can even offer a quantitative basis for assessing visitors' satisfaction or happiness levels (Kytä et al., 2016). The primary objective of this study is to understand the underlying mechanisms behind these "big smiles" exhibited by tourists, shedding light on the factors that contribute to visitors' overall satisfaction and enjoyment from leisure amenities like cultural heritage or authentic places (see Lai et al., 2010; Refisch et al., 2024).

Tourism, as an integral part of the leisure society, offers visitors the opportunity to embark on new and immersive experiences in destination areas, providing a relaxed and unexplored sense of place (Bachimon et al., 2016; Löfgren, 1999; McCain & Ray, 2003). Geographical mobility and the enjoyment of tourist amenities form the fundamental elements that drive leisure and tourism. Despite occasional setbacks caused by e.g. pandemics or geo-political conflicts, the global hospitality sector has experienced rapid and sustained growth. The unique allure of specific destinations, shaped by cultural, historical, architectural, and natural factors, presents travelers with a plethora of choices, each offering its own distinctive appeal (Robinson, 2015; Sharpley, 2002).

The spatial behaviour and decision-making process of visitors are nowadays significantly influenced by the presence and utilization of digital technology. The emergence of electronic booking systems, comprehensive digital information on websites, and interactive tourist-specific advice has revolutionized the tourism landscape, providing visitors with seamless access to information and enhancing their leisure planning and decision-making processes (Buhalis, 2003; Buhalis et al., 2023; Meier et al., 2020). Consequently, an abundance of information

is readily available on tourist profiles, preferences, choices, and appreciations, allowing for a comprehensive understanding of the factors that contribute to the local or regional attractiveness of destinations (Ruth & Franklin, 2014).

In recent years, extensive research has been conducted on digitally-driven segments of the tourist market, with particular attention given to the rapid growth of the Airbnb sector as a newcomer. The wealth of studies conducted in this domain can mainly be attributed to the open and accessible platform data provided by Airbnb, which has facilitated in-depth exploration of various aspects of this sector (Kourtiti et al., 2022a; Zach et al., 2020). These studies encompass a wide range of topics, including the competition between Airbnb supply and local hotels, the pricing dynamics within the Airbnb system, and the competitive advantages that Airbnb offers to both hosts and guests. Additionally, research has sought to understand the relationship between a city's regular housing market and the presence of urban Airbnb facilities, often employing standard hedonic price models to evaluate the impact of external factors on property prices within local neighbourhoods (Wilkinson, 1973; Basu & Thiboudeau, 1998; Doran et al., 2015; Guttentag et al., 2018; Suess et al., 2021; Benítez-Aurióles & Tussyadiah, 2021).

Furthermore, recent applied modeling studies utilizing Airbnb data from cities such as Los Angeles and Amsterdam have focused on analyzing pricing elements within the Airbnb market. These investigations have revealed key determinants of Airbnb listing prices, including the influence of frequent price adjustments and the number of properties per host on revenue and daily average rates (Gunter et al., 2020; Sainaghi & Baggio, 2020). Moreover, the experience and expertise of hosts on the Airbnb platform have been shown to enhance their ability to effectively price the available accommodations. Research on Airbnb listings in Verona, for example, has demonstrated that hosts gain experience over time, refining their marketing and pricing strategies to optimize their offerings (Gibbs et al., 2018; Oskam et al., 2018). Reputation management has also emerged as a critical aspect in these studies, as consumer reviews and sentiment analysis techniques have been employed to evaluate the impact of reputation on pricing and demand. Interestingly, the findings have often defied conventional wisdom, with the number of reviews for an Airbnb listing showing a moderate but negative impact on prices, diverging from expectations in traditional hotel services (Gibbs et al., 2018; Magno et al., 2018).

Against the backdrop of the growing impact of digital technology and the dynamic nature of accommodation options in the tourism industry—especially during corona times -, this paper aims to conduct an extensive and pioneering sentiment analysis of visitors' appreciation of accommodations in London employing digital text information. By employing advanced analytical techniques, we seek to discover the underlying sentiments expressed by visitors in their reviews and assess the factors that contribute to their overall satisfaction and enjoyment. Specifically, we aim to explore the relationship between visitors' sentiments and various place-specific factors such as location, amenities, and pricing, providing valuable insights to decision-makers in the tourism industry. Ultimately, the objective is to enhance the overall experience for future travellers seeking or using accommodations in the vibrant city of London.

The remainder of this paper is organized as follows. After this introductory section on the scope and aims of this paper, Sect. "[The Crucial Role of Sentiment Analysis and Text Analysis in the Tourism Industry](#)" contains the basics of sentiment and text analysis. Next, in Sect. "[Data](#)", the database on the London case study will be described, for both the Airbnb and the hotel sector. The methodology employed in this paper – based on a stepwise multilevel approach (including the model specification) – will be outlined in Sect. "[Research Approach](#)", while the empirical results for London – including site-specific findings – will be presented and interpreted in Sect. "[Empirical Results](#)". Sect. "[Conclusion](#)" offers concluding remarks.

The Crucial Role of Sentiment Analysis and Text Analysis in the Tourism Industry

Introduction

Sentiment analysis and text analysis have become indispensable tools in digital well-being research, in particular in the tourism industry, playing a pivotal role in comprehending customer feedback, preferences, and user sentiments. Sentiment analysis is a computational technique that examines the emotions, opinions, and subjective elements within a given text (Medhat et al., 2014). It can analyze substantive content generated by individuals or content that reflects events and topics. This process involves detecting the sentiment expressed by individuals in their text and evaluating it for further evidence-based insights. In today's rapidly evolving digital landscape, the surge in user-generated content across online platforms presents a formidable challenge: extracting valuable insights systematically from the vast volume of information available. Nevertheless, researchers have risen to this challenge, employing a multitude of techniques and approaches to adeptly extract and distill customer reviews, decipher sentiment within online content, and gain profound insights into customer behavior. This issue turned out to be very important during the corona period, in which the tourist market became very volatile.

