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The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona

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HIGHLIGHTS

- The spatial distribution of Airbnb listings and hotels in Barcelona is analysed.
- New geolocated data sources (Airbnb listings and photographs on Panoramio) are used.
- Airbnb accommodation offered in Barcelona tend to be concentrated in the city centre.
- Airbnb benefits more than hotels from proximity to the sightseeing spots in Barcelona.
- Airbnb expands the tourism pressure over residential areas in the centre.

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ABSTRACT

In recent years, what has become known as collaborative consumption has undergone rapid expansion through peer-to-peer (P2P) platforms. In the field of tourism, a particularly notable example is that of Airbnb. This article analyses the spatial patterns of Airbnb in Barcelona and compares them with hotels and sightseeing spots. New sources of data, such as Airbnb listings and geolocated photographs are used. Analysis of bivariate spatial autocorrelation reveals a close spatial relationship between Airbnb and hotels, with a marked centre-periphery pattern, although Airbnb predominates around the city's main hotel axis and hotels predominate in some peripheral areas of the city. Another interesting finding is that Airbnb capitalises more on the advantages of proximity to the city's main tourist attractions than does the hotel sector. Multiple regression analysis shows that the factors explaining location are also different for hotels and Airbnb. Finally, it was possible to detect those parts of the city that have seen the greatest increase in pressure from tourism related to Airbnb's recent expansion.

1. Introduction

Over the last few decades urban tourism has undergone huge growth and has become an extremely important activity in many cities, which have seen themselves inundated by crowds of tourists pursuing diverse activities. It is therefore possible to talk of urban tourisms, depending on the activities carried out. The plural is necessary because urban tourism is not like other adjectival tourisms. The additional adjectives ‘cultural’ (including festival or art), ‘historic’ (‘gem’) and even ‘congress’, ‘sporting’, ‘gastronomic’, ‘night-life’, and ‘shopping’ could all precede ‘city tourism’ as different clusters of urban features and services are utilised in the service of an array of tourism markets (Ashworth & Page, 2011).

The relationship between tourists and the city is complex. Cities benefit from tourism. All cities stress the importance of tourism for the local economy: the tourism industry contributes to the local income and provides many people with jobs. In some cities, tourism is the main economic activity and the only current source of local economic development (van der Borg, Costa, & Gotti, 1996). However, there are cities that find themselves under enormous pressure from tourism. Mass tourism alters the relationship between tourists and residents. The growing demands from tourists, particularly in historic cities, have brought about a reactive

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response to the problems of coping with increased visitation, a situation perhaps most commonly experienced in Europe (Pearce, 2001). In a growing number of cities, pressure from tourism is becoming a real source of conflict between tourism stakeholders and residents.

Tourists make very selective use of the city. Studies analysing spatial patterns of tourist mobility in cities show that they tend to be concentrated in specific areas of city centres, where they make intensive use of the facilities and services available there (Shoval & Raveh, 2004). Pressure from tourism is particularly intense in the central areas of historical cities. Such areas become overcrowded when the number of tourists exceeds a certain threshold. Crowding is specifically seen as the violation of the sociocultural carrying capacity (Neuts & Nijkamp, 2012). The first visible sign of excessive tourism growth is saturation of the central supply of facilities. Resources (land, buildings, roads, parking places) in the proximity of the central attractions are limited, but continue to be used until they become saturated (Russo, 2002).

City centres are transformed by tourism. The very nature of tourism—its intensive use of central space, its seasonal pattern, its "transversality" across industries—can greatly affect sensitive urban areas. Its pressure on the value of urban facilities and premises creates an incentive for citizens and firms to abandon central locations (Russo, 2002). These processes are known as tourism gentrification, which, in extreme cases, can be understood as the transformation of a middle-class neighbourhood into a relatively affluent and exclusive enclave marked by a proliferation of corporate entertainment and tourism venues (Gotham, 2005).

