Short-Term Rental Platform in the Urban Tourism Context: A Geographically Weighted Regression (GWR) and a Multiscale GWR (MGWR) Approaches

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This article contributes to advancing the knowledge on the phenomenon of the most popular short-term rental platforms, Airbnb. By implementing a geographically weighted regression (GWR) and its multiscale form, MGWR, we examine the relationship between Airbnb locations and the core elements of urban tourism including hotels, food and beverages (F&B) venues, as well as access to public transport. This article's contributions are twofold: methodological and empirical. First, the results show that incorporating localities improve overall model performance. It allows us to account for the nuance of each area of interest as the MGWR performs slightly better than the GWR in the case of spatially sparse data. Second, both models show that Airbnbs collocate with hotels supported by various amenities, but Airbnbs also go beyond traditional hotel zones. This analysis highlights and extends the latter where Airbnb concentrations are those for which there are strong associations with F&B establishments and access to public transports. This suggests that Airbnbs might benefit local businesses outside the reach of major tourist zones. However, there is further work to be done to understand whether the economic benefit to the local economy is worth the associated social costs raised by previous studies.

Introduction

The travel and tourism industry is one of the most prominent sectors of the global economy, contributing nearly 10.2% of the world's GDP in 2016 and affecting more than 109 million jobs worldwide (World Travel and Tourism Council 2017). Despite constantly changing economic conditions, tourism has been experiencing steady growth worldwide, as the sector has been developing continuously over the last several decades, influencing the world's socio-economic as well as cultural progress (UNWTO 2010). It is an important source of welfare in many countries

in the world, with direct impacts, indirect impacts (to the supply chain) and induced impacts (to the local economy both directly and indirectly) from tourism spending (World Travel and Tourism Council 2017).

Various places are largely dependent on the tourism sector to support their economic growth. This includes urban tourism that uses city elements or spectacles as the fundamental components in attracting visitors (Ashworth 1989; Pearce 2001; Edwards, Griffin, and Hayllar 2008; Bramwell 1998). Law (1992) argues that systematically, to support urban tourism, primary elements must be available in cities. These include the clusters of attractions: museums, art galleries, concert halls, historic buildings, urban-scapes, etc. Secondary elements need to be present as well in assisting these attractions, such as accommodations, transports, catering, shopping facilities and tourism agencies (Law 1992).

Perhaps the biggest and the most important transformation in the way we do tourism today is how it has been largely affected by the rapid development of information and communications technology (ICT), especially in big cities where the influx of tourists generate huge tourism demands. This is especially true as at present, traditional intermediaries (such as travel agents) are bypassed by the emergence of platforms that can connect consumers and suppliers directly (Buhalis and O'Connor 2005; Minghetti and Buhalis 2010). These platforms allow small individuals and businesses, often referred to as micro-entrepreneurs, to market their goods and services (Buckley et al. 2015). Tourism has now been steered towards these demand-oriented technologies, in a more informal setting, that enables peer-to-peer (P2P) and dynamic interactions (Boswijk 2016; Shabrina et al. 2017). This is also the idea for emerging platform-based companies such as Airbnb that offers short-term holiday rentals mainly for tourists, which is the focus of this article.

The aim of this study is twofold. First, we examine the comparative use of two local models, namely geographically weighted regression (GWR) and multiscale GWR (MGWR) on spatially sparse data. We do this with an analysis of the association between the presence of a home-sharing platform, Airbnb, and three core elements of urban tourism: the traditional hotel, the food industry, and public transport accessibility, for each lower super output areas (LSOA) in London. Second, we investigate based on our model, the areas where these elements have strong positive and negative interlinks. We then further discuss the implications of the results.

Urban tourism: Using city elements to attract visitors

We can differentiate urban tourism from other tourism forms based on several features. First, there is a considerable portion of visits for non-leisure purposes, such as businesses, conferences, and family visitations. Second, the attractions vary and are large in scale as tourism is just one of the many economic activities in the city, so it collides with other industries. Thus, attractions and infrastructures are utilized by residents as well as visitors (Edwards, Griffin, and Hayllar 2008). Specifically, urban tourism can be defined further based on its setting, which is in complex urban areas. It can also be distinguished by the type of cultural activities, in which tourists share and/ or compete with residents for services, space, and amenities (Ashworth 1989; Pearce 2001). Although facilities favored by tourists might be different from those preferred by residents (Law 1993), the overlap is somewhat inevitable, as there is a social convergence between local and tourist consumption (Ashworth 2003). Moreover, residents also consume tourist attractions regularly as a source of entertainment. Another element is that cities offering urban tourism generally have easy access to the key gateways for national and international visitors such as multiple nodes for air transport systems (Law 1993; Edwards, Griffin, and Hayllar 2008).

Fig. 1 provides a visualization of urban tourism containing primary, secondary, and conditional elements. The primary aspects include activity places and leisure settings, such as cultural and entertainment facilities, green spaces, waterfronts, and other sociocultural activities. The core model proposed by Jansen-Verbeke and Lievois (1999) suggests that without these first components as the primary tourism product or "the draw," there will be little reason for a leisure visit to cities that do not offer such tourism. Furthermore, the second elements are the supporting factors required to substantiate and enhance the visitor's experiences. This includes adequate and diverse choices of accommodation as well as facilities providing food and goods for consumption. Integration of these elements can further present socio-cultural and economic benefits for cities.

Relationship between Airbnb, hotels, food industry, and public transport accessibility

In this article, we analyze the association between the presence of a short-term rental platform, Airbnb, with the secondary and conditional elements of urban tourism: hotel, food and beverage (F&B) venues, and public transport accessibility. Interests have been shown surrounding the topic of the short-term rental platform and the hospitality industry. Many argue that there is an apparent overlap in demand within the users of the short-term rental platform and traditional tourist accommodation such as hotels (Jamie Lane 2016; Zervas, Proserpio, and Byers 2016; Guttentag et al. 2018). It has been particularly prominent within the lower-end categories of hotels that may not cater to the needs of the entire cross-section of potential tourists and travelers (Zervas, Proserpio, and Byers 2016). The competitive impact of Airbnb over traditional hotels was substantiated in a recent study by Dogru, Mody, and Suess (2017) indicating a revenue decline of approximately 2.5% across all hotels in Boston. Several studies suggested that the
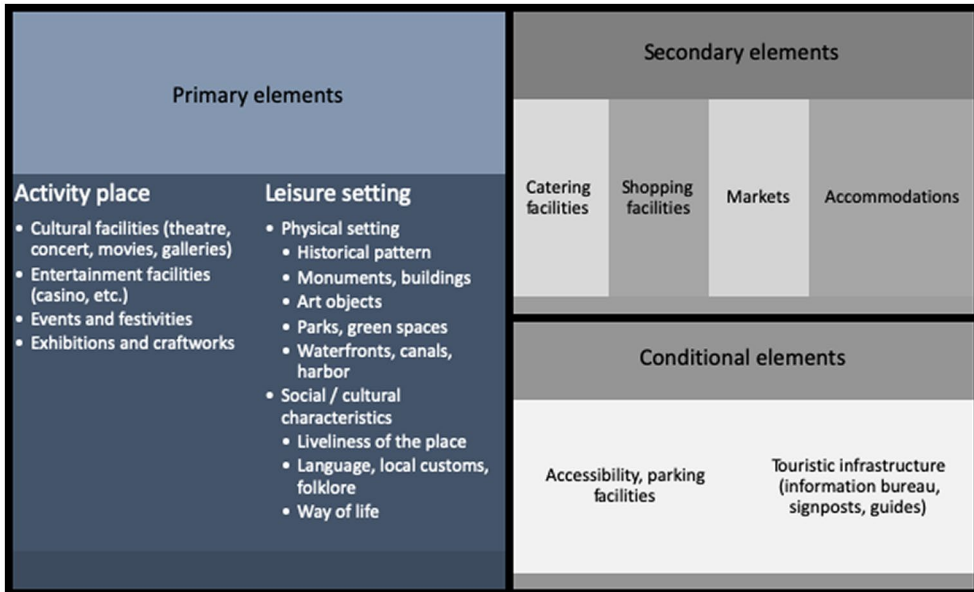

