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The Influence of Neighbourhood Environment on Airbnb: a Geographically Weighed Regression Analysis

ABSTRACT: Sharing accommodation has emerged recently as a new business model in the accommodation sector. Due to the potential gentrification Airbnb might bring to an area, it is critical to understand the spatial patterns of sharing economy and its possible determinants. The neighbourhood environment has proven to be an important factor in the traditional hotel business, and whether it is the same for sharing accommodation is worth investigating. In this study, location data of 29,780 houses/apartments on Airbnb.com in London was collected. Using Ordinal Least Square and Geography Weighed Regression analysis, the spatial distribution features of Airbnb and its relationship with neighbourhood environment in London were explored. The results show that sharing accommodation is mainly located in the city centre and around tourist attractions. Neighbourhood elements such as Water, Vegetation Coverage, Art & Human Landscape, Travel & Transport, University, Nightlife Spot emerged as important factors influencing Airbnb. In addition, the distribution of Airbnb in London is spatially non-stationary, in some areas high Airbnb is associated with higher transportation accessibility, in other areas, high Airbnb is associated with more attractions or nightlife spots, suggesting that the role of different factors varies in different regions, proving Tobler's first law of geography.

KEYWORDS sharing economy; sharing accommodation; spatial distribution; Airbnb; London; neighbourhood environment

Introduction

As a new phenomenon, the sharing economy, has grown quickly in recent years and has been widely applied in tourism and hospitality sector (Belk, 2014; Böcker and Meelen, 2016; Tussyadiah, 2016; Gutierrez et al., 2017; Benítez-Aurioles, 2017). One of the successful examples is Airbnb, which has become the largest platform of accommodation sharing in the world after its establishment in 2008 and by 2017 it covered 65,000 cities globally (Airbnb.com). Due to its profound impact, accommodation sharing has become a focus of both academics and industry practitioners, who have investigated areas such as the effect of accommodation sharing on the traditional hotel industry (Guttentag, 2015; Varma et al., 2016; Zervas, Proserpio and Byers, 2017), the sharing experiences (Bae et al., 2016; Tussyadiah, 2016; Brochado, Troilo and Shah, 2017), and the related issues of trust in sharing (Ert, Fleischer and Magen, 2016). Recently, considering its potential economic, social and cultural impacts to the community, researchers have investigated the features of its spatial distribution in some cities. Admiak (2018) examines Airbnb listing in different scales of European cities, and concludes that Airbnb offerings are mainly concentrated in major tourist cities. Gutierrez et al. (2017) find that Airbnb offerings in Barcelona are mainly located in the city centre and are closely related to the main tourist attractions, which is supported by Benítez-Aurioles (2017) and Quattrone et al. (2016). However, besides tourist attractions, the other factors that might influence the distribution of sharing accommodation are not clear, especially the neighbourhood elements. As sharing economy is mainly peer to peer (Guttentag, 2015, Tussyadiah, 2016), the environmental characteristics of the neighbourhood may also influence residents' decision on Airbnb offering and tourists' decision on choosing where to stay. Hutington and Williams (1922) point out that geographical conditions shape business activities. Some researchers (Chou, Hsu and Chen, 2008; Yang et al., 2017) also suggest that geographical conditions have been influential for hotel businesses. However, it is still unclear if the neighbourhood geographical conditions would influence sharing accommodation.

As a well-known theory in geography, Tobler's (1970) first law suggests; everything is related to everything else but nearer things are more related than distant things. Goodchild (2003) further explains its heterogeneity by indicating nearby things are more similar than distant things. Similar theories include Christaller's central place theory (1933), which is also used to describe geographical proximity (Xu et al., 2018). But Tobler's first law is well used as its capability of quantitative analysis such as spatial autocorrelation analysis in GIS, which helps understand how similar closer objects are to other nearby objects, it has been well applied in fields such as business and housing (Soler & Gemar, 2018; Lu et al., 2014; Sunding & Swoboda, 2010). According to the first law, every location will have some degree of uniqueness relative to the other locations, which affects the spatial autocorrelation and therefore the spatial heterogeneity (Kemp et al., 2008; Knegt et al., 2010). However, "tourism scholars have been relatively slow in incorporating the law into their research" (Joo, 2017 p. 351). Recently, the rapid development of ICT and the spread of today's Airbnb provide a new dimension, as spatially enabled things have increased their functional utility (Foresman and Luscombe, 2017). As sharing platform is based online, whether geographical elements such as surrounding environment and traffic accessibility will have an influence on Airbnb clustering need further investigation.

Therefore, this study aims at exploring the neighbourhood environments' influence on the spatial distribution of accommodation sharing in London. In total, data from 29,780 houses/apartments were collected from 14 boroughs of Inner London, and Ordinary Least Squares and Geography Weighted Regression analysis were used. The paper begins with a discussion on sharing accommodation, the spatial distribution feature of Airbnb and its influencing factors. The methodology part includes a background information on the study area, London, and a discussion on data collection and analysis. Followed by a discussion of the main findings, the paper ends up with a conclusion and recommendations for future research.