Most tourists seek hotels that are within walking distance of major attractions in the city (Arbel & Pizam, 1977). The growing demand for accommodation in the centre is reflected in the Average Room Rate (ARR) for hotels, which decreases with distance from the centre towards the periphery, making it possible to identify a hierarchy of hotels based on location, from luxury hotels (4/5-star quality located in the city centre) to budget hotels located at the edge of the city (Egan & Nield, 2000). Hotel location has a profound impact on tourist movements, with a large share of the total tourist time budget spent in the immediate vicinity of the hotel (Shoval, McKercher, Ng, & Birenboim, 2011). Therefore, the concentration of hotels in the city centre leads to an increase in tourist pressure and is a decisive factor in the transformation of the surrounding urban area. Tourists spend more in the proximity of the hotels, and these areas adapt to satisfy their needs. As a result, the business structure of such areas is transformed, as in the case of shops and restaurants, which become increasingly geared to tourism.

Pressure from tourism is intensified in city centres by the availability of accommodation offered through the new peer-to-peer (P2P) platforms.[1] The exchange of accommodation between private individuals has historically developed informally, but the Internet, and more specifically Web 2.0, has allowed it to grow exponentially and take on new characteristics (Russo & Quaglieri, 2014). P2P platforms in the field of accommodation go well beyond marketing and advertising the properties. They screen both parties, have access to the owners' inventories, manage rental bookings, collect payments and provide some form of insurance coverage for damages caused by the renters (Pizam, 2014).

Airbnb is the most successful P2P platform in the field of accommodation. It connects people who have space to spare (hosts) with those who are looking for a place to stay (guests). Airbnb reaches more than 2,000,000 listings in 190 countries, mainly entire apartments and homes (57%) and private rooms (41%). Airbnb's valuation of over $10 billion now exceeds that of well-established global hotel chains like Hyatt (Zervas, Proserpio, & Byers, 2014). As a disruptive innovation in the field of tourism accommodation,[2] Airbnb proposed a novel business model, built around modern Internet technologies and Airbnb's distinct appeal, centred on cost-savings, household amenities and the potential for more authentic local experiences. Most importantly, Airbnb's relatively low costs appear to be a major draw (Guttentag, 2013).

It has been argued by Airbnb that its listings are more scattered than hotels, so Airbnb guests may be especially likely to disperse their spending in neighbourhoods that do not typically receive many tourists (see Guttentag, 2013). However, as Zervas et al. (2014) point out, Airbnb can potentially expand supply wherever houses and apartment buildings already exist, in contrast to hotels, which must be built at locations in accordance with local zoning requirements. Therefore, expanding in historic centres would be easier for Airbnb than for hotels, which not only requires whole buildings to be available but also the relevant permits from the authorities. If Airbnb shows a clear tendency towards expansion in historic centres, then this could aggravate the problems of crowding and tourism gentrification that some of these areas have to support in certain heritage cities (Neuts & Nijkamp, 2012; Russo, 2002).

Academic studies on Airbnb and its effects on the tourism sector and cities are particularly scant. Guttentag (2013) studied Airbnb as a disruptive innovation in the accommodation sector. Zebras et al. (2014) and Choi, Jung, Ryu, Do Kim, and Yoon (2015) focused their attention on competition from Airbnb with the traditional accommodation sector. Yannopoulou, Moufahim, and Bian (2013) analysed the construction of user-generated brands (UGBs), using discursive and visual analysis of UGBs' social media material, taking Airbnb and CouchSurfing as examples. None of these studies examined the spatial distribution patterns of Airbnb listings.

Exploratory Spatial Data Analysis (ESDA) provides an appropriate framework for studying the location patterns of accommodation in cities. In general, ESDA spatial analysis is concerned with how spatial phenomena pattern themselves and interact with one another (Fischer and Getis, 2009). Spatial distributions tend to show a spatial order (spatial autocorrelation). When there is a tendency for high-value and low-value spatial clusters to form, spatial autocorrelation is positive. When high values tend to be surrounded by low values, and vice-versa, spatial autocorrelation is negative. Finally, random patterns indicate the absence of spatial autocorrelation. ESDA techniques allow analysis of the global spatial autocorrelation of a distribution, identify atypical locations or spatial outliers, and discover spatial clusters or hot spots. Among the most commonly used ESDA tools are the Global Moran's I statistic and the Anselin Local Moran's I (LISA statistic). The first of these measures the degree of spatial autocorrelation of a set of geolocalized data and the sign of this autocorrelation (positive or negative), while the second is used to identify and map local