Sentiment analysis and text analysis now play also a critical role for decision-makers in the tourism industry. These techniques offer invaluable insights into visitor sentiments, preferences, and perceptions. They assist policymakers in evaluating destination attractiveness, monitoring city capacity, adapting strategies to changing trends, and ensuring visitor safety. By leveraging sentiment analysis and text analysis, destination managers can make informed decisions, develop effective strategies, enhance long-term destination attractiveness and competitiveness in hospitality, and create a sustainable and appealing tourism environment that fosters positive word-of-mouth, ultimately boosting local economic growth and visitor satisfaction.

Sentiment Analysis in the Tourism Sector

This section explores the significance of sentiment analysis and text analysis within the tourism domain, drawing insights from key studies and contributions. The initial

set of studies focuses on the effective extraction of sentiment and opinions by mining and summarizing customer reviews. For example, Hu and Liu (2004) propose practical tools for sentiment analysis and review summarization, empowering businesses with valuable insights to drive data-driven decisions for product enhancements and service improvements. Zhang et al. (2017) compare supervised and unsupervised approaches for sentiment analysis of online hotel reviews, shedding light on their effectiveness and implications for the hospitality industry. Sigala and Chalkiti (2014) explored the relationship between customer reviews and hotel classification, emphasizing the significant influence of specific review aspects on ratings. Collectively, these studies underscore the critical role of sentiment analysis in comprehending customer feedback, enhancing products and services, and managing online reputation.

Additionally, other references explore broader aspects of text analysis within the tourism context. Xiang et al. (2017) use social media analytics on hotel reviews, employing customer sentiment and satisfaction levels to categorize hotels into distinct clusters and gain insights into guest perceptions and market structure. Xiang and Fesenmaier (2017) discuss the pivotal role of data analytics and text mining in extracting valuable insights from user-generated content, emphasizing the impact of information and communication technologies in the hospitality and tourism industry. Wang et al. (2012) examine the multifunctional nature of smartphones and the necessity for businesses to adapt to mobile technology in mediating the touristic experience.

Furthermore, specific studies apply sentiment analysis to various tourism contexts. For example, Xiang et al. (2015) utilize sentiment analysis to understand tourists' satisfaction with specific destinations, revealing key factors influencing sentiment and assisting destination marketers in tailoring their marketing efforts. Liu et al. (2017) highlight the effectiveness of sentiment analysis techniques in analysing user-generated content on social media platforms for tourism, distinguishing domestic and international tourists. Cao et al. (2011) address travellers' electronic word-of-mouth (eWOM) evaluations on social networking sites, emphasizing the pivotal role of eWOM in decision-making and the significance of sentiment analysis in assessing review sentiment and credibility. Lastly, Ekinci and Hosany (2006) investigate the application of brand personality concepts to tourism destinations, underscoring their influence on destination choice and visitor satisfaction. These studies provide unique insights into the impact of sentiment analysis and text analysis on destination branding, perception, and visitor satisfaction.

In conclusion, the studies reviewed above demonstrate innovative approaches by proposing place-specific sentiment analysis techniques, exploring the impact of customer reviews and social media content, and providing valuable insights into customer behaviour and the role of technology in the tourism industry. However, certain weaknesses exist, including the narrow focus of some empirical studies, a limited exploration of specific sentiment analysis or text analysis techniques, and the omission of broader contextual aspects of text analysis. Therefore, this research significantly contributes to advancing the understanding of sentiment analysis and text analysis in the tourism context. Its comprehensive insights serve as a guiding compass for policymakers and various stakeholders, empowering them to make

data-driven decisions. By leveraging sentiment analysis and text analysis techniques, policymakers can enhance the attractiveness of destinations, effectively profile products and services, and ultimately elevate the overall customer experience and satisfaction. Such research supports them with the necessary tools and knowledge to optimize resource allocation (see e.g. Reid & Gatrell, 2013; Lee et al., 2023), develop targeted strategies, and create an environment that aligns with the evolving needs and preferences of tourists (see e.g. Kain & Quigley, 1970). Through its valuable findings, this research paves the way for informed decision-making, fostering sustainable tourism growth and positive outcomes for all stakeholders involved.

Data

In this study, the data collection process was conducted with thorough attention to detail, drawing predominantly from two distinct information sources: Airbnb listings and hotels located in London. These datasets served as invaluable resources for investigating the spatial satisfaction of visitors ('smiles') during both the pre- and during-COVID periods. Our analysis focused specifically on the reviews provided by visitors who had firsthand experience staying at these lodging establishments.

To ensure the utmost accuracy and reliability of the data, we obtained the Airbnb dataset from the well-regarded Inside Airbnb webpage, renowned for its comprehensive and reliable information. In parallel, we systematically gathered information on satisfaction, regarding hotels from the TripAdvisor webpage, which has long been recognized as a reputable source of traveler reviews and insights. The datasets derived from these sources provided an extensive array of information, encompassing essential details such as pricing, the diverse range of listings available (including single rooms, shared accommodations, entire apartments, and more), and precise geo-location data at the coordinate level in London. In addition to visitor information, other sources of information were used, e.g. on green areas or cultural amenities in the city. Therefore, to further augment our analysis, we also leveraged the wealth of information provided by OpenStreetMaps, which allowed us to gain valuable insights into the amenities and attractions surrounding these short-term lodging services.

The datasets we collected were characterized by a substantial number of observations, ensuring a robust and comprehensive sample size for our analysis. Specifically, we obtained a considerable number of observations for Airbnb facilities and hotels, respectively. However, to ensure the integrity of our analysis and focus solely on active listings, we implemented stringent inclusion criteria. For Airbnb listings, we only included those that had received a minimum of 10 reviews from visitors during both the pre- and during-COVID periods. Likewise, for hotels, we selectively incorporated the properties that had also accumulated a minimum of 10 reviews during the corresponding time periods. This approach guaranteed consistency and reliability across the datasets, enabling us to draw meaningful conclusions.