Literature Review

Sharing Accommodation

Sharing economy refers to a new type of activity that peers share their resources online

(Heo, 2016). Belk (2014: p.1597) emphasizes this as "people coordinating the acquisition and distribution of a resource for a fee or other compensation." Sharing economy shows a huge potential of future development (Gregory et al., 2016). It is predicted that the business model of sharing economy will achieve $ 335 billion in total by 2025 (Cadman, 2014; Matzeler et al., 2015).

The accommodation sector in the tourism industry has already witnessed the influence of sharing economy (Heo, 2016), such as Airbnb, Couchsurfing, Homeaway, and 9flats (Voytenko, 2016), among which, Airbnb has become one of the leading sharing platforms (Gutierrez et al., 2017). Sharing accommodation has influenced city tourism and it has inevitably become a threat to traditional hotels particularly those cheap hotels and hotels not catering to business travellers (Zervas et al., 2014). Some researchers have reported a much broader coverage of Airbnb than hotels in some cities (Guttentag, 2015). And Admiak (2018) confirms the capacity of Airbnb is much larger than hotel capacity in some cities. Due to its potential impact it might bring to the local area, such as tourism gentrification (Gotham, 2005) and overcrowding (Hajibaba & Dolnicar, 2017), researchers need to understand the spatial features of this eruption (Gutiérrez et al., 2017).

The Influencing Factors of the Spatial Distribution of Airbnb

Researchers have studied various related issues of accommodation sharing including both the demand side and the supply side, which covers the guest sharing experiences (Guttentag et al., 2016), the trust between the guest and the host (Ert et al., 2016), the impact to traditional hotels(Guttentag, 2015; Varma et al., 2016; Zervas et al., 2017), the price (Quattrone et al., 2016; Wang and Nicolau, 2017), and spatial distribution (Sarrión-Gavilán et al., 2015; Gutierrez et al., 2017; Benítez-Aurioles, 2017; Gunter and Onder 2018). Researchers suggest that the factors influencing the spatial distribution of accommodation sharing mainly include the following aspects: distance from tourist attractions, distance from city centre, and transportation accessibility.

Distance from tourist attractions

Case studies on different tourist cities all suggest Airbnb listings are concentrated around tourist attractions. For example, Gutierrez et al.'s study (2017) of Airbnb in Barcelona finds that there is a negative correlation between the spatial distribution and the distance from the beach, which suggests that the farther away from the attractions, the less offering on Airbnb. Benítez-Aurioles (2018) and Quattrone et al. (2016) also agree that distance to tourist attractions is an important factor influencing Airbnb listing. This is the same as the findings from hotel studies. When Sarrión-Gavilán et al. (2015) studied the supply of tourism resources in Andalusia, they found that the spatial distribution of bed supply gradually shifted from inland to coastal areas, which is popular tourist attractions.

Distance from city centre

As most attractions in the above studies are located in the city centre, researchers also suggest that distance to the city centre might be an influencing factor. Gutierrez et al. (2017) prove that the distance from the city centre is one of the key factors of Airbnb's distribution. Based on regression analysis in Barcelona, they conclude that the farther away from the city centre, the less offering of Airbnb; and Wegmann & Jiao (2017) reach the similar conclusion of Airbnb distribution based on data from five cities of the US. Therefore, it can be concluded that the distance from the city centre has a significant influence on the adoption of Airbnb, that is, the farther away from the city centre, the less offering of sharing accommodation.

Transportation accessibility

In the relevant studies on hotels, transportation has been mentioned by many researchers. The accessibility to transportation services, for example, airport (Wall et al., 1985), train station (Ashworth and Tunbridge, 1993), subway (Yang et al., 2012), and main road (Yang et al., 2012), are important factors that are considered when choosing hotel locations. In accommodation sharing studies, some researchers reported similar role of transportation. For example, in Wegmann and Jiao's (2017) study, the distribution of Airbnb in the five cities of the United States mainly follows the major transportation line. The closer to the major traffic line, the more concentration of Airbnb listing. As major traffic line represents high traffic, which indicates that the number of sharing accommodation is located in areas with higher traffic accessibility.