Figure 1. Urban tourism elements. Source: Adapted from Jansen-Verbeke (1986).

presence and availability of the Airbnb platform have steadily fulfilled a growing need for alternative accommodation within the hospitality industry (Guttentag et al., 2018; Zervas, Proserpio, and Byers 2016). As such, the overlap of potential customers for all forms of holiday accommodations, whether provided by digital platforms or not, is said to have had a significant increase over recent years (Dogru, Mody, and Suess 2017; Gutiérrez et al. 2017). It is evident in both the rising trend in hotels offering typical Airbnb attributes through purchase and partnerships (Solon 2018), and similarly, with Airbnb following this trend in capturing a larger market share through the acquisition of other hotel booking platforms (Ting 2018).

In terms of spatial locations, Arbel and Pizam (1977) found that the travel patterns of tourists within a city remain close to the vicinity of their chosen accommodation and their intent to visit individual areas of interest. This is a result that has been expanded upon in research by Shoval et al. (2011), illustrating that large shares of tourist travel within a city often lie in a definable area. These are areas that might have saturated city facilities including transport links, entertainment center, etc., within many central tourist areas (Shoval and Raveh 2004). That is why it is assumed that areas where hotels are located, there is likely to be an increased number of establishments offering amenities such as F&B, to meet increased tourist demands.

Although findings from previous studies have pointed to a strong spatial relationship between the distribution of hotels and constructed tourist amenities, indicating the critical role these amenities play within proximate locations to hotels (Lee et al. 2018; Li et al. 2015), this relationship is not very clear for Airbnb. While the spatial pattern of hotels can often be predicted by several factors, such as local zoning and planning regulations that further limit their densities and distribution, this is not likely to be the case for Airbnb. After all, Airbnb can locate without such rigid restrictions, and thus, it is operating more flexibly. Joining Airbnb and listing a property as a holiday rental is relatively straightforward, as there is no special permission to rent a property as a short-term holiday rental for less than 90 days annually in London (HM Government United Kingdom 2015). Thus, this study attempts to examine the location's attributes associated with Airbnb distribution and advancing our knowledge regarding this phenomenon.

To examine the relationship between Airbnb and urban tourism elements, we use four datasets.

1. *Airbnb listings available in 2018 from Inside Airbnb* (http://insideairbnb.com). This Airbnb dataset contains the count data of listings in each of three categories: entire property, private room and shared room listings. Fig. 2a shows the distribution of Airbnbs are spread out, with some concentration centrally. The raw data contains over 69,000 Airbnb listings based on data from May 2018; however, we only consider active listings (these are proxied by the presence of at least one review). Airbnb listings which satisfy this condition are aggregated into LSOA in London for a total of approximately 50,000 active listings across 3982 LSOAs (82% of the total LSOA in London). We then calculate the Airbnb density for each LSOA by dividing the active Airbnb count with the total area.

2. *Traditional accommodation from the Ordnance Survey Points of Interest (POI) data 2018*. including guest houses, bed and breakfast, hostels, hotels, motels, country houses, inns, youth hostels, and other youth classifications. Fig. 2b shows the data across London. It illustrates the concentration of 1382 hotels distributed in only 644 LSOAs (13% of the total LSOAs). We can see that a significant hotel density only presents in certain areas, arguably in areas of high tourist demand. From the same data source, we also use the *F&B venues*. It
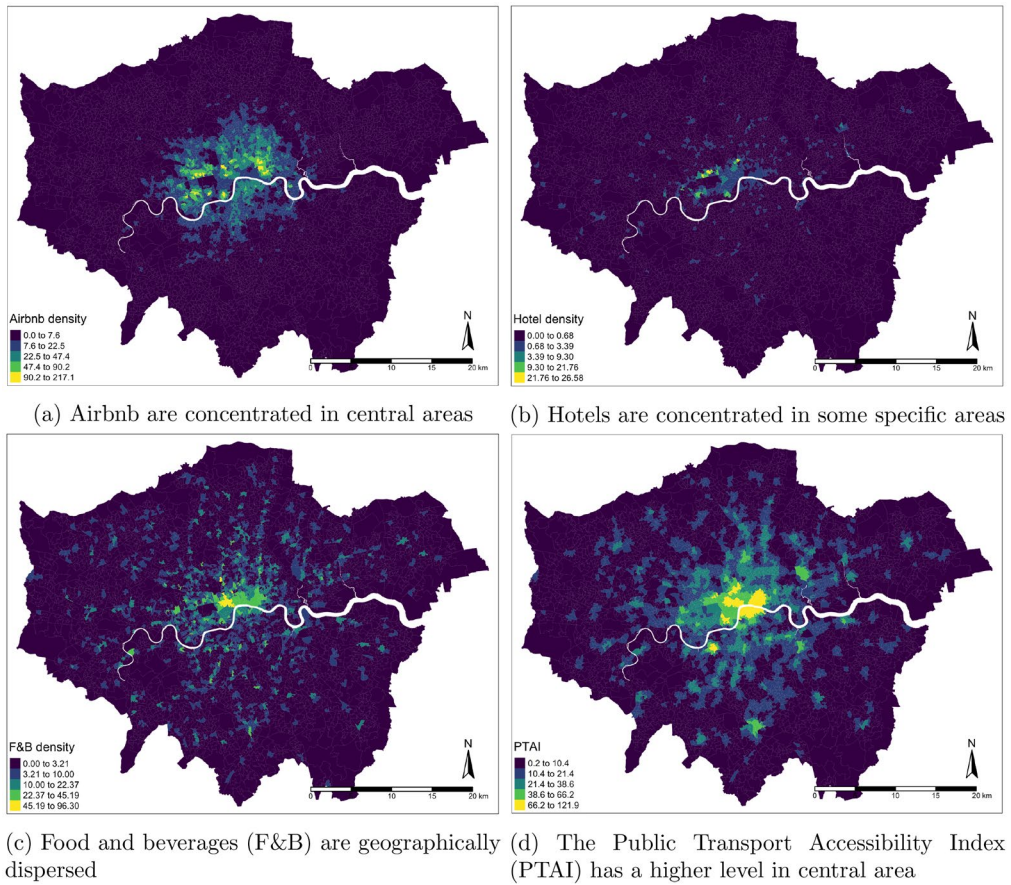
(a) Airbnb are concentrated in central areas

(b) Hotels are concentrated in some specific areas

(c) Food and beverages (F&B) are geographically dispersed

(d) The Public Transport Accessibility Index (PTAI) has a higher level in central area

Figure 2. The spatial distribution of the density for the dependent variable (a) and the explanatory variables in (b), (c), and (d).

includes restaurants, fast food outlets, pubs, and other similar types of venue. Fig. 2c shows the spatial distribution of 27,716 F&B establishments in London, distributed in 3306 LSOA (68% of the total LSOA), many dispersed across London in different geographic areas, but mainly concentrated in central locations. Fig. 2c represents this data as a density map of F&B establishments by dividing the count with the total area.