To provide an extensive and detailed overview of the data, we present Table 1, which showcases descriptive statistics for both Airbnb and hotel rooms in London based on TripAdvisor and Airbnb data. This comprehensive summary offers

Table 1 Descriptive statistics for Airbnb and hotel rooms

<i>Variable</i>	<i>Tripadvisor</i>		<i>Airbnb</i>	
	Mean	SD	Mean	SD
<i>Review Sentiments</i>	0.2758	0.1757	0.4024	0.2788
<i>Minimum Distance to Parks (km)</i>	0.3334	0.2411	0.4487	0.4978
<i>Minimum Distance to Public Transportation (km)</i>	0.114	0.1204	0.1425	0.2083
<i>Minimum Distance to Tourism Amenities (km)</i>	0.4937	0.5196	0.8976	0.9399
<i>Minimum Distance to Parking Loads (km)</i>	0.2901	0.218	0.4682	0.4593
<i>Minimum Distance to Natural Amenities (km)</i>	0.1127	0.1385	0.195	0.2739
<i>Minimum Distance to Central Station(km)</i>	4.0518	3.1196	7.1175	5.1355
<i>Price(\$)</i>	115.0113	173.7389	133.4003	262.3759
<i>Reviews: Share of Clean Related</i>	0.0527	0.0851	0.012	0.0317
<i>Reviews: Share of Transport Related</i>	0.0723	0.1218	0.0109	0.0241
<i>Reviews: Share of Retail Related</i>	0.0102	0.0191	0.0018	0.0082
<i>Reviews: Share of Geography Related</i>	0.107	0.1635	0.0412	0.0672
<i>Reviews per Month</i>	4.5992	7.9525	2.0925	3.0338
<i>Minimum Nights</i>	-	-	4.0883	21.8769
<i>Room Type</i>	-	-	2.0489	1.00622
<i>Number of Observations</i>	58,376		851,497	

valuable insights into various aspects of these accommodations, shedding light on their characteristics and distributions.

In summary, the rigorous and detailed data collection process undertaken in this study has resulted in a robust and comprehensive dataset, enabling a thorough investigation of the spatial satisfaction of visitors in London. By harnessing the power of the data derived from Airbnb listings, hotels, and additional open-access sources such as OpenStreetMaps, we were able to gain a comprehensive understanding of visitor experiences and the broader dynamics of the hospitality industry. These insights will serve as a valuable foundation for subsequent analyses, enabling us to draw meaningful conclusions and contribute to the body of knowledge in the field of tourism research.

Research Approach

The intra-urban choices and contentment of visitors have seen widely fluctuating patterns during the corona time all over the world. The COVID-19 crisis has not only created a deep perturbation in medical health care, but also a new awareness of the significance of health as an alignment of human, social and spatial behaviour. It is noteworthy that in the post-corona time new issues like health tourism (e.g. well-ness tourism, green tourism) and health-oriented mobility (e.g. walking and cycling) have come to the fore, not only from a physical or mental health perspective but also from a subjective wellbeing perspective. The space–time patterns of perceptions of

a healthy environment, for instance, by different classes of visitors to a city, deserve a thorough analysis, as these may shape disparities in spatial resilience and in place-specific recovery profiles in case of health crises or induce changes in health awareness and spatial choices of visitors. Such developments have great implications for the hospitality sector, the choice of accommodation, the use of urban space, and spatial mobility patterns in tourism. Clearly, digital information technology plays a critical role in changing spatial choice patterns of visitors. This issue will be further empirically examined in the present study on London.

In this section, we first describe the methods used in our research to analyse visitors' spatial satisfaction during both the pre- and during-COVID periods. To quantitatively identify the determinants of customer satisfaction, our research incorporated a combination of text analysis, sentiment analysis, multilevel analysis, and geographically weighted regression. Each method offered unique insights into the factors influencing visitor satisfaction and allowed us to examine spatial variations in customer satisfaction levels.

- *Text Analysis*

To explore the factors contributing to visitors' spatial satisfaction, we conducted a rigorous text analysis of visitor reviews. Our analysis focused on identifying the presence of words related to cleanliness (hygiene), transportation, retail, and geography within these reviews. By quantifying the occurrence of these relevant words and assessing their prevalence in the reviews, we gained valuable insights into their significance to visitors' spatial satisfaction. This analysis provided a comprehensive understanding of the key elements influencing overall satisfaction and helped us evaluate the relative importance of these factors in visitor experiences. The relevant words were extracted from all reviews using RegEx commands.

- *Sentiment Analysis*

To assess visitor satisfaction in London, we employed sentiment analysis on the reviews as an indirect measurement. We conducted the sentiment analysis using the 'sentimentr'¹ package in R. This method assigns polarity values to each sentence based on a sentiment dictionary to identify polarized words. Words in each sentence are compared to a dictionary of polarized words and tagged as +1 for positive and -1 for negative polarity. Additionally, a polarized context cluster of words is extracted around each polarized word, typically spanning four words before and two words after the polarized word, to account for valence shifters. This approach offers the advantage of delivering rapid results, even for lengthy reviews, and addresses polarity inversions by considering valence shifters. Using various weighting schemes, the system calculates an unbounded polarity score for each listing.

- *Multilevel Analysis*

To account for the hierarchical structure of the data and analyze the pre-COVID and during-COVID periods separately, we employed multilevel anal-

¹ <https://github.com/trinker/sentimentr>

ysis for both Airbnb and hotel data. Our multilevel approach considered time as the first level, listings and hotels as the second level, and neighborhoods as the third level in the multilevel model. This allowed us to explore variations in spatial satisfaction at different levels and understand how these variations contributed to overall satisfaction. In general, the multilevel (three-level) composite model can be specified as follows:

$$y_{tij} = \alpha_{0ij} + \alpha_{tij}x_{tij} + \varepsilon_{tj} + \varepsilon_t + e_{tij} \quad (1)$$

where y_{tij} is visitor satisfaction for listing i located in the neighbourhood j at time t , α_{0ij} is initial visitor satisfaction, x_{tij} are time-variant listing level predictors, and ε_{tj} , ε_t , e_{tij} are residuals at the second, third and first level. By incorporating multilevel analysis, we gained insights into the factors influencing satisfaction across different levels of data analysis. We used the intraclass correlation coefficient to assess the extent of spatial variation in visitor satisfaction and identify the factors that influence satisfaction across different levels.