As can be seen from the above discussion, researchers have identified some geographical factors which might influence sharing accommodation, such as distance and transportation. However, other neighbourhood environmental factors have been ignored. Crecente et al. (2012) and Yang et al. (2017) refer to the surrounding environmental factors as natural geographical conditions (air quality, water views, and vegetation), public facilities (parks, public area), POI（Point of Interest）, security, and cultural diversity. Neighbourhood elements have been considered important for hotel business in previous studies (Yang et al., 2012; Adam and Amuquandoh, 2013). In the relevant hotel studies, it emerged that the surrounding environment has an influence on guest experience and satisfaction (Rigall-I-Torrent and Fluvia, 2011; Walker, 2008; Yang et al., 2017). In the new business of accommodation sharing, it was reported that 42% of guest spending is in the neighbourhoods where travellers stayed (https://www.airbnb.co.uk/economic-impact). This shows how important it is to have catering, retail and other commercial facilities in the neighbourhood when choosing accommodation sharing. However, sharing accommodation is an unconventional type of business, which differs from traditional hotels in the following aspects. First, it is peer to peer, C2C (customer to customer) rather than B2C (business to customer). However, more and more professional investors come into this business, making it more commercial. Yet, this phenomenon needs further exploration. Second, the accommodation offerings are based on owners' idle property, rather than construction. As Zervas et al.(2014) and Gutierrez et al.(2017) suggest, the expansion of Airbnb supply is easier than hotels. Airbnb can expand its supply in already existing houses and apartment buildings, which is in contrast to hotels. Location of hotels is limited by local planning requirements, which also requires the whole building and the permission of the local authority. Therefore, the relationship between neighbourhood environment factors and hotel spatial distribution may not suit this new type of accommodation. However, empirical research is very limited. Most efforts have been made on socio-economic factors on sharing (Quattrone et al., 2016; Gunter and Onder, 2018). But, geographical conditions of neighbourhood on sharing should not be ignored.

In addition, although different researchers have reported different factors in their own research, it is unclear among all the factors, which is the most important factor? Besides, most studies are based on regressions analysis without consideration of spatial bias, with only few exemptions (Sarkar et al. 2017). Sarkar et al. (2017) state that, “without accounting for spatial bias, regression-based associations of factors may be misleading” (p107). Therefore, it is critical to consider this and introduce spatial autocorrelation as an alternative (Sarkar et al., 2017). Indeed, even for a particular factor, the spatial heterogeneity needs to be considered as it might vary in different regions (Tobler, 1970). Zhang et al., (2017b) suggest that it is critical to identify not only the possible determinants of the spatial distribution, but also investigate the spatial heterogeneity of these factors in different regions. For example, considering the spatial heterogeneity, Zhang et al. (2017b) employed geographically weighted regression (GWR) method to construct a model of Airbnb house price with a better explanatory power than global regression model (GRM).

Methodology

London Case

This study examines the critical factors of spatial distribution of Airbnb in London. London is one of the world's most famous tourist destinations, where people actively participate in sharing activities. And the number of Airbnb rooms (including house sharing and whole house/apartments) in London has reached over 55,000 (Adamiak, 2018). Airbnb offerings are mainly concentrated in popular tourist areas, such as City of Westminster, Camden, and Tower hamlets (see Figure 1).

Tourism industry, which employed about 276,000 people and contributed 8 percent of total GDP (Gross Domestic Product), is an important part of London's industry (Visit Britain, 2017). Greater London is divided into 32 London boroughs and the City of London (a separate county but still part of the region. For the purpose of the calculations in this study, we treat it as a borough as well) (Zhang et al., 2017a). According to the Office for National Statistics (https://www.ons.gov.uk), Inner London includes Camden, Hackney, Hammersmith and Fulham, Haringey, Islington, Kensington and Chelsea, Lambeth, Lewisham, Newham, Southwark, Tower Hamlets, Wandsworth, Westminster and the City of London. For the purpose of this study, this definition of Inner London has been used. According to Greater London Authority (https://www.london.gov.uk), Central London comprises the City of London, most of Westminster and the inner parts of Camden, Islington, Hackney, Tower Hamlets, Southwark, Lambeth, Kensington & Chelsea and Wandsworth. This is where many important organizations are located such as Central government offices, company headquarters and embassies, financial and business services sector and the offices of trade, professional bodies, institutions, associations, communications, publishing, advertising and the media. Therefore, the areas above are referred to Central London.

According to Visit London the popular attractions of London include London Eye, British Museum, National Gallery, Tower of London, Victoria and Albert Museum, Churchill War Rooms, Big Ben, Tower Bridge, Houses of Parliament, St. James's Park, which are mainly located in city of Westminster. And the attractions of London are mainly located in inner London, especially City of Westminster, Camden, Islington, Hackney, Tower hamlets（see Figure 2）.

Data Collection and Variables

Location information of 29,780 sharing apartments/houses in Inner London was collected from the Airbnb website (http://insideairbnb.com/get-the-data.html) from 21 July to 11 September, 2017. Meanwhile, 72,609 points of interests (POI) and their locations in Inner London were downloaded from Openstreetmap.com in November 2017. These points were classified into 7 different categories of activities (see Table 1). The measurement of green space coverage was normalized difference vegetation (NDVI) calculated from Landsat8 remote sensing image in USGS.gov, which was taken on 9 April, 2015. Census units were collected from the London Datastore via https://data.london.gov.uk/census/. As suggested by Quattrone et al. (2016), census units can be used as statistical units of Airbnb calculation. In this paper, we only used the calculation unit of 'ward' in the census units as a division unit of London administrative area.