3. *Public Transport Accessibility Index data (PTAI) from* Transport for London 2015. It is a form of accessibility indicator providing assessment using several key attributes. These include places (such as houses, offices, shops, etc.), public transport stops or service access points (SAP), walking networks, and other transport services in terms of routes and frequencies (Transport for London 2015). Fig. 2d shows that the distribution follows a radial pattern with high levels of PTAI in Central London and along with transport links throughout London.

A summary of the coverage for each of our four datasets is provided in Table 1. We can immediately see that especially for hotels, there are many areas (87%) that have no hotels present, followed by F&B data where 32% of the LSOAs have no recorded data. Thus, we need to find an appropriate way to model our system that could best explain the phenomenon without

Table 1. Overview of the Data Used for the Study Area for all 4835 LSOAs in Greater London

Type (density is per-hectare)	LSOA Containing (%)
Airbnb density	82
Hotel density	13
F&B density	68
PTAI	100

compromising the validity of our model. Hence, the proposed methodology is GWR, so that we can examine each local area and analyze in which localities the explanatory variables could be best used to explain Airbnb distribution.

The Geographically Weighted Regression and multiscale GWR (MGWR)

Simple linear regression, the most used technique in geographical analysis, assumes changes across space to be universal, which is not always the case in every spatial context. Variations across geographical space, known as spatial non-stationarity, might be lost when using simple global fitting methods such as ordinary least squares (OLS) (Brunsdon, Fotheringham, and Charlton 1996). Therefore, GWR provides an alternative method to analyze and model the complex spatial variations in local parameter estimates (Fotheringham 1997; Brunsdon, Fotheringham, and Charlton 1996; Fotheringham, Charlton, and Brunsdon 1998). The developed method extends the traditional linear regression technique to incorporate spatial heterogeneity in different regions by allowing the parameter estimate to vary locally (Fotheringham, Brunsdon, and Charlton 2003). GWR has been used extensively to describe relationship in various fields, including but not limited to crime analysis (Cahill & Mulligan 2007), population research (e.g., drug resistance distribution (Shoff and Yang 2012)), nutritional epidemiology (Yoo 2012), infectious disease epidemiology (Liu et al. 2011), physical environment (e.g., rainfall and altitude study Brunsdon, McClatchey, and Unwin 2001, land use and water quality study Tu 2011), and various other disciplines.

The core specification for conducting a GWR is the choice of the optimum bandwidth and kernels. We can compute an optimum bandwidth for all the independent variables by taking into consideration the choice of the kernel (fixed or adaptive) and how neighboring points are weighted. Fotheringham, Brunsdon, and Charlton 2003 discuss this in detail. Fig. 3 shows an overview of how both kernels work. The fixed spatial kernel uses distance as a parameter and often used when the distribution of data is uniform. Fig. 3a shows that in this case, each local regression is computed based on a specific bandwidth distance. When data is sparse, this type of kernel is insufficient as in areas with very few regression points, a fixed spatial kernel provides insufficient variations, resulting in a large standard deviation of errors (Fotheringham, Brunsdon, and Charlton 2003). In this case, an adaptive kernel-based on k-nearest neighbors is more favorable. As shown in Fig. 3b, the size of the kernel follows the density of the data, with larger bandwidths for sparse data, and smaller bandwidths for clustered data (Fotheringham, Brunsdon, and Charlton 2003).

Another consideration is the weighting functions of the kernels (Fotheringham, Brunsdon, and Charlton 2003). Gaussian weighting considers all the data points where the weight gradually decreases from the center of the kernel. In this case, weights are never assigned zero values. In contrast, the bisquare weighting has a clear-cut range for which the weights are non-zero. All the data points outside the optimum bandwidth are set to zero and thus do not influence our local
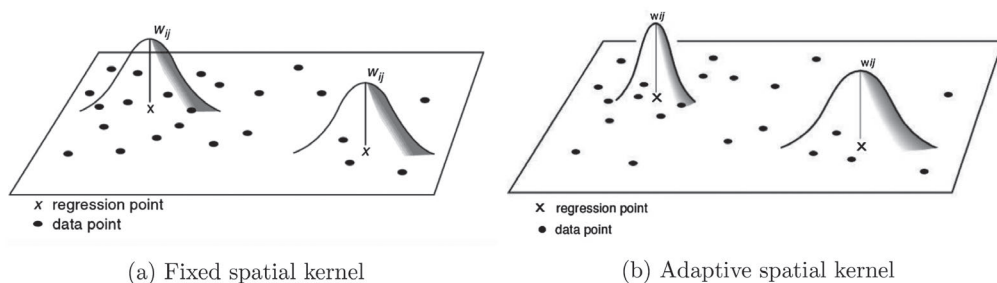
(a) Fixed spatial kernel   (b) Adaptive spatial kernel

Figure 3. Spatial kernel types adapted from Fotheringham et al. (2003).

regression. After specifying these elements, we can find an optimum bandwidth using iterative optimization processes, that either minimizes the corrected Akaike Information Criterion (AICc) or the cross-validation (CV) statistic. The AICc optimization measures the information distance by capturing the divergence between the predicted and observed values (Charlton, Fotheringham, and Brunsdon 2009). CV minimization examines the sum of the squared error when estimating the predicted dependent variable at each regression point (Brunsdon, Fotheringham, and Charlton 1996).

However, the GWR method has several known limitations. These include the possibility of obtaining false positives as a result of multiple hypothesis testing (da Silva and Fotheringham 2016) and accuracy problems due to the assumptions on a univariate scale by using a single bandwidth for every variable (Yu et al. 2020). To overcome some of these issues, Fotheringham, Yang, and Kang (2017), Yu et al. (2020) and Oshan et al. (2018) proposed an extension of the GWR method to include the computation of optimum bandwidths of the local parameters in each iteration, using MGWR. This new method improves the common GWR model mainly by eliminating the assumption that variations occur within the same scale (Yu et al. 2020). In contrast, MGWR allows multiscale modeling, overcoming the issue of multiple testing as well as increasing the reliability by introducing multiple bandwidths (Fotheringham, Yang, and Kang 2017).

MGWR recasts GWR as a generalized additive model (GAM) and uses a back fitting algorithm, an iterative process of calibrating a series of GWR models based on the models' partial residuals until the MGWR model converges to a solution (Fotheringham, Yang, and Kang (2017)). In other words, the algorithm allows us to update each iteration process using an appropriate smoothing function by refining the partial residuals. Oshan et al. (2018) argues that an MGWR needs to be initialized using a starting value (generally the optimum parameter estimates based on the GWR model) for faster model calibration.

This article implements three models–OLS, GWR, and MGWR. The purpose of the models is to understand the locational attributes of Airbnb. In all models, we quantify the relationships between Airbnb and three specific elements of urban tourism: hotels, F&Bs and the accessibility to public transportation as indicated by the Public Transport Accessibility Index (PTAI). It adds to our comprehension the effect of spatial heterogeneity on Airbnb locations. The emergence of holiday rentals in a city can be thought of as reactive to the impacts of urban tourism (Page et al. 1995). We examine if this is also the case for Airbnb. For example, if Airbnb presence is strong in hotels locations, there might be an overlapping or possible competition in the most desirable locations. As indicated in previous studies, there is a strong positive relationship between traditional accommodation (hotels) and places of interest (attractions) in cities (Lee et al. 2018). However, the rapid rise of holiday accommodation, through the utilization of digital platforms

such as Airbnb has somewhat changed the nature of tourism, especially in urban settings. Given that Airbnb can fundamentally be anywhere wherever residential properties are available, it has been argued by Guttentag (2015) that this leads to increased dispersal of tourists in areas not typically regarded as central tourist destinations. Zervas, Proserpio, and Byers (2016) expand on this, suggesting that Airbnb also pervades traditional tourist accommodation, such as hotels.