- *Geographically Weighted Regression (GWR)*

Previous research has highlighted the existence of spatial heterogeneities in pricing, demand, and supply within the short-term accommodation sector (Zhang et al., 2017; Voltes-Dorta & Sánchez-Medina, 2020; Eugenio-Martin et al., 2019; Kourtiti et al., 2022a). To delve deeper into this spatial heterogeneity and gain a more comprehensive understanding of the factors influencing visitor satisfaction in the city, we employed in our econometric model geographically weighted regression (GWR). This analytical approach allowed us to estimate the varying effects of the model's variables based on specific geographic locations. Using the 'AIC' criterion, we delineated neighbourhoods and explored how the determinants of visitor satisfaction fluctuated across different geographical areas. The following model was used:

$$y_i = \alpha_0(u_i, v_i) + \alpha_i(u_i, v_i)x_i + e_i \quad (2)$$

where, in contrast to Eq. (1), Eq. (2) incorporates now the coordinates of listings (u_i, v_i) and where parameter α_i is estimated by least squares, weighted by a spatial weight matrix based on distances.

By integrating text analysis, sentiment analysis, multilevel analysis, and geographically weighted regression, our research approach provided a comprehensive and robust framework for analysing visitors' spatial satisfaction. These methods complemented each other, allowing us to explore the complexities of visitor experiences, identify key factors shaping satisfaction, and understand the spatial variations in visitor sentiments. The combination of these methods enabled us to gain in-depth insights into visitor satisfaction across different spatial contexts and effectively address the research objectives of this study.

Empirical Results

In this section, we present the results obtained from our rigorous statistical-econometric analysis, offering valuable insights into the spatial satisfaction of visitors during the pre- and during-COVID periods. Through the use of these novel methodologies and comprehensive data analytics, we have uncovered interesting findings that reveal the critical factors influencing visitor satisfaction in both the Airbnb and hotel sectors in London.

Neighborhood-Level Variation

Our research reveals intriguing variations in neighborhood-level satisfaction ('smiles') between the pre- and during-COVID periods. During the pre-COVID period, neighborhood-level satisfaction variation was found to be 1% for Airbnb listings and 5% for hotels. However, in the post-COVID period, we observed a decrease in neighborhood-level variation for Airbnb visitors to 0.6%, while the variation increased significantly to 13% for hotel visitors' satisfaction. These compelling results provide robust evidence for the impact of COVID-19 on visitor satisfaction levels, highlighting the evolving dynamics of the hospitality industry in response to the pandemic.

Listing-Level Factors in Airbnb

An innovative and thought-provoking finding from our study is the growing importance of listing-level factors in determining visitor satisfaction within the Airbnb market. Our analysis clearly demonstrates that specific characteristics and attributes of individual listings play a substantial role in shaping visitor experiences and overall satisfaction. This signifies a shift in focus from traditional hotel offerings to the unique features and offerings provided by each individual Airbnb accommodation. Therefore, it is imperative for hosts and stakeholders in the Airbnb ecosystem to recognize the significance of curating exceptional listings that cater to the diverse needs and preferences of visitors.

Determinants of Visitor Satisfaction

Our in-depth analysis also identifies several key determinants that significantly impact visitor satisfaction across different types of accommodations. These determinants are supported by robust statistical evidence from the regression analysis conducted on the data:

- *Minimum distance to parks:* The findings indicate that as the distance to the nearest green amenity increases, visitors' satisfaction with the services pro-

vided decreases. This consistent relationship between distance and satisfaction holds true across all periods and for both hotels and Airbnb listings ($p < 0.01$).

- *Relationship with natural amenities:* A remarkable finding is that the relationship between distance and satisfaction with natural amenities is observed solely within the Airbnb market. This suggests the presence of distinct visitor profiles in the Airbnb sector, with leisure travelers being more prevalent compared to traditional hotel guests. Consequently, understanding the diverse preferences of these distinct visitor segments becomes crucial for crafting tailored experiences that enhance satisfaction ($p < 0.01$).
- *Distance to public transport and parking:* Our analysis reveals that the minimum distance to public transport positively influences visitor satisfaction. However, this relationship is statistically significant only within the Airbnb data. The abundant public transportation options in London may introduce certain complexities and nuances that can lead to some degree of dissatisfaction. Similar findings were observed for the minimum distance to parking opportunities ($p < 0.05$).
- *Distance to central railway station:* Interestingly, the minimum distance to the central train station negatively affects satisfaction consistently across all periods and for both Airbnb listings and hotels. This suggests that centrally located areas, while commanding higher accommodation prices, may not always meet visitors' expectations in terms of services and amenities. Factors such as noise and other urban complexities may contribute to this perceived dissatisfaction ($p < 0.01$).
- *Price:* The analysis indicates that there is no substantial relationship between price and visitor satisfaction, as the coefficient for price is effectively zero. While the p-value indicates statistical significance ($p < 0.01$), the magnitude of the coefficient suggests that price does not meaningfully influence visitor satisfaction. This finding highlights that, in the context of this study, price alone is not a key driver of visitor satisfaction for either Airbnb listings or hotel accommodations.
- *Accommodation type:* Within the Airbnb dataset, private rooms receive more favorable ratings compared to entire apartments, while hotel rooms and shared rooms are rated lower than entire apartments in both periods. Comparatively, hotels listed on the Airbnb platform demonstrate lower satisfaction levels for hotel rooms compared to entire Airbnb apartments, while shared rooms exhibit similar satisfaction levels to those found on the Airbnb platform ($p < 0.01$).
- *Cleanliness:* Our text analysis highlights the strong association between cleanliness-related comments and visitor satisfaction, particularly within the Airbnb market across all periods. Cleanliness assumes greater significance in the hotel industry during the COVID period, reflecting the increased focus on hygiene and sanitation in the wake of the pandemic ($p < 0.01$).
- *Transport-related comments:* The impact of transport-related comments on satisfaction demonstrates variations across different periods. In the pre-COVID period, Airbnb visitors appreciated transport services, while in the COVID period, the effect reversed. In the hotel industry, transport-related comments were associated with lower satisfaction in both periods, possibly due to a reliance on taxis rather than public transport ($p < 0.01$).
- *Geography-related comments:* The visitor comments on city planning and walkability suggested a positive influence on satisfaction levels. This finding empha-

sizes the importance of well-designed and accessible urban environments in shaping visitor experiences and satisfaction ($p < 0.01$).