In the following section, all relevant spatial factors would be aggregated to their density of units for subsequent regression, including sharing accommodation density, 7 activity categories density, water area density and average NDVI.

Table 1. Information of points of activity category used in OLS and GWR model. (Data from openstreetmap.com)

Activity Category (Label)	Definition	Examples of Venue Type	Number of points
Art & Human Landscape (Ar)	Number of Art & Human Landscape per census unit	gallery, museum, monument, attraction	276
University (Un)	Number of Universities per census unit	university	128
Food & Shop (Fo)	Number of Food & Shops per census unit	shop, mall, market place, vending machine, pharmacy, fast food, café, restaurant	7355
Nightlife Spot (Ni)	Number of Nightlife Spots per census unit	casino, nightclub, bar, pub, spa	1973
Travel & Transport (Tr)	Number of Transport codes per census unit	bus station, subway entrance, bus stop, secondary link	18206
Residence (Rs)	Number of Residences per census unit	apartments, house	42820
Recreation(Rc)	Number of Recreation codes per census unit	picnic site, street cabinet, park, theme park	1851

Data Analysis

Considering the influence of spatial factors to their neighbourhoods, Kernel Density Estimation (Donthu et al., 1989) was used to calculate the density of those point features. This method can continuously calculate each location's density based on a dataset, so the result can be expressed as raster surface. For points in ‘Ar’, valuable weights (depending on the numbers of reviews of the top 10 attractions according to TripAdvisor (https://www.tripadvisor.cn), are given as population field to different types (Table 2). For water area features, each independent shape was transferred to its geometric centre point with the corresponding shape's area as a weight.

Table 2. Weights for elements in ‘Ar’ (Data from TripAdvisor.com)

Type	Name	Weight
Top 10 attractions	London Eye	69447
	British Museum	57,069
	National Gallery	30693
	Tower of London	50296
	V&A - Victoria and Albert Museum	24757
	Churchill War Rooms	16917
	Big Ben	26679
	Tower Bridge	27227
	Houses of Parliament	13642
	St. James's Park	14385

The density values and NDVI value were aggregated to each census unit by Zonal Statistic (ESRI, 2010), so for all statistical units, each one of them would have 10 variables. To solve the differences in the dimension of each variable, Min-Max Normalization (Suarez-Alvarez et al., 2012) was used to normalize interval ranges of every variable to section 1 to 100.

In order to explore how Art & Human Landscape (Ar), University (Un), Food & Shop (Fo), Nightlife Spot (Ni), Travel & Transport (Tr), Residence (Rs), Recreation (Rc), Water and greening rate (NDVI) contributed to sharing accommodation density, Ordinary Least Squares (OLS) regression was first applied. This is expressed as:

$$\mathbf{y_i = \beta_0 + \sum_{k=1}^{p} \beta_k X_{ik} + \varepsilon_i} \quad \mathbf{(1)}$$

Where y_i denotes the normalized sharing accommodation density observation of the $i_{\text{-th}}$ ward ; X_{ik} denotes the $k_{\text{-th}}$ explanatory variable observation of the $i_{\text{-th}}$ ward, composing the explanatory variable matrix ; number p denotes 8 variables mentioned above; β_0 and β_k represent the intercept and coefficients; and ε_i is an error term.

However, OLS regression takes no account of location in its analysis of relationships between variables and subsequently all the coefficients remain fixed over space. While Geographically weighted regression (GWR) was proposed in 1996 (Brunsdon et al., 1996) to explore this phenomenon. GWR deals with spatial heterogeneity and spatial autocorrelation (Wooldridge et al., 2003; Mitchell et al., 2005). On one hand, in the spatial weight matrix, the observation points within the bandwidth are given the weight value, and a weighted ordinary least squares regression is used within the bandwidth. Each $\mathbf{p_i}$ is not isolated, and the surrounding objects contribute to its $\mathbf{b_{ij}}$ due to distance-decayed-based function. On the other hand, the correlation coefficients of each influential factor at each observation point are given. If there exists spatial autocorrelation, their coefficients can reflect similarity. Based on it, our final contour map also highlights this feature, and the adjacent coefficients have more analogous color (Mitchell et al., 2005).