[1] The last few years have seen the emergence of the so-called sharing economy (also known as collaborative consumption), within the framework of a lifestyle in which more importance is attached to sharing goods than to owning them (Leismann, Schmitt, Rohn, & Baedeker, 2013). Collaborative consumption has been driven by the development of Internet platforms that facilitate P2P relations (Belk, 2014; Botsman and Rogers, 2010). Collaborative consumption could therefore be broadly defined nowadays as P2P-based activity for obtaining, giving, or sharing the access to goods and services, coordinated through community-based online services (Hamari, Sjöklint, & Ukkonen, 2015). One of the fields in which collaborative consumption has burst onto the scene with greater intensity is that of accommodation.

[2] The disruptive innovation theory describes how products that lack in traditionally favoured attributes but offer alternative benefits can, over time, transform a market and capture mainstream consumers (Guttentag, 2013).

tendencies, that is, clusters and outliers. With LISA analysis it is possible to distinguish High-High clusters (a high value surrounded primarily by high values), Low-Low clusters (a low value surrounded primarily by low values), and spatial outliers, either High-Low (high values surrounded primarily by low values) or Low-High (low values surrounded primarily by high values) (Anselin, 1995). In addition, Global and Local Bivariate Moran's I are used to measure spatial autocorrelation between variables and to identify spatial clusters in which the high values of one variable are surrounded by high values of the second (i.e. lagged) variable (High-High clusters) and so on.

Spatial autocorrelation exists because real-world phenomena are typified by orderliness, (map) pattern, and systematic concentration, rather than randomness, "but not necessarily through the same mechanisms" (Griffith, 2015). The results of spatial autocorrelation analyses should therefore be interpreted in relation to the matter being investigated. As described above, different studies show that hotels present patterns of spatial concentration in city centers (see, for example, Arbel & Pizam, 1977), thereby forming a hotel district. It is therefore to be expected that this variable will show a positive global spatial autocorrelation and that the hotel district can be identified locally as a hot spot. Hotels benefit from the economics of location by being concentrated in city centers. This is related to the tendency of tourists in cities to stay in places that are near the main sightseeing attractions (Shoval et al., 2011). Thus, a bivariate positive spatial autocorrelation between hotels and tourist attractions would be expected. The literature also recognizes a certain dispersion of hotels in peripheral areas of the city, where land prices are lower and there may be other relevant determining factors, such as proximity to motorways or suburban business parks. With LISA univariate statistics it is expected in such cases to identify the presence of High-Low outliers. With respect to location patterns of P2P companies, the assertion of companies like Airbnb that their offer tends to be spread over more of the city than that of hotels suggests a lower degree of univariate and bivariate global spatial autocorrelation for Airbnb accommodation (with relation to sight-seeing spots) than for hotels. Nevertheless, the news from different tourist cities does not appear to confirm this fact; rather, it points in the opposite direction.

ESDA tools (particularly univariate techniques) have been used in order to investigate the spatial distribution of certain tourist phenomena, as for example inbound tourist flows to cities (Xingzhu & Qun, 2014; Yang & Wong, 2013; Zhang, Xu, & Zhuang, 2011), tourism related employment (Chhetri, Corcoran, & Hall, 2008) or tourist hot spots within cities using geotagged photographs (García-Palomares, Gutiérrez, & Mínguez, 2015). However, as far as we know, there has been very little use of ESDA tools to analyze the spatial distribution of accommodation (one exception being Sarrión-Gavilán, Benítez-Márquez, & Mora-Rangel, 2015), particularly inside cities.

The aim of this study is to carry out a comparative analysis of the spatial patterns of Airbnb and hotel accommodation, together with the factors explaining these distributions, using ESDA and, additionally, OLS (Ordinary Least Squares Regression). This is the first time this issue has been addressed. The main hypotheses put forward in this study are: 1) Airbnb increases tourist pressure on the city centre by covering central space not covered by hotels; 2) Airbnb is more favourably located than hotels with respect to the main sightseeing spots in the city; 3) The factors explaining Airbnb location patterns are different from those explaining hotels. These hypotheses have been confirmed in the case of Barcelona but it should be possible to extend the results obtained to many other European cities.