- *Average number of reviews*: Our findings indicate that in the pre-COVID period, a higher average number of reviews for Airbnb services was associated with lower satisfaction levels. This suggests that visitors were more inclined to write reviews when dissatisfied. However, in the COVID period, traditional hotel services experienced higher satisfaction levels as visitors sought more information and became more inclined to provide reviews to aid others in making informed decisions ($p < 0.01$).

Our comprehensive analyses have yielded compelling evidence-based outcomes that illuminate the complex dynamics of visitor satisfaction within spatial environments (see Table 2). These findings hold important implications for destination managers, policymakers, and industry stakeholders, equipping them with the means to make informed decisions based on data and implement precise strategies to elevate visitor experiences, cater to evolving needs, and foster sustainable growth in the tourism industry. By harnessing these insights, stakeholders are better able to create a thriving ecosystem that ensures long-term satisfaction and sustains the industry's vitality.

In analyzing the Geographically Weighted Regression (GWR) results, we also discover interesting new insights into the associations between land use variables and visitor satisfaction, which exhibit remarkable spatial heterogeneity across different periods (see Fig. 1). Our findings shed thus also light on the unique patterns that emerged from the data, revealing innovative perspectives on the relationship between urban location and visitor satisfaction.

For Airbnb users during the pre-COVID period, we obtained an interesting observation regarding the minimum distance to parks and its impact on satisfaction. While a negative association was found overall, a closer examination of the maps exposed a distinct north/south division within the city. Interestingly, having a park nearby significantly contributed to visitor satisfaction, particularly in the Northern parts of London. This suggests that the presence of nearby green spaces in the Northern areas played a crucial role in enhancing satisfaction levels. These geographical and land use characteristics specific to the Northern parts of the city might have created a favourable environment for visitors, elevating their overall experience. Remarkably, for Airbnb during the COVID period, we observe a higher degree of variation in the coefficient, particularly as we move from the Western to the Eastern parts of the city. Specifically, in the Western areas, the presence of parks has a significantly more pronounced positive impact on visitor satisfaction compared to the pre-COVID period.

We note a similar shift from a North/South division in London to a more pronounced heterogeneity, particularly as we move from West to East. This pattern is also evident in the availability of parking amenities. While the presence of parking options continued to have a substantial positive impact in the Northern parts of the city, various Southern areas displayed a similar effect during the COVID period compared to the pre-COVID period. However, there was an overall decrease in the Western and Eastern parts of the city.

Table 2 Three-level multilevel regression outputs from Airbnb listings and hotels

VARIABLES	Airbnb			Hotels				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EmptyPrecovid	Precovid	Emptycovid	Covid	EmptyPrecovid	Precovid	EmptyPostcovid	Postcovid
MinDistToParks		−0.0071*** (0.0020)		−0.0060*** (0.0019)		−0.005 (0.0150)		−0.0316* (0.0168)
MinDistToPublicTransport		0.0230*** (0.0045)		0.0073* (0.0042)		0.0195 (0.0293)		0.0416 (0.0313)
MinDistToTourism		−0.0027** (0.0011)		−0.0003 (0.0010)		−0.0147 (0.009)		−0.0187* (0.0097)
MinDistToParking		0.0072*** (0.0019)		0.0091*** (0.0019)		0.0129 (0.0172)		0.0014 (0.0184)
MinDistToNatural		−0.0093** (0.0036)		−0.0154*** (0.0034)		0.0139 (0.0282)		0.0163 (0.0304)
MinDistToCentralstation		0.0049*** (0.0003)		0.0043*** (0.0003)		0.0060*** (0.0019)		0.0049*** (0.0019)
Minimum_Nights		−0.0003* (0.0002)		0.0001*** (0.0000)				
HotelRoom (Ref:EntireApt)		−0.0029 (0.0081)		−0.0224*** (0.0075)				
PriveRoom		0.0369*** (0.0013)		0.0198*** (0.0013)				
SharedRoom		0.0033 (0.0084)		−0.0269*** (0.0074)				
Price		0.0000*** (0.0000)		0.0000 (0.0000)		0.0000*** (0.0000)		0.0000*** (0.0000)
ShareClean		2.7670***		2.3510***		0.3600***		0.4520***

Table 2 (continued)

VARIABLES	Airbnb			Hotels				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EmptyPrecovid	Precovid	Emptycovid	Covid	EmptyPrecovid	Precovid	EmptyPostcovid	Postcovid
ShareTransport		(0.0127)		(0.0126)		(0.0268)		(0.0446)
		0.0706***		-0.0664***		-0.0475**		-0.2450***
		(0.0158)		(0.0180)		(0.0187)		(0.0352)
ShareRetail		-0.3890***		-0.6330***		0.2540***		0.6570***
		(0.0470)		(0.0525)		(0.0578)		(0.1210)
ShareRelGeography		0.6580***		0.4870***		0.0091		0.0517*
		(0.0060)		(0.0060)		(0.0160)		(0.0290)
Reviews_per_month		-0.0027***		-0.0002		-0.0002		0.0005*
		(0.0005)		(0.0003)		(0.0003)		(0.0003)
Constant	0.411***	0.281***	0.434***	0.328***	0.277***	0.2090***	0.2791***	0.2190***
	(0.00563)	(0.00394)	(0.00395)	(0.00426)	(0.00782)	(0.0130)	(0.0127)	(0.0121)
Observations	458,931	458,078	392,566	391,554	20,417	20,417	37,959	17,542
IccNeighbourhood	0.01329	0.0039	0.0064	0.0039	0.0558	0.0185	0.1284	0.0062
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Log likelihood	-62517.571	-28012.349	-53973.926	-30355.306	9196.8077	13125.773	12491.747	5533.5348
Number of neighbourhoods	33	33	33	33	28	28	28	28