Previous studies have highlighted how hotels benefit strongly from the locational attributes of their proximate tourist and retail amenities (Arbel and Pizam 1977; Shoval et al. 2011; Shoval and Raveh 2004). Thus, in this article, we investigate whether Airbnb landscapes equally exhibit spatially dependent distributions in relation to retails, as well as access to public transport. However, the knowledge surrounding the relationships between Airbnb and retail land-use as well as transport links is limited. Understanding the dynamics here might help us to uncover insights into the association between Airbnb and retail such as F&B locations and access to public transportation. The hypothesis is that the demand for tourist accommodation is often associated with the number of reachable amenities and easiness to travel to other parts of the city. It is unclear if this also the case for Airbnb. Xu et al. (2020) analyzed various neighborhood factors and found that geographical elements–including water, green space, human landscape, transportation, educational institution, and nightlife—are influential factors that vary across space. We expand this by focusing on elements of urban tourism for Airbnb in London, given the fact that London contains the highest Airbnb supply globally (based on data from Inside Airbnb).

Statistical base-lining

In the first instance, it was necessary to ensure that the chosen parameters exhibit no strong correlation with one another. Thus, we calculate the variance inflation factor (VIF) that assesses how much variances increase if predictors are correlated. No correlation would yield a VIF score of 1 while a VIF above 5 indicates problematic multicollinearity (Wheeler and Tiefelsdorf 2005; Wheeler 2007). We can obtain the VIF value by dividing the ratio of the total variance of the model's parameters with the variance of these parameters if they were fit alone. Table 2 shows the descriptive statistic of the data and the VIF. It shows that all covariates do not exhibit multicollinearity since the VIF is close to 1.

We set a baseline for the model using simple linear regression with Airbnb density as the dependent variable and a set of independent variables. These are hotel density, the density of F&B venues, and the Public Transport Accessibility Index (PTAI). Table 3 shows the result of the regression analysis suggesting a positive relationship between Airbnb and the independent variables. The model performance shows an adjusted-R^2 of 0.3997 where almost 40% of the data variance is explained by the global model.

However, considering the distribution of our data, where many LSOAs do not contain hotel and F&B, the parameter estimates in the global model are unlikely to describe the relationship. The global regression assumes that we have independent observations. However, this is not

Table 2. Descriptive Statistics of the Data

Variable	Mean	SD	Min	Max	VIF
Airbnb density	0.772	1.495	0	21.714	–
Hotel density	0.019	0.115	0	2.658	1.157
F&B density	0.303	0.585	0	9.629	1.699
PTAI	13.34	12.54	0.19	121.89	1.772

Table 3. The Global Model Result Using OLS Regression

Residuals				
Min	1Q	Median	3Q	Max
-6.4331	−0.3917	−0.1720	0.0204	19.5092
Coefficients				
	Estimate	Std. Error	*t* value	Pr(>−*t*−)
(Intercept)	−0.034223	0.024822	−1.379	0.168
Hotel density	2.776062	0.155725	17.827	<2e-16***
F&B density	0.477264	0.037052	12.881	<2e-16***
PTAI	0.045664	0.001769	25.816	<2e-16***

Signif. codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1
Residual standard error: 1.159 on 31° of freedom
Multiple R^2: 0.4001, Adjusted R^2: 0.3997
F-statistic: 1074 on 3 and 4831 DF, *P*-value: <2.2e-16.

always the case in spatial data as the variables might exhibit spatial dependence. Spatial autocorrelation captures the spatial relationships in a dataset, where closer observations are more related than distant ones (Anselin 2001). To check for spatial autocorrelation, we test the residual of our OLS regression using Moran's I by checking if our residuals show a pattern where neighboring locations show similar magnitudes and (or) signs. Our result for Moran's I test indicates that the OLS residuals show spatial dependence (*P*-value of <0.01) and we can also see the effect of spatial auto-correlation in Fig. 4. There is a clear pattern in space: the highest under predictions (dark blue) are clustered in central London, whereas over predicted residuals (red) are in the periphery, with smaller clusters in the northern and southwestern boroughs.

When spatial data exhibit spatial autocorrelation, the parameter estimates from the global model might be inefficient. The global statistic, such as in the linear regression used above, generalizes across a study area. Thus, it reduces the inherent variability within data at localized scales. Thus, heterogeneity might be lost across space. For this reason, there is a virtue in using an approach that can take into account spatially heterogeneous processes (Brunsdon, Fotheringham, and Charlton 1996). GWR is a method to localize regression modeling and to understand the relationships between variables across space, thereby addressing the issue of spatial autocorrelation (Brunsdon, Fotheringham, and Charlton 1996; Fotheringham 1997; Fotheringham, Charlton, and Brunsdon 1998). GWR extends traditional regression analysis to allow local (instead of global) parameters to be estimated.

Given a dependent variable y in location i with coordinates u_i, v_i, the parameter estimates that can be represented as continuous function $a_k(u_i, v_i)$ at point i, and independent variables x_{ik} at point i with k representing the number of independent variables (Brunsdon, Fotheringham, and Charlton 1996; Fotheringham 1997; Fotheringham, Brunsdon, and Charlton 2003), the GWR model can be written as follows (Equation 1):

$$y_i = a_0(u_i, v_i) + \sum_k a_k(u_i, v_i)x_{ik} + \epsilon_i \tag{1}$$

Thus, using the GWR, the resulting parameter estimates are specific to that location, instead of being universal across space. In our case, the parameter estimates are generated for each
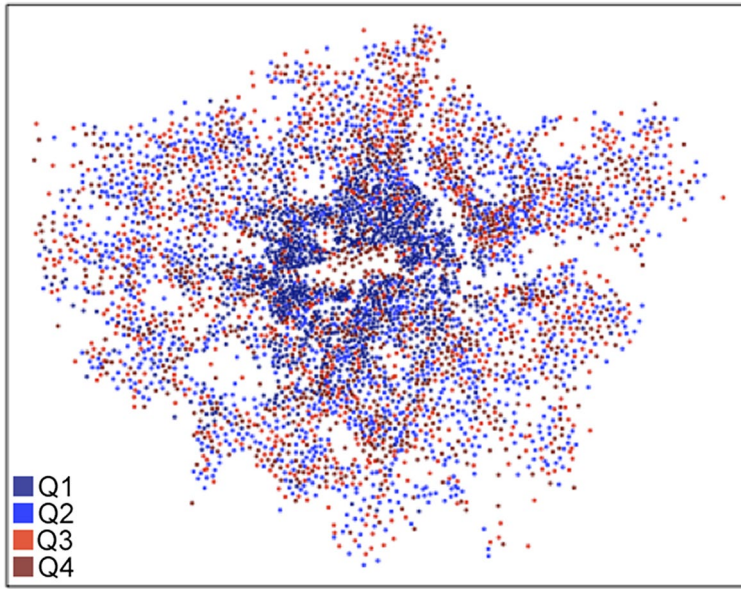
Figure 4. Spatial OLS residuals plotted by quantiles. The OLS residuals are between Airbnb (dependent variable) and hotel, F&B and PTAI (independent variables).

regression point, which are the LSOA centroids containing information about Airbnb, F&B, hotel densities, and the PTAI within that LSOA.

In analyzing our data using the GWR method, we first need an understanding of what is local. We need to construct a weight matrix that varies according to the locations of the regression points. We specify the type of kernel used, which can be fixed (specified) or made adaptive for providing the spatial weighting for the model. As our data contains sparse distributions, we use an adaptive bisquare kernel (refer to Charlton, Fotheringham, and Brunsdon 2009, pp. 5–8), where only observations inside the computed bandwidth are taken into account, nullifying the rest.