Researchers suggest that results of OLS can be optimized via GWR if related parameters meet some conditions: 1) Regression coefficients have the long-established sign; 2) No redundancy among explanatory variables; 3) Coefficients are statistically significant (Hamilton et al,1992); 4) Residuals are normally distributed; 5) Strong Adjusted R-Square value (Wooldridge et al., 2003; Mitchell et al.,2005); and 6) Residuals are not spatially auto correlated (ESRI: How OLS regression works, 2010). These conditions excludes Rs, Rc and Fo. GWR was then applied to explore how Ar, Un, Ni, Tr, Water and NDVI contributed to sharing accommodation density spatially. This is expressed as:

$$\mathbf{y_i} = \boldsymbol{\beta_0}(\mathbf{u_i}, \mathbf{v_i}) + \sum_{k=1}^{m} \boldsymbol{\beta_k}(\mathbf{u_i}, \mathbf{v_i})\mathbf{X_{ik}} + \boldsymbol{\varepsilon_i} \quad (2)$$

$$\boldsymbol{\beta}(\mathbf{u_i}, \mathbf{v_i}) = [\boldsymbol{X^T W}_{(\mathrm{i})}\mathbf{X}]^{-1}\boldsymbol{X^T W}_{(\mathrm{i})}\mathbf{Y} \quad (3)$$

where $(\mathbf{u_i}, \mathbf{v_i})$ is the coordinates of location **i**; $\boldsymbol{\beta}(\mathbf{u_i}, \mathbf{v_i})$ is the locally estimated coefficient for independent variable at location **i**, which indicates that the parameter is specific to location **i**; and $\boldsymbol{\varepsilon_i}$ denotes error at location **i**. $\boldsymbol{W}_{(\mathrm{i})}$ denotes an n by n diagonal spatial weighted matrix and can be expressed as:

$$W_{(\mathrm{i})} = \begin{vmatrix} \boldsymbol{W^{i1}} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \boldsymbol{W^{i2}} & \ldots & \mathbf{0} \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \ldots & \boldsymbol{W^{in}} \end{vmatrix} \quad (4)$$

$$\boldsymbol{W^{ij}} = \mathbf{exp}\ (\text{-}\mathbf{d}_{ij}^{2}/2\mathbf{b}^{2}) \quad (5)$$

$\boldsymbol{W^{ij}}$ in equation (4) is computed by Gaussian function. It can be expressed as equation (5), where $\boldsymbol{d_{ij}}$ denotes the distance between the $\mathrm{i}_{\text{-th}}$ ward location and observed point ***j***; number n denotes the amount of wards; b denotes the bandwidth. The selection of optimal bandwidth can be determined by selecting the model with lowest Akaike

Information Criterion (AIC) score; the model with the lowest AIC is the optimal model (Fotheringham et al., 2002). Relative parameters in this GWR model are set as shown in Table 3.

Table 3. GWR Model settings (Data from Software : GWR 4.09)

Model type	Gaussian
Geographic kernel	adaptive bi-square
Method for optimal bandwidth search	Golden section search
Criterion for optimal bandwidth	AIC_c
Number of varying coefficients	7
Number of fixed coefficients	0

Through GWR, for each variable ***j*** of each statistical unit ***i*,** it would have a unique coefficient$\boldsymbol{\beta_j}(\mathbf{u_i}, \mathbf{v_i})$. These coefficients were displayed as contour maps (Zhen et al., 2013) to show different degrees of influence in space to sharing accommodation. The peaks mean the most positive and the valley is the most negative.

Results

The Spatial Distribution of Airbnb

According to Admiak (2018), a high concentration of Airbnb listing can be found in London. It can be seen from Figure 1 that the spatial distribution of Airbnb is uneven, the apartments/houses are highly concentrated in the central areas and expands to the outside. Central areas and popular tourist areas, such as City of Westminster, Kensington & Chelsea, Hackney and Tower Hamlets have the highest density of Airbnb offering (Figure 1). This demonstrates a similar result with other studies on London

(Quattrone et al., 2016), Barceona (Gutierrez et al., 2017), Los Angeles (Sarkar et al., 2017), confirming that Airbnb listing is concentrated in city centres (Dudás et al., 2017; Benítez-Aurioles, 2018) and is spreading outside.

The Neighbourhood Environmental Influence on the Distribution of Airbnb

As Table 4 shows, the 1st round of OLS analysis indicates that variables Rs and Rc do not correspond to a statistically significant p-value ($p < 0.05$). Variables Ni and Fo (VIF> 7.5, indicate redundancy among these two explanatory variables (ESRI, 2010). Rs, Rc and Fo, which have higher VIF value, were eliminated for the 2nd round OLS. The 2nd round of OLS regression indicates an eligible result. The non-significant result of Jarque-Bera test (ESRI, 2010) indicates that residuals from the regression model are normally distributed. Residuals Global Moran's I (Goodchild et al., 1986) is a positive number close to 0, indicating there exists no spatial autocorrelation.