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

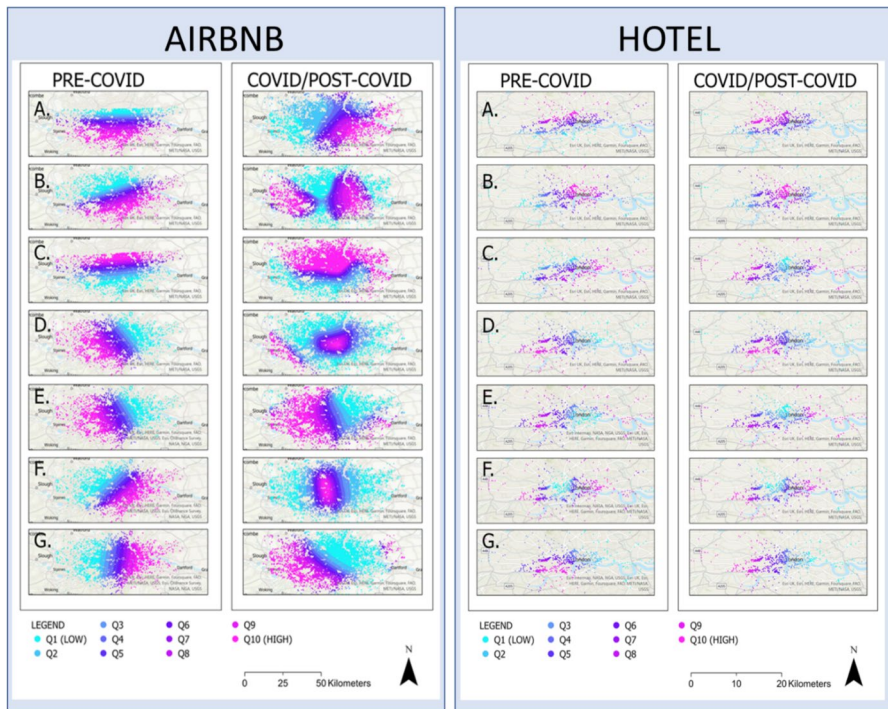


Fig. 1 GWR outputs for land use variables in the pre-COVID period and COVID-period for the Airbnb listings in the left section, and for hotels in the right section. Legend: A=Min. distance to parks, B=Min. distance to parking, C=Min distance to Nature, D=Min distance to Transport, E=Min Distance to Tourism, F=Min Distance to Central Station, G=R2

When exploring the impact of natural amenities, we identified a distinct division between the North and South parts of the city in the pre-COVID period. Our analysis revealed higher visitor satisfaction in the Southern and South-West areas where natural amenities were more abundant. This spatial pattern suggests that the availability and accessibility of natural attractions in these regions positively influenced visitor satisfaction. The Southern and South-West areas of London, with their rich natural landscapes and attractions, created a more enjoyable and fulfilling experience for visitors during the COVID period.

Furthermore, our study revealed a noteworthy finding regarding the minimum distance to public transportation. We found a positive association between proximity to public transportation and visitor satisfaction, particularly in the Eastern parts of London. The effect spreads around the city in the COVID period, except the city center. This suggests that easy access to public transportation options began to exert an overall positive influence on visitor satisfaction levels. However, it is worth noting that the extensive transportation infrastructure in central London may have created negative externalities, such as noise and crowding, which did not enhance visitor satisfaction. During the COVID period, people

seemed to be inclined to avoid crowded public transportation, and this factor might have contributed to decreased satisfaction in these areas. The impact of the COVID period on visitor behavior in Central London is also apparent in the coefficient of the variable "distance to central station" (panel F in Fig. 1). In the pre-COVID period, being closer to the city center in the North-West region improved Airbnb visitor satisfaction. However, during the COVID period, proximity to central London was associated with less satisfaction, likely for the same reasons that include noise and crowding.

These innovative and spatially differentiated findings from the GWR analysis of Airbnb data provide valuable insights into the complex relationship between land use, location, and visitor satisfaction. By uncovering these spatial patterns, we can better understand the specific factors that contribute to visitor satisfaction in several areas of the city (e.g. Kuentz-Simonet & Rambonilaza, 2024). This knowledge can inform destination planners, policymakers, and tourism stakeholders in their efforts to strategically allocate resources, develop targeted interventions, and enhance visitor experiences in specific locations within London.

It is intriguing to note that the spatial distribution of the effect related to accessing tourism attractions remained relatively stable from the pre-COVID period to the COVID period. However, there were distinct changes in the magnitude of this effect, as indicated by the results of the multilevel model. Finally, the R-squared (R^2) value of the GWR model reveals a significant shift in areas where the model performs better.

For Airbnb users in the pre-COVID period, visitor satisfaction was more effectively explained by the specified covariates in the Western parts of London. However, in the COVID period, this relationship appears to be reversed, with the Eastern parts of the city becoming better explained in visitor satisfaction by the model specification. In addition, Appendix Figs. 2 and 3 display maps of standard errors associated with specific covariates for Airbnb listings and hotels, respectively. The standard errors indicate a stable model with a consistent degree of errors in both the pre- and COVID-periods. There is, however, one other exception in the case of access to public transport, where standard errors are smaller in a broader geographic area extending from the city center. In contrast, for other covariates, the standard errors remain consistently small in the center for both periods.

The right-hand section of Fig. 1 shows the GWR model outputs using data from the hotel sector in London. It is worth noting that hotels are fewer in number and tend to cluster toward the city centre. The results align with the order presented for Airbnb. It is interesting to observe that while we noticed similar dynamics in most cases between the Airbnb and hotel sectors, as indicated by our multilevel model, the GWR analysis reveals minimal spatial changes in the direction of effects of the specified covariates from the pre-COVID to COVID periods. Consequently, similar maps emerge for the two periods. This phenomenon may be attributed to hotels' ability to maintain strategic management during the COVID-19 pandemic, which made them less sensitive to the overall changes experienced. Hotels across different parts of the city appeared to develop strategies that responded to these changes

to a similar degree. In contrast, the Airbnb market seemed more vulnerable to the changes brought about by COVID-19. Additionally, the distribution of Airbnb listings across the city made it more susceptible to shifts in consumers' locational preferences. Statistical test information can be found in the [Appendix](#).