As mentioned previously, an adaptive kernel is arguably more favorable when dealing with nonuniform spatial distributions (Fotheringham, Brunsdon, and Charlton 2003; Oshan et al. 2018). Using an adaptive kernel allows GWR to compute the optimum bandwidth by iterating the number of nearest neighbors that should be taken into account for the local regression model. The data points near the locations (u_i, v_j) will be assigned higher weights than the ones further away. The weight (w_{ij}) of data point j at regression point i based on the optimum number of nearest neighbors (b) between regression point i and data point j (d_{ij}) can be calculated as follows in Equation 2. If the number of computed nearest neighbors d_{ij} is beyond the value of b, then it is given 0 value. In this model, the optimal proportion of the bandwidth is returned by minimizing the corrected Akaike Information Criterion (AICc) score or simply minimizing the loss information in the local model (Fotheringham, Charlton, and Brunsdon 1998).

$$w_{ij} = (1 - (d_{ij}/b)^2)^2 \text{ if } d_{ij} < b, \text{ 0 otherwise} \tag{2}$$

Because a GWR uses a bandwidth that is constant for each relationship, there are possi-bilities for mispecification at one or more scales (Oshan et al. 2018). Thus, MGWR further extends the functionality of GWR by allowing the use of a specific bandwidths for each variable denoted as *bw*. This allows the model to operate at different spatial scales (Fotheringham, Yang, and Kang 2017) accounting for their different spatial distributions. As mentioned previously, MGWR is using a back fitting algorithm, with an iterative procedure that relates a univariate response variable (in this case the GWR model) to predictor variables (partial residuals from a previous iteration), until a solution is obtained (Fotheringham, Yang, and Kang 2017; Yu et al. 2020). The computation is based on iterations of optimum bandwidth for each parameter estimates. All the computations are performed using the Python based package called mgwr (for complete methodology, see Oshan et al. 2018). The MGWR model can now be written as follows (Equation 3):

$$y_i = a_{bw0}(u_i, v_i) + \sum_k a_{bwk}(u_i, v_i)x_{ik} + \epsilon_i \tag{3}$$

Results and discussion

As the global regression might suffer from the inefficiency of the parameter estimates due to the spatial autocorrelation of the residuals, we model our variables using local models: GWR and MGWR to capture the spatial heterogeneity in the local system.

Model comparison and performance

Table 4 shows the comparison between the results of the implemented models, including the global model and two local models, through the models' goodness of fit. It shows that both local models have a significantly better fit than the global regression model, where the adjusted R^2 has almost doubled. The local models improved the adjusted R^2 from 0.4 (OLS) to 0.72 (GWR) and 0.77 (MGWR). The adjusted R^2 indicates the level of model variance that can be captured by the model, where the local models can explain more than 70% of the model variance. The adjusted R^2 might be biased for examining the model goodness of fit, due to the nature of the method. Thus, we also demonstrate the model fit using other statistic measures.

The residual sum of squares (RSS), indicating unexplained variations, are very high in the OLS model (2900) and the RSS values are down to almost one third in the local models, 1212 (GWR) and 1124 (MGWR). The generally AICc is used for model selection in GWR (Charlton, Fotheringham, and Brunsdon 2009), representing the relative amount of lost information in the model by considering both the risk of overfitting and underfitting (Akaike 1998). The local re-gression shows an AICc of 11260, while the GWR AICc is 8072 and the MGWR further brings AICc down to 7561. We aim for lower AICc values as this means that we retain most of the important information and that leads to a better fit of the model. Based on this information, we can be sure that the local model indeed has improved the model performance.

Table 4. Comparing the OLS, GWR and MGWR Model Fits

Model	Adj-R^2	RSS	AICc
OLS	0.400	2900.463	11260.412
GWR	0.722	1211.924	8072.117
MGWR	0.767	1124.203	7560.638

The performance of both models depends largely on the optimum use of bandwidths or neighboring values for model smoothing (Charlton, Fotheringham, and Brunsdon 2009). When the computed bandwidth is too small, the model might suffer from under smoothing while large bandwidths tend to have a poor fit and over-smoothed patterns. We must ensure that the bandwidth correctly represents the optimum number of nearest neighbors. The adaptive kernel helps us achieve this condition by finding the optimum bandwidth automatically using the chosen statistical criteria, which is AICc in our case. Table 5 shows that the GWR model has a single bandwidth of 95 - thus considering 95 nearest neighbors to inform the construction of parameter estimates in each local regression point (each LSOA). The use of the 95 bandwidth for each variable, correctly classifies 72% of the observations (refer back to Table 4).

In the case of MGWR, the difference is that instead of assigning a single bandwidth for all independent variables, the MGWR computes the optimum bandwidth for each variable as shown in Table 5. By allowing multiple bandwidths in MGWR, the model accounts for an optimal number of neighbors for each parameter estimate, thus allowing better predictions for the response variables, theoretically. The GWR model has a universal bandwidth of 95. In the case of MGWR, the bandwidth for each parameter is higher. The bandwidths are 412 for hotel density, 195 for F&B density, and 384 for PTAI. There are 4835 LSOAs in London aggregated into 33 London boroughs with each borough consist of roughly 100–200 LSOAs. Thus, if we examine the bandwidths for MGWR result, each variable accounts for around one or two boroughs as the nearest neighbors.

We examine the residuals from both local models. As previously discussed, the residuals from the global regression (OLS) show heavy spatial clustering. Although the local model using GWR and MGWR is not designed to specifically address spatial autocorrelation issues, less structured residuals can be obtained. Fig. 5 shows the plotted standardized residuals for both GWR (Fig. 5a) and MGWR (Fig. 5b) using quantile classification. We can observe that the GWR and MGWR residuals appear to be distributed more randomly, showing that more random errors remain. Upon conducting the Moran's I test for spatial autocorrelation to the residuals, the GWR and MGWR show P-value of 0.083 and 0.035, respectively. Thus, under the 0.01 level or 99% confidence interval, the pattern of the residuals is slightly more random.

Model interpretation
We have modeled the relationship between Airbnb and other elements of urban tourism using both GWR and MGWR models. For our dependent variable, the Airbnb density is examined

Table 5. The GWR and MGWR Results for the Spatial Variability of Parameters Using Adaptive Bandwidth

Model	Variable	Mean	STD	Min	Median	Max	Bandwidth
GWR	Intercept	−0.058	0.602	−0.694	−0.344	3.699	95
	Hotel density	0.004	0.219	−2.138	0.007	1.176	
	F&B density	0.051	0.120	−0.247	0.012	0.715	
	PTAI	0.114	0.184	−1.203	0.074	1.126	
MGWR	Intercept	−0.006	0.710	−0.473	−0.348	4.540	43
	Hotel density	0.062	0.101	−0.384	0.036	0.482	412
	F&B density	0.068	0.083	−0.012	0.030	0.283	195
	PTAI	0.041	0.056	−0.129	0.048	0.167	384

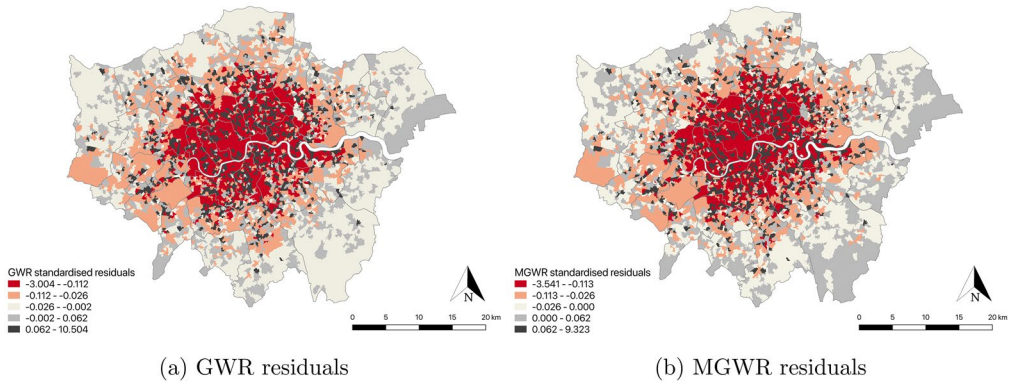(a) GWR residuals   (b) MGWR residuals

Figure 5. Spatial distribution of GWR and MGWR residuals. The GWR residuals (a) still show some clustering in central London, while MGWR residuals (b) are more randomly distributed.

using a series of independent variables: hotel density, F&B density, and PTAI score for transport accessibility. In this section, we present our model results by visualizing the model's parameter estimates that have a statistically significant relationship with Airbnb. We analyze this relationship individually, by comparing the GWR and MGWR results and examine their empirical implications.

In presenting the models' results, we use a cartographic technique proposed by Mennis (2006) to visualized the parameter estimates along with the local *t*-value and the *P*-values. Each parameter is presented individually by displaying the GWR and MGWR results side by side. The purpose is to enhance our understanding of the models while also increasing the accuracy of our model interpretation.

Hotels
Looking at the spatial configuration of our hotel's data (refer back to Fig. 2), we can see that hotel has concentrated distribution. The distribution depends heavily on accommodation demand, which usually takes into account a long and continuing process of drafting a location strategy (Lockyer 2005). Hence, hotel locations are often adjacent to the main elements of urban tourism such as main tourist attractions, convention centers, major transport (i.e., airport and rail stations), and agglomeration of activities (Yang, Luo, and Law 2014). It is also the case in London. Hotels are located mainly in areas that attract many visitors with a diverse mix of overlapped activities. Such places stretch from Westminster toward the City of London along the River Thames.

Through the local models, we can start to analyze whether hotel presence shows a positive or negative relationship with Airbnb density in given areas. Fig. 6 shows the spatial variation in the local parameter estimates for hotel density. Both GWR and MGWR models indicate that some spatial variation exists in the effects of hotel density on Airbnb density. This relationship only happens in some central areas around Hammersmith and Fulham, Westminster, Kensington and Chelsea, the City of London, as well as areas in Camden, Tower Hamlets, and Hackney that are adjacent to the City of London. The MGWR results have slightly larger values of statistically significant areas, although the differences are not large. The main difference is the range of parameter estimates, where the GWR results are larger. Based on our analysis, in both models, the

(a) GWR parameter estimates for hotel based on 95 nearest neighbours.)

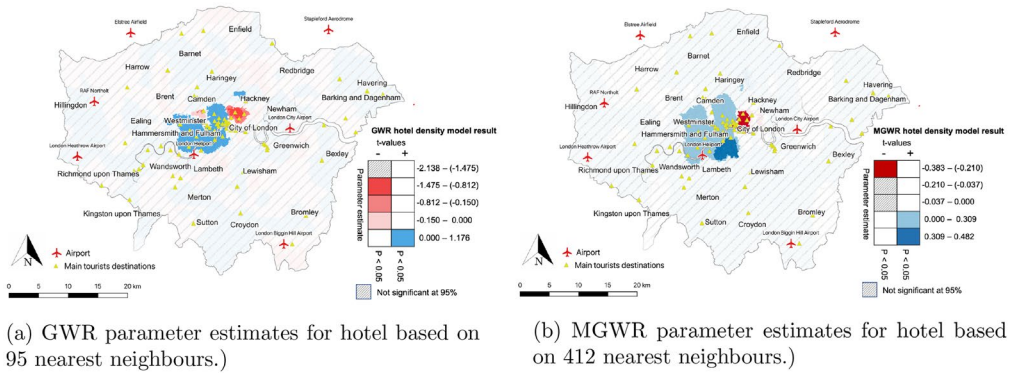(b) MGWR parameter estimates for hotel based on 412 nearest neighbours.)

Figure 6. Hotel parameter estimates with magnitudes and significance level for GWR (a) and MGWR (b) models. All the spatial distributions in this paper are mapped using quantile ranges.
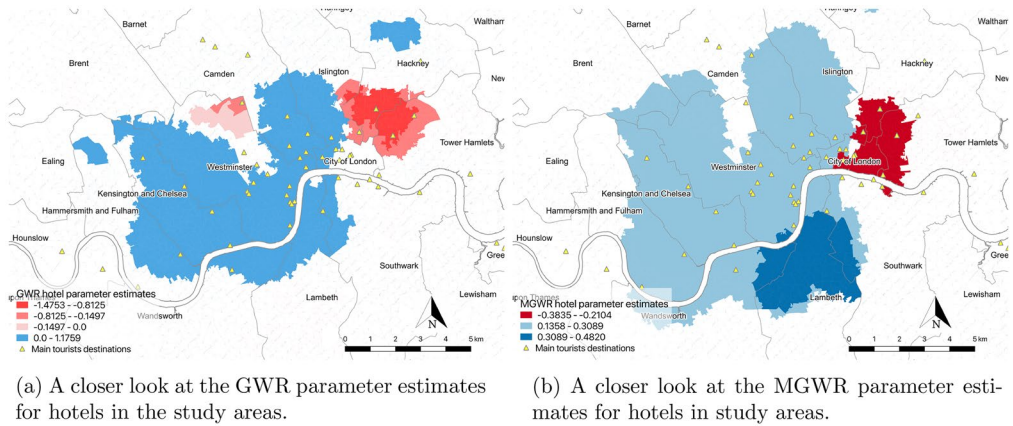

(a) A closer look at the GWR parameter estimates for hotels in the study areas.

(b) A closer look at the MGWR parameter estimates for hotels in study areas.

Figure 7. Areas where hotel presence shows significant relationship with Airbnb density.

presence of hotels could be an explanatory variable for Airbnb presence, but the relationships are not always positive.

Fig. 7 gives a closer look at the areas that have statistically significant results based on GWR and MGWR models. The yellow triangles show the spatial locations of the main tourist attractions based on the data from Visit Great Britain, 2015. The GWR parameter estimates in Fig. 7a using the single bandwidth of 95 nearest neighbors show negative values in the border between Hackney and Tower Hamlets as well as some LSOAs near Westminster that is adjacent to Camden. In these areas, according to the GWR model, hotel density is a negative estimator for Airbnb presence with a -1.5 to -0.15 decrease in hotel density associated with one unit increase of Airbnb density.

The MGWR estimates shown in Fig. 7b extend this negative relationship to the City of London where Airbnb density is also quite high, but the estimate is rather low with a -0.3 to -0.2 decrease in hotel density associated with one unit increase in Airbnb density. Both models

in Fig. 7 show that in areas such as Westminster, Kensington and Chelsea, as well as part of Camden, Islington and Hammersmith, and Fulham there are overlaps between Airbnb and hotel density where hotels can be a positive estimator for Airbnb. Around Westminster, there is a concentration of main tourist attractions in the areas. These are well-developed areas with high activity mix embedded within its urban fabric. The estimate is a bit different with higher values given by the GWR results, which are likely to be a slight overestimation. Also, the MGWR result using the 412 nearest neighbors bandwidth extends the analysis to focus on Lambeth, just south of Westminster and across the river, where overlaps between Airbnb and hotel density occur, as indicated by the dark blue patch in Fig. 7b.

The local models have given us insight that although in central areas Airbnb thrives in areas where there is a strong presence of hotels, Airbnb also thrives in areas outside the hotel concentration, where hotels estimates are negatives including the border of Tower Hamlets and Hackney. It is a well-known up and coming neighborhood that attracts many younger and diverse visitors to their street markets and artsy commerce. It is an area where a lot of Airbnb present, but not so much for hotels.

Food and beverages

Fig. 8 shows the local variations of F&B in association with Airbnb in statistically significant areas. Both GWR and MGWR models show that F&B is a consistently positive estimator for Airbnb density, with up to a 0.71 increase in F&B density associated with one unit increase in Airbnb density. This estimate is lower for the MGWR result (0.28). The MGWR model assigns larger bandwidth for F&B with 195 compared with 95 for MGWR. The effect is that the MGWR model accounts for larger areas with a statistically significant relationship between Airbnb and F&B. The model also has larger clustering of parameter estimates (refer to Fig. 9a) compared to the GWR model (refer to Fig. 9b).

According to the MGWR result, there are two clusterings of areas with the highest positive cumulative estimates in the west of London and east of London, followed by the City of London and Islington. The highest estimate in East London is Hackney and Tower Hamlets which are famous for their food environment, with many famous street markets such as Spitalfields and Hoxton market that attracts many local and international visitors. It is also the case of Westminster
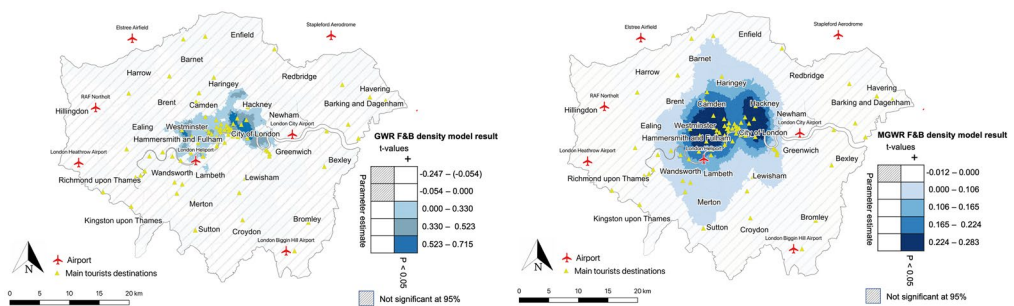
(a) GWR parameter estimates for F&B locations based on 95 nearest neighbours.)

(b) MGWR parameter estimates for F&B locations based on 195 nearest neighbours.

Figure 8. Food and beverages (F&B) parameter estimates with magnitudes and significance level for GWR (a) and MGWR (b) models. All the spatial distributions in this paper are mapped using quantile ranges.
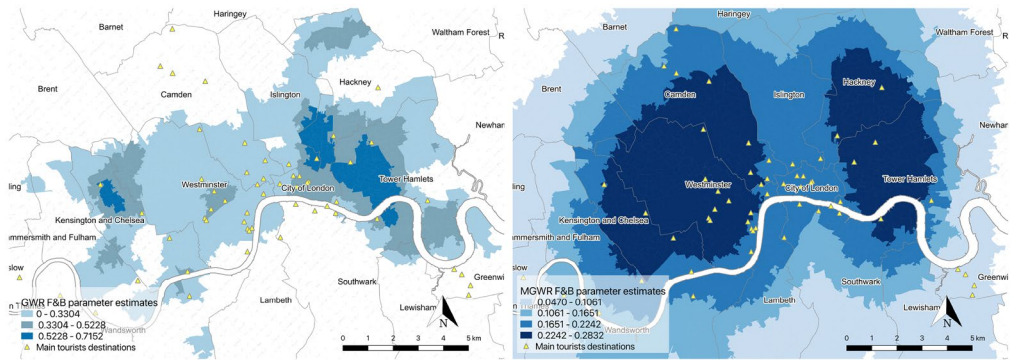
(a) A closer look at the GWR parameter estimates for F&B in the study areas.

(b) A closer look at the MGWR parameter estimates for F&B in study areas.

Figure 9. Areas where F&B presence shows significant relationships with Airbnb density.

and Camden, where the concentration of F&B venues is a positive estimate for Airbnb with up to a 0.3 increase in F&B density associated with one unit increase in Airbnb density. For the case of the City of London and Islington, this estimate is slightly lower at 0.22.

F&B could be a proxy for street life or how lively the residential area is, where the higher number of F&B establishments caters to more urban activities. A study by Sparks, Bowen, and Klag (2003) shows that the availability of the diverse type of restaurants is perceived to be an essential attribute for tourist destinations. Also, extending beyond satisfying daily needs, food is now seen as an aspect of tourism, especially with the rapid popularity of culinary tourism that emphasizes the experience using food-related theme (Long 2004). As many Airbnb users are motivated by tourism purposes (Guttentag et al. 2018), it is understandable that the model shows that F&B is a positive estimator for Airbnb.

The public transport accessibility index

Public transportation is an integral part of tourism, especially in an urban setting. In London, the highest proportion of the population (up to 46%) uses public transportation to commute, 35% relies on cars, 11% travels daily on foot, and 3.8% uses bicycles to get around (Florida and Bendix 2015). Arguably, tourists visiting London are likely to use public transportation since London has an integrated system with the underground tube and busses that run frequently. Through the local models, we analyze the linear relationship between accessibility to public transportation and Airbnb density. The spatial pattern of the GWR model (bandwidth = 95) in Fig. 10a and the MGWR model (bandwidth = 384) in Fig. 10b show slight differences in terms of the smoothness of the parameter estimates. The MGWR model results in less but bigger clustering of the parameter estimates. The GWR model shows a higher range of parameter estimates, and the MGWR model result shows a higher level of smoothing.

At first glance, we could sense that the model result is not as straightforward as the other explanatory variables: hotel and F&B density. The spatial variations of Airbnb show both positive and negative relationships with PTAI according to specific localities. Considering the geography of the public transport links in London, we might assume that high PTAI index in tourist areas along the north of the River Thames stretching from Westminster to the City of London is a positive estimator of Airbnb density. However, this is not exactly what the model results
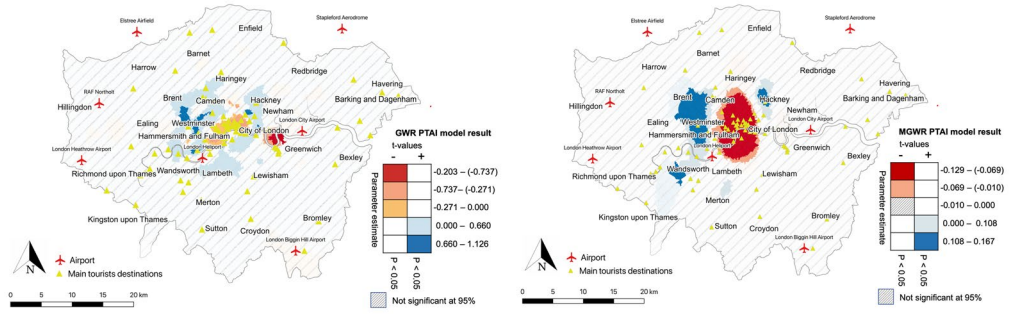
(a) GWR parameter estimates for LSOAs based on their PTAI score using 95 nearest neighbours.)

(b) MGWR parameter estimates for LSOAs based on their PTAI score using 384 nearest neighbours.

Figure 10. Public Transport Accessibility Index (PTAI) parameter estimates with magnitudes and significance level for GWR (a) and MGWR (b) models. All the spatial distributions in this paper are mapped using quantile ranges.
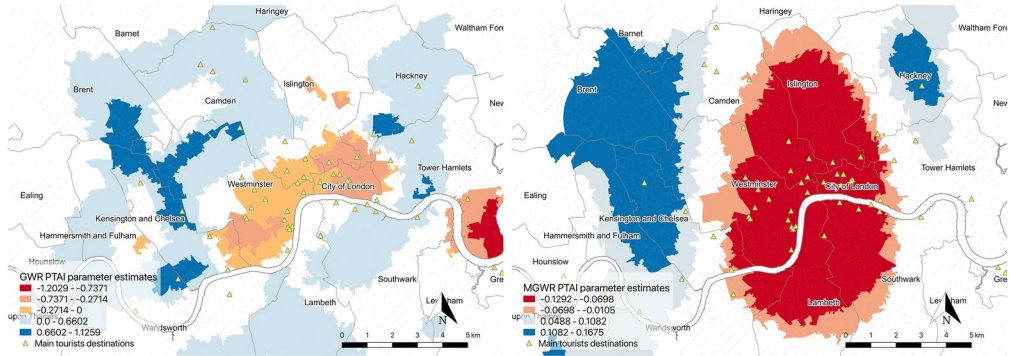
(a) A closer look at the GWR parameter estimates for hotel in the study areas.

(b) A closer look at the MGWR parameter estimates for PTAI in study areas.

Figure 11. Areas where PTAI presence shows significant relationship with Airbnb density.

show. Areas, where PTAI are negative estimates, are also areas with very high accessibility, but they are expensive in terms of the rental values. With respect to the extreme centralization of in London's accessibility, the difference of PTAI is rather large in the central areas compared to others, but this is not consistently the case for Airbnb distribution.

Fig. 11 shows a zoomed-in view of the study areas with Fig. 11a showing the GWR and Fig. 11b showing the MGWR model results. Many Airbnbs are not located in areas with the highest PTAI, and this might be due to the tension between rents and public transport accessibility. Based on the models' results, PTAI does not solely explain Airbnb location choices, and the effects of other variables are likely to be more complex. In areas that have a high density of residential properties such as Kensington and Chelsea, PTAI is indeed a positive estimator for Airbnb density—although the PTAI value is considerably lower compared to those in the more central areas. This is also true in the case of Hackney, where higher PTAI values are also associated with higher Airbnb density.

Conclusions and implications of research

Airbnb is a platform that provides alternative accommodation in residential areas, thereby offering services like hotels. In the accommodation sector, Airbnb is now a prominent player with more than 50,000 listings in London alone (based on data from Inside Airbnb in 2018). As an online platform, the proliferate usage of Airbnb has raised many planning and regulatory concern worldwide (Gurran and Phibbs 2017). Research related to this topic is expanding, especially with regards to Airbnb's direct competition with hotels (Zervas, Proserpio, and Byers 2016; Guttentag et al. 2018). However, the relationship between Airbnb and other urban tourism elements, including F&B establishments and public transport accessibility, has received less attention. Based on our study, we offer two contributions to enhance our understanding of Airbnb in the urban tourism context.

Methodological contribution

This article has compared two local models (GWR and MGWR) against the global OLS model, to understand the fast-changing urban phenomenon of the short-term platform. Methodologically, the value of our article lies in the model specification and results that allows the comparison between a single bandwidth (GWR) and multiple bandwidths (MGWR). We have provided examples using three datasets that have distinct and non-uniform spatial distributions. By allowing the use of different optimum scales among the three independent variables in our analysis, we can demonstrate the utility of the MGWR for showing effects across different spatial scales.

Overall, when compared, the MGWR results do not deviate far from the GWR results in terms of the model performance. However, the MGWR consistently provides a larger bandwidth for all parameter estimates. This is likely because the data used is sparse. In our case, MGWR yields a larger degree of clustering and smoothing of the coefficients. Also, in comparing the methods, we find that for our case study, the MGWR model consistently yields lower parameter estimates compared to the GWR. Fotheringham, Yang, and Kang (2017) demonstrate that introducing multiple scales to the model could improve the overall model performance. We find this improvement to be minor. However, presenting both GWR and MGWR models does give an advantage especially when there is a stark difference in the bandwidth values.

Practical implication

The results of this article provide a more nuanced understanding of the spatial distribution of Airbnbs. Using our local model, Airbnb distributions can be split into two contrasting categories based on their relationship with the core urban tourism elements as discussed above.

Many Airbnbs thrive in areas where hotels are located as shown by previous studies. These indicate that short-term rentals provide direct competition with hotels, due to their spatial overlap (Zervas, Proserpio, and Byers 2016; Dogru, Mody, and Suess 2017; Gutiérrez et al. 2017). This is true for central areas where tourists are staying near major city attractions. Volgger et al. (2018) found that just like hotel guests, Airbnb guests are also motivated to stay within the vicinity of these attractions. In these areas, hotels can be a positive estimator for Airbnb. These are also areas where F&B establishments are abundant. Although, the relationship with public transport access is not as clear as PTAI can be both positive and negative estimators for Airbnbs. Within London, places such as Westminster as well as Kensington and Chelsea are the typical prime areas for accommodation services, both traditional hotels and the platform based short-term rentals such as Airbnb.

Mody and Hanks (2020) study the consumer-based perspective on authenticity in accommodation consumption between Airbnb and hotel users. One of the findings is that people relate to "brand authenticity" for hotels which manifests itself in predictability or brand consistency. Whereas for Airbnbs the "experience authenticity"—the diversity offered by unique Airbnb homes—is more important. Whether or not the quantity or the diversity of F&Bs adds to the "experience authenticity" for Airbnb consumers is an open question. Airbnb has long claimed that one of its uniqueness is the multiplication of the economic benefit for the local establishments with their branding "live like a local" (Airbnb 2020). Although many Airbnb locations overlap with those of hotel concentrations, we found the distribution also goes beyond that. There is a niche to offer Airbnb in up-and-coming areas outside the hotel zones. Access to public transports becomes an important element for these locations, as it is important that guests are able to travel and reach the main tourists' destinations. In these Airbnb hotspots, F&B is a positive estimator, as many Airbnb listings are located near these food venues. There is a strong association between Airbnb and agglomerations of pubs as well as restaurants for the case of London.

This has the potential of bringing economic benefit to the local businesses and communities, notably those working in the food services. To better understand if it is indeed the case, further study on Airbnb guests' consumption needs to be conducted, as there is limited evidence that Airbnb creates value to the local economy (Boswijk 2016). The Airbnb economic impact is often followed by nuisance associated with the presence of short-term rentals into residential neighborhoods that are challenging for the government to regulate (Boswijk 2016; Gutiérrez et al. 2017; Gurran and Phibbs 2017). For example, potential social costs including the noise disturbance (Gutiérrez et al. 2017), the rise of housing costs (Lee 2016; Horn and Merante 2017), and the loss of revenue from accommodation taxes (Varma et al. 2016) might outweigh the economic benefit to the local communities.

Future studies

We have presented our research using the local GWR and MGWR models and investigated the relationship between Airbnb, hotels, F&B, and public transport accessibility. It contributes to understanding the spatial distribution of Airbnb in the context of urban tourism. Further studies informed by this work could involve predictive models of Airbnb locations to identify potential areas at risk of short-term rental oversaturation. Additionally, we suggest that the impacts of Airbnb on the local businesses, notably F&B have scope for further research. Specifically, future Airbnb studies would benefit from analyzing the guests' consumption patterns during their stay. This could then directly inform the discussion on whether the economic benefit brought by Airbnb to local establishments, comes with a social cost when converting long-term residential areas into short-term rentals. Studies in regulating this matter also remain limited, thus this would prove a separate avenue for future research.

To conclude, this article has contributed to advancing our knowledge in terms of demonstrating the link between Airbnb and the core elements of urban tourism: hotels, F&B and public transport accessibility.

Acknowledgment

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