Table 4. OLS regression result (Data from software: ArcGIS 9.3)

Variable	**Coefficient[1]**	**Probability[3-1]**	**VIF[2]**	**T-Statistic[3-2]**
		The 1st round OLS regression		
Water	-0.362	0.000*	1.248	-5.335
NDVI	-0.496	0.000*	2.396	-7.658
Ar	0.281	0.000*	3.508	2.808
Tr	-0.252	0.010*	1.361	-2.619
Un	-0.473	0.000*	2.840	-3.562
Rs	0.073	***0.463***	1.023	0.734
Rc	0.106	***0.081***	1.518	1.754
Ni	-1.163	0.000*	***24.441***	-4.849
Fo	0.869	0.000*	***28.338***	3.373
		The 2nd round OLS regression		
Water	-0.412	0.000*	1.197	-6.073
NDVI	-0.580	0.000*	2.030	-9.533

Ar	0.419	0.000*	3.052	4.389
Tr	-0.194	0.046*	1.305	-2.008
Un	-0.420	0.002	2.784	-3.130
Ni	-0.440	0.000*	3.477	-4.759
Residual Moran's I[4]		**0.014**	**Adjusted R square[5]**	**0.320**
Koenker (BP) statistic[6]		**0.012**	**Residual Squares**	**55997.045**
Parameter[1]-[6] corresponds to Condition[1] to [6] referred in step3 in Data Analysis above.				

As Table 4 indicates that six variables, namely, Water, NDVI, Art & Human Landscape, Transportation, University and Nightlife have a significant correlation with the spatial distribution of sharing accommodation, suggesting the importance of neighbourhood environment to the location of sharing accommodation.

The Spatial Heterogeneity of Key Elements

However, the significant result of Koenker (BP) test (ESRI: Interpreting OLS results, 2010) in Table 4 ($p < 0.05$) indicates relationships between some or all of explanatory variables and dependent variable are non-stationary. That means the same element in different regions may play a different role (Tobler, 1970; Kemp et al., 2008; Knegt et al., 2010) and the model would perform a better result by using GWR.

From the comparison of diagnostic information between GWR and OLS model (Table 5), 6 iterations were computed where AIC changed from 2092 to 2086. The lowest AIC indicates the best bandwidth 43, which means the search range for every statistical unit is expanded to the 43^{rd} neighboring unit. Units whose standard residual error are in the interval of more than 2.5 times become less and the overall residual errors decrease greatly. Adjusted R square is 0.70, which indicates the simulation degree of model increased compared to the 2nd round of OLS regression. Based on the above results, it proves that GWR model works better than OLS model (Mcmillen et al., 2002; Mitchell et al., 2005).

Table 5. The comparison of diagnostic information between GWR and OLS model (Data from software ArcGIS 9.3 and software GWR 4.09)

Variable name	GWR result	OLS result
Residual squares	13536.985	55997.045
Effective number of parameters (model: trace(S))	65	—
Degree of freedom (model: n - trace(S))	208	—
-2 log-likelihood	1910.354	2228.078
Best Bandwidth size	43	—
AICc	2086	2092
R square	0.793	0.337
Adjusted R square	0.700	0.320

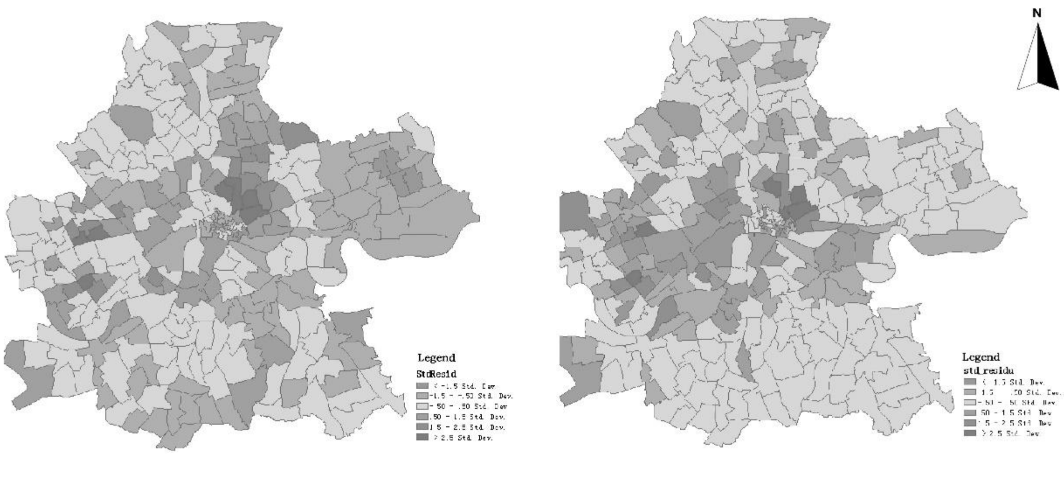

Fig 3.