In summary, our study introduces a fresh perspective on the spatial dynamics of visitor satisfaction, demonstrating the power of geospatial analysis in uncovering nuanced associations. The findings underscore the importance of considering location-specific factors and tailoring strategies to enhance visitor satisfaction based on the unique characteristics of different areas within the city. The paper confirms in general the relevance of wellbeing (or happiness) research for understanding the complex dynamics of sectoral developments in space and time (see Burger et al., 2020; Veenhoven, 2000).

Conclusion

In conclusion, our study provides a comprehensive understanding of the spatial satisfaction of visitors in London during both the pre- and during-COVID periods. Through innovative methodologies and detailed data analysis, we have identified key factors influencing visitor satisfaction and identified spatial variations in satisfaction levels.

Our findings highlight the significance of listing-level factors in shaping visitor experiences and satisfaction within the Airbnb market. We observe a shift in focus from traditional hotel offerings to the unique features and offerings provided by individual Airbnb accommodations. This emphasizes the importance of hosts and stakeholders in curating exceptional listings that cater to the diverse needs and preferences of visitors.

In particular, our analysis found no substantial relationship between price and visitor satisfaction, as the coefficient for price was essentially zero. This finding suggests that visitor satisfaction is more influenced by location-specific factors than by the cost of accommodation.

Among the determinants of visitor satisfaction, we find that the minimum distance to parks plays a crucial role. Having a park nearby significantly contributes to visitor satisfaction, particularly in the western parts of London. This suggests that the presence of green spaces in these areas creates a more favorable environment and enhances overall satisfaction levels. Additionally, proximity to public transportation positively influences visitor satisfaction, except at the center of the city. The availability and accessibility of public transportation options in these areas contribute to convenient and efficient travel, enhancing visitor experiences.

Our study also identifies a distinct division between the north and south parts of the city in terms of visitor satisfaction related to natural amenities. Higher satisfaction levels are observed in the southern and southwest areas where natural attractions are more abundant. The availability and accessibility of these natural amenities contribute to a more enjoyable and fulfilling experience for visitors.

Text analysis and sentiment analysis reveal additional insights into visitor satisfaction. Cleanliness-related comments appear to play a significant role, particularly within the Airbnb market, with visitors emphasizing the importance of cleanliness for their satisfaction. Comments related to transportation and geography also influence satisfaction levels, highlighting the significance of well-designed and accessible urban environments.

The Geographically Weighted Regression (GWR) analysis appeared to provide spatially differentiated findings, uncovering unique patterns and associations between land use, location, and visitor satisfaction. These findings offer valuable insights into the specific factors that contribute to visitor satisfaction in different parts of the city.

Overall, our research highlights the importance of considering location-specific factors and tailoring strategies to enhance visitor satisfaction based on the unique characteristics of different areas within London. The findings provide valuable guidance for destination planners, policymakers, and tourism stakeholders in allocating resources, developing targeted interventions, and enhancing visitor experiences in specific locations.

By exploring the complex relationships between geographic location, density, land use, and visitor satisfaction, our study contributes to the field of tourism analysis by integrating quantitative modeling techniques with place-specific subjective social media data. The profound insights derived from our research empower decision-makers with knowledge for making informed choices, cultivating sustainable growth within the tourism industry, and elevating the holistic visitor experience in London.

Clearly, a caveat on the use of information from digital review platforms (like Airbnb and TripAdvisor) is needed, as such reviews are not by definition always robust or representative. However, since most Airbnb and hotel bookings are made in digital form, it seems plausible that such users are able to express their opinion on assessment of tourist facilities also in a proper form. The open access of information on such platforms will most likely create a reasonable balance or credibility of the sentiments expressed by individual users.

In conclusion, our study identifies the fundamental factors that exert a significant influence on visitor satisfaction in London, encompassing the proximity to parks, the ease of access to public transportation, and the abundance of natural amenities. These findings articulate the importance of location-specific considerations and tailored strategies to enhance visitor experiences. By leveraging innovative methodologies, we provide valuable insights for decision-makers to optimize the tourism industry and elevate visitor satisfaction in various areas of the city. The methodology adopted in our study is rather generic in nature and can also relatively easily be applied to other tourist destinations.

Appendix: Statistical Test Indicators

Please see Figures 2 and 3.