The article is structured as follows. After the introduction, Section 2 outlines the area of study, Sections 3 and 4 describe the data and the methodology, respectively, Section 5 shows the main results and Section 6 presents the conclusions and final remarks.

2. Study area: Barcelona

The area selected for study was the city of Barcelona. Barcelona is a historic city that suffers serious problems from mass tourism and has a large concentration of accommodation on offer on the Airbnb website. Delimitation of the study area was based on the administrative reference unit: the municipality of Barcelona (Fig. 1). This is a relatively compact area of 10,130 ha around the traditional city. With 1,604,000 inhabitants, the population density of the municipality of Barcelona is high, with more than 158.3 inhabitants per hectare.

In 2014, Barcelona was the fifth city in Europe in terms of the number of international tourists, behind only London, Paris, Berlin and Rome (European Cities Marketing, 2015).[3] On a global scale, it is among the twenty-five favourite city destinations for international tourism (Top Cities Destination Ranking 2013; Euromonitor International). Its popularity rose considerably after it hosted the 1992 Olympic Games. In 1990 the number of overnight stays totalled 3.8 million, involving 1.7 million tourists. In 2000, there were 7.9 million overnight stays and 3.1 million tourists. By 2014 this total had reached almost 17 million overnight stays, with 7.8 million tourists (79.5% of them international tourists). This huge influx of visitors has an enormous economic and social impact on the city, generating more than 26 million euros a day and more than 120,000 jobs in tourism (Barcelona Turisme: Barcelona Tourism Annual Report, 2014),[4] but also producing a high pressure on the city centre that led to a significant gentrification process (Cócola, 2015).

3. Data

This research is mainly based on the analysis of the Airbnb geolocated data obtained from the Inside Airbnb website http://insideairbnb.com/. Inside Airbnb is an independent initiative and the data made available through its website are "*not associated with or endorsed by Airbnb or any of Airbnb's competitors*". The data utilises public information compiled from the Airbnb web-site, including not only the location of all Airbnb lodgings but also the availability calendar for 365 days in the future, and the reviews for each listing.[5] These data are available for more than 30 cities, including the main cities in Europe (London, Paris, Berlin, Madrid …), the United States and Canada (New York City, San Francisco, Los Angeles, Washington D.C., Montreal, Vancouver, Toronto …) and Australia (Sydney and Melbourne).

Data compiled for Barcelona refers to October 2015. Two files called *listings.csv* were downloaded. These contained ample information on each listing with respect to *Room Type* (entire homes/apartments; private vs shared rooms; number of bedrooms and beds), *Activity* (estimated nights/year; reviews/listings/month; reviews; estimated occupancy; price/night; estimated income/month), *Availability*, *Listings* per *Host*, and so forth. From the x, y coordinates stored in each record a point layer map was created in a geodatabase in ArcGIS with the location and features of each accommodation (Fig. 2a). The map shows a clear concentration of points in the city centre. This spatial pattern is the result of an

[3] http://www.cvent.com/events/ecm-benchmarking-report-2013-2014/event-summary-9dc7593d7ca947d995cd7ca658a0777d.aspx.

[4] http://professional.barcelonaturisme.com/imgfiles/estad/Est2014b.pdf.

[5] All information on this source can be consulted at http://insideairbnb.com/about.html.

Fig. 1. Municipality of Barcelona.

explosive growth, as illustrated in the supplementary video on the evolution of Airbnb accommodation in Barcelona (see video). By using the number of reviews per month as a proxy for the level of occupation of the lodgings, an average value of 1.48 was obtained for the centre of the city [6]and 1.14 for the rest, data that also expresses the higher pressure exerted by Airbnb on the city centre. With regard to the type of accommodation, 54% were entire homes/apartments, 45% were private rooms and only 1% were shared rooms, with prices averaging about 35 euros/bed. The database also reveals that this platform is not only used by private individuals but also by professionals. The proportion of Airbnb hosts who rent out more than one room or apartment is about 27% and 22% of the rooms or apartments are rented out by hosts who offer more than 5 lodgings.