The density of variables in regions and the effect of Explanatory variables on the density of Airbnb listings are shown in Figure 4. The difference of coefficients in regions shows the existence of significant spatial heterogeneity of the effect of explanatory variables. It also implies that GWR may better explain the impact of environment factors on spatial distribution of Airbnb listings than OLS.

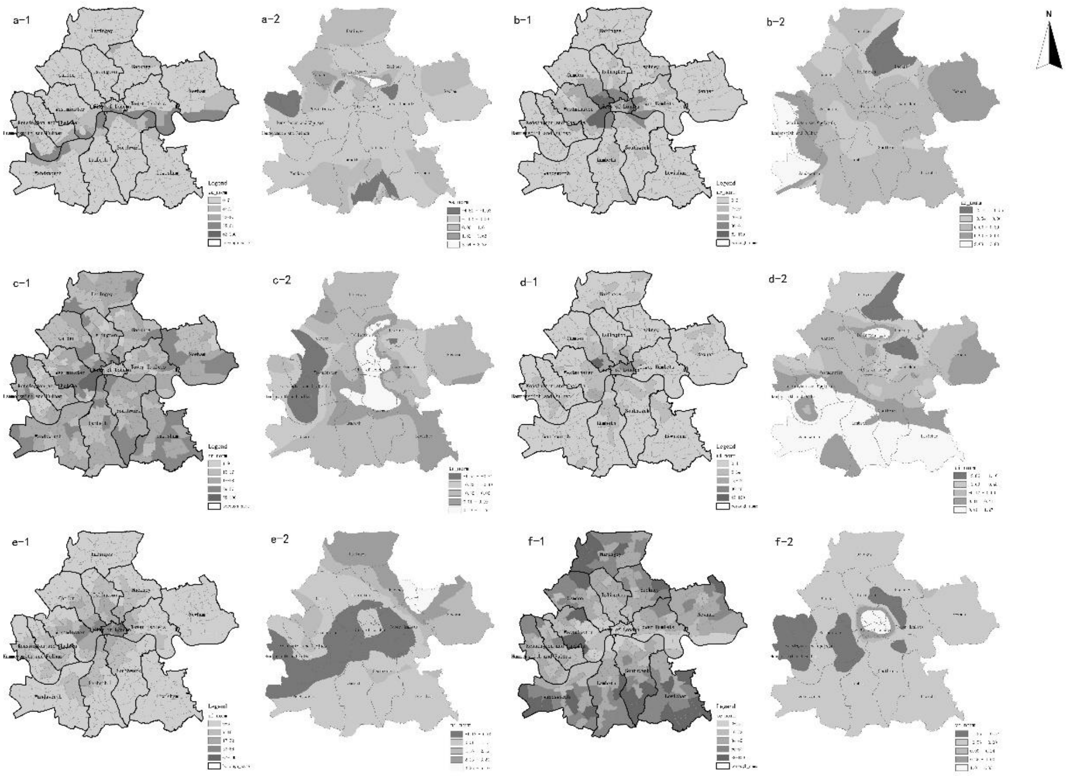

Fig 4.

Next, we explore the influence of these geographical factors in detail. As shown in Figure 1, the region with the highest density of Airbnb distribution is Western Tower Hamlets, Southern Hackney, Western and Southern region of City of Westminster, and Southwest of Kensington & Chelsea. Considering the spatial difference of the coefficient result in GWR, the above areas are selected to analyse the effect of environmental factors on the Airbnb listings.

For Western Tower Hamlets and Southern Hackney, the effect of Art & Human Landscape on the density of Airbnb listings is significant and positive (Figure 4b). The closer the distance from the tourist attractions, the more listing of sharing accommodation. The result is consistent with previous research (Quattrone et al., 2016; Dudás et al. 2017; Gunter and Önder 2018), confirming the role of tourist attractions in the spatial distribution of Airbnb. Traffic has a significant and positive impact on Airbnb listings (Figure 4c). It is understandable that convenient transportation offers much more benefits in accessing attractions, service facilities, resulting in higher accommodation demand and high listing. This confirms previous study on Airbnb and hotels (Ashworth and Tunbridge, 1990; Yang et al., 2012; Wegmann and Jiao, 2017). In Figure 4e, the coefficient suggests that the effect of nightlife on Airbnb listings is minor. It seems that nightlife spots are mainly located in the City of London (a borough of London). It is possible that convenient transportation and accessibility can facilitate people to access nightlife entertainment facilities, so the density of Airbnb listings is not sensitive to the nightlife spots in these areas.