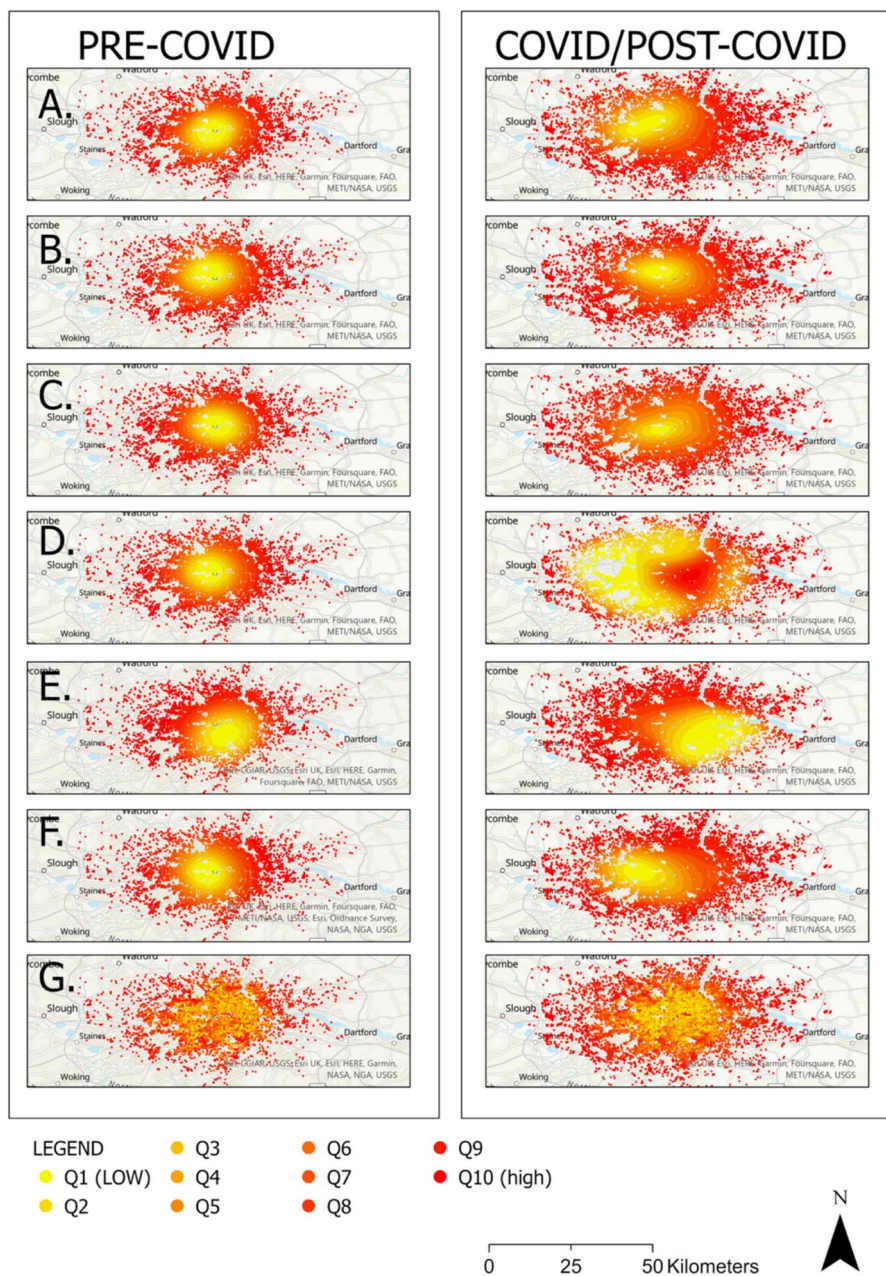


Fig. 2 Standard errors from the GWR of Airbnb listings. Legend: A=Min. distance to parks, B=Min. distance to parking, C=Min distance to Nature, D=Min distance to Transport, E=Min Distance to Tourism, F=Min Distance to Central Station, G=Residuals from the whole model

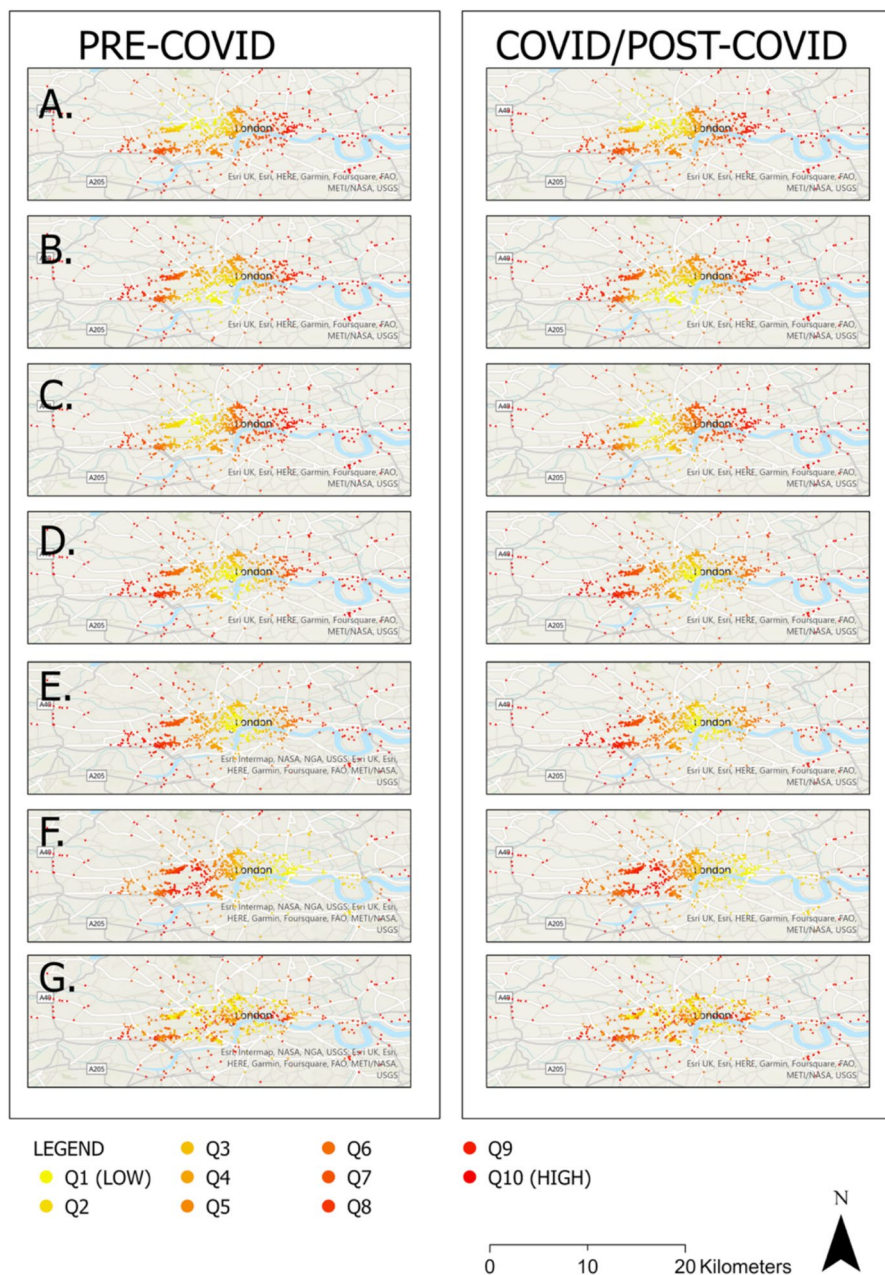


Fig. 3 Standard errors from the GWR of hotel rooms. Legend: A = Min. distance to parks, B = Min. distance to parking, C = Min distance to Nature, D = Min distance to Transport, E = Min Distance to Tourism, F = Min Distance to Central Station, G = Residuals from the whole model

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Data Availability The data that support the findings of this study are available on request from the corresponding author.

Declarations

We have included the Disclosure of potential conflicts of interest as required. Additionally, our research does not involve human participants or animals, and therefore, informed consent is not applicable.

Conflicts of Interest We wish to confirm that there are no known conflicts of interest associated with this publication.

Human and Animal Rights Our work does not include animals as subjects.

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