Supplementary video related to this article can be found at http://dx.doi.org/10.1016/j.tourman.2017.05.003.

Accommodation offered by Airbnb was compared with that of the city's hotels (Fig. 2a). Data on hotels were taken from the Catalonia Tourism Registry,[7] compiled and updated weekly by the regional government (*Generalitat de Catalunya*). The records for each hotel contain data on the number of rooms and beds available as well as the corresponding postal address. Geolocation of these data was carried out using ArcGIS address matching tools. There are 670 hotels in Barcelona offering more than 70,000 beds. In the case of Airbnb, the number of lodgings is 14,500, with an offering of approximately 51,000 places (Table 1). However, the Airbnb data should be put into context. While the hotel offering covers 365 days of the year, Airbnb beds are available over less time. In Barcelona, the average availability of the listings is for 280 days a year

[6] Ciutat Vella and Eixample districts.

[7] http://empresaiocupacio.gencat.cat/es/treb_ambits_actuacio/emo_turisme/emo_empreses_establiments_turistics/emo_registre_turisme_catalunya/emo_llistat_establiments_turistics/index.html.

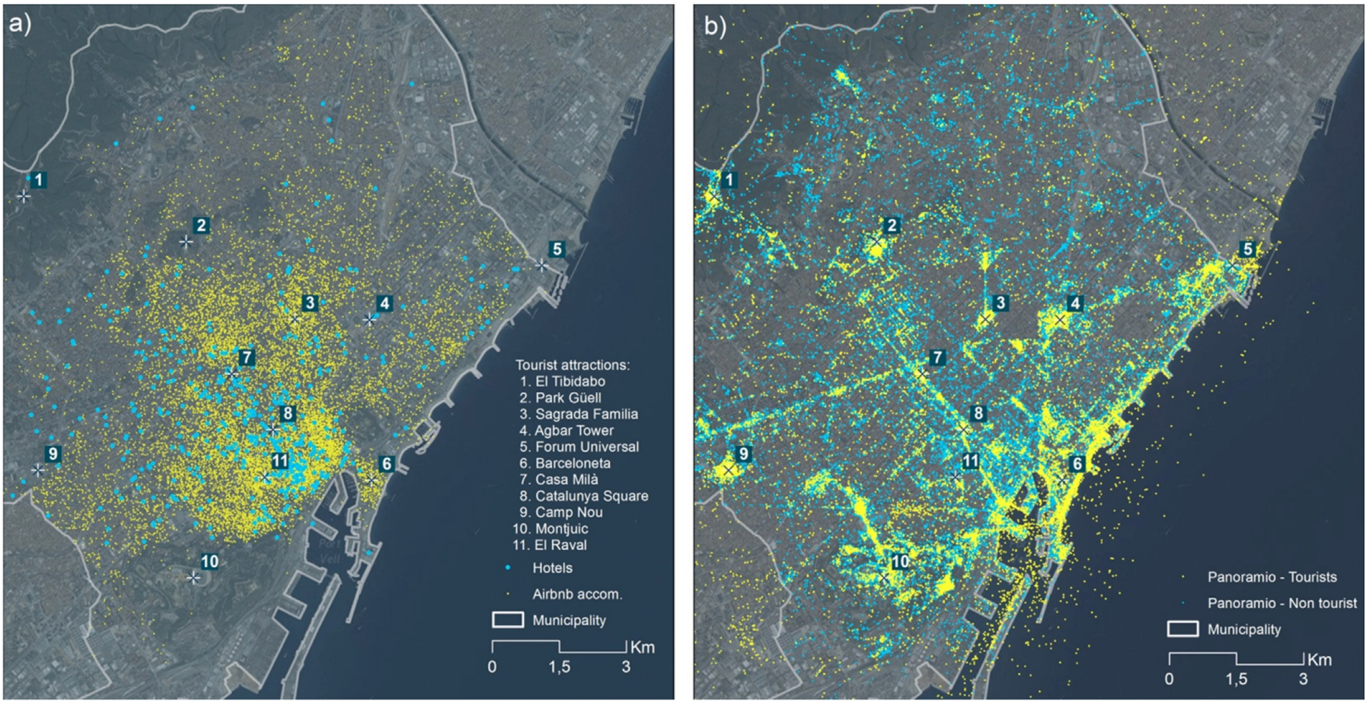

Fig. 2. Location of hotel and Airbnb offers (a) and density of photographs taken by tourists and residents (b).

Table 1
Data on tourism accommodation in Barcelona: hotels versus Airbnb.

	Hotels/Airbnb listings	Bedrooms	Beds
Hotels	670	37,405	73,158
Airbnb	14,539	22,059	50,969

Source: InsideAirbnb and Generalitat de Catalunya.

(Table 2). Of these listings, 1706 (12%) are available for fewer than 90 days a year.

In order to identify sightseeing hot spots, geolocated photographs from the Panoramio data source were used. The data were downloaded through the Panoramio website API[8] to obtain samples of all the photographs stored, and contained information about the geographic coordinates, the ID of the owner of the photograph, a url link to the photograph and the date on which it was uploaded. Downloading generated ".csv" files, which contained the geographical coordinates of the location of each of the photographs. These coordinates were used to create a layer of points for each of the locations in a GIS. Geolocated photographs were differentiated according to whether they had been taken by tourists or residents. We used the same criterion as Fischer for his Geotaggers' World Atlas and García-Palomares et al. (2015): if this period exceeded one month, then the photographs were attributed to residents; if the period was less than one month, then they were attributed to tourists. The number of photographs taken in Barcelona was more than 92,000, of which 28.5% were taken by tourists (Table 3). The spatial distribution of photographs taken by tourists is much more concentrated than that of those taken by residents, reflecting the location of the city's main tourist attractions (Fig. 2b).

Finally, population data from sections of the Barcelona municipal census were used. The population data were obtained from the official registry of inhabitants (Padrón del Instituto Nacional de Estadística: http://www.ine.es/), taking 2013 as the date of analysis.

In order to explain location factors with respect to hotel and Airbnb accommodation, data have been gathered at census section level on land use, distance to the city centre and the beach, and sightseeing spots in the near vicinity. Land use data was collected from the Cadastre 2014 in order to explore the relationship between different urban activities and the greater or lesser presence of Airbnb and hotel beds. In particular, the density of areas of leisure and hospitality activities was computed for each census tract, as was that of areas given over to offices, residential, shows or

Table 2
Basic data on lodgings offered by Airbnb in Barcelona.

		Lodging type			Total
		Entire home/apt	Private room	Shared room	
Listings		7816	6566	157	14,539
Price (Euros)	Mean	111.8	39.3	27.3	78.2
	SD	140.2	26.8	21.5	110.5
Availability (days per year)	Mean	276.1	285.8	305.8	280.1
	SD	103.8	111.0	107.0	107.3
Beds	Mean	3.1	1.3	3.6	2.3
	SD	2.0	1.0	3.4	1.8
Reviews/lodging per month	Mean	1.28	1.41	1.18	1.34
	SD	1.31	1.56	1.51	1.43

Source: InsideAirbnb.

Table 3
Photograph statistics.

	Tourists' photographs		Locals' photographs		All photographs	
	Total	Density[a]	Total	Density[a]	Total	Density[a]
Barcelona municipality	26,361	1.50	66,114	3.75	92,475	5.25

[a] Photographs/hectare.

[8] http://www.panoramio.com/api/data/api.html.

performances, retail and industrial development. The Euclidean distance to the city centre (i.e. Catalunya Square) and pedestrian access to the beach were computed using GIS tools. Finally, the presence of sightseeing spots in the near vicinity of the section was obtained from the number of photographs in Panoramio at a distance of less than 1 km.

4. Methodology

The following methodology was employed to analyse the spatial distribution of Airbnb and Hotel accommodation and photographs:

a) Data aggregated by census tract were used to produce density maps and descriptive statistics, and thus determine the intensity and degree of concentration of the accommodation (by number of beds, differentiated into hotels and Airbnb