For the west of City of Westminster, and southwest of Kensington & Chelsea, Figure 4c shows that the effect of transportation on the density of Airbnb listings is negative. As shown in Figure 7, the effect of Art & Human Landscape on Airbnb listings density is significant and positive, and the coefficient indicates that the density of Airbnb listings is more sensitive to attractions in these areas than in other areas. And nightlife has a significant and positive effect on the density of Airbnb listings (Figure 4e). It is logical that due to the limited traffic accessibility in these areas (Figure 4c), the location of attractions and nightlife would have a significant influence on the accommodation demand. Therefore, in these areas, Art & Human Landscape and nightlife have become more powerful determinants on the density of Airbnb listings than in other areas.

For the southern region of City of Westminster, the effect of transportation on Airbnb listings is significant and positive (Figure 4c). University has a significant positive effect on the density (Figure 4d). Art & Human Landscape and nightlife are negatively related to Airbnb listings density (Figure 4b&4e). It can be seen that due to limited scenic spots and nightlife spots in this area (Figure 4b&4e), the high density of Airbnb listings is mainly related to the university.

Conclusion

Sharing economy is an important phenomenon for business. An understanding of spatial distribution is critical to the future of this business, considering its profound impact to the local area, such as security, community spirit, and gentrification (Quattrone et al., 2016; Gutierrez et al., 2017). Although social economic factors are important determinates of Airbnb, the neighbourhood environment is also critical. This paper uses Ordinal Least Square and GWR analysis, and explores the spatial distribution of Airbnb in London. The results suggest that the sharing accommodation has a high concentration in certain areas, such as city centres and tourist attractions. The results confirm previous research that Airbnb listings are mainly located near tourist attractions (Gutierrez et al., 2017). The distribution of sharing accommodation is more scattered and covers a wider area than that of traditional hotels, which is supported by Quattrone et al.(2016)'s study on the number of hotel and Airbnb in London. As Gutierrez et al.(2017) points out, sharing accommodation can extend to residential areas, however, the location of hotels is limited to the local zoning requirement.

The paper also investigates the relationship of spatial distribution of accommodation sharing and the surrounding neighbourhood environmental elements. Two rounds of OLS analysis revealed that six (Water, NDVI, Art & Human Landscape, Transportation, University and Nightlife) of the nine variables in the study have a significant correlation with the spatial distribution of sharing accommodation, suggesting the importance of neighbourhood environment to the location of sharing accommodation, which is similar with hotel studies (Rigall-I-Torrent and Fluvia 2007; Walker, 2008; Yang et al., 2017). This partially confirms previous research on the role of tourist attractions and transportation (Quattrone et al., 2017; Gutiérrez et al., 2017; Benítez-Aurioles, 2017), but extends the discussion to surrounding geographical environments. A further exploration of spatial heterogeneity with GWR suggests the distribution of Airbnb in London is spatially non-stationary, in some areas high Airbnb is associated with higher transportation accessibility, in other areas, high Airbnb is associated with more attractions or nightlife spots, suggesting that the role of different factors varies in different regions, proving Tobler's First Law of Geography. Tobler (1970) and Goodchild (2003) suggest nearby things are more related than distant things. In our study, the relationship of Airbnb listings and geographical factors are different in different regions, therefore, spatial heterogeneity of these factors need to be considered.

In conclusion, the study contributes to the literature related to the sharing economy by providing a comprehensive and novel understanding of the location determinants in the sharing accommodation. First, we extend previous research on Airbnb from social economic factors (Quattrone et al., 2016) to geographical elements. The research also explores the spatial heterogeneity of each element in different regions, proving that Tobler's first law of geography (1970) can also be used in sharing accommodation and tourism studies. In addition, previous research on sharing accommodation has mainly used multiple regression analysis, which cannot characterize the spatial pattern of urban land uses and its underlying driving factors. While in our study, Ordinary Least Squares (OLS) and GWR model were compared. The results of GWR demonstrated a better model fit and stimulation power, showing the advantages of the GWR method compared with OLS. Considering the existence of spatial heterogeneity, GWR has a better explanatory power and prediction accuracy than OLS, which is in line with Zhang et al's findings (2017) on the determinants of London's Airbnb housing price. This investigation has empirically demonstrated the usefulness of GWR method, which can be a better choice to deeply investigate the factors affecting the spatial distribution of the accommodation industry.

Practically, the study can be used as urban housing management. With the growth of Airbnb offering in the community, attention needs to be paid on potential impacts to the community such as the tourist gentrification. This study can also help governments and urban planners to manage and control the suppliers of sharing accommodation. Therefore, governments should focus on the management of these popular areas, avoid too many rentals and take some measures, such as limiting or transfer the right to share.

As many other studies, this research also has its limitations. Geographical conditions are important influence of location, they work together with other social economic factors to have a profound influence on human activities. This research only considers geographical elements, but there are lots of other factors that might influence Airbnb, future research could explore other factors as well. And this research is only based on the case of London, considering the differences of countries, future researchers can explore other areas and other countries, which might have a different result. Future studies can also explore how these environmental elements of sharing accommodation influence tourists' experience of staying and satisfaction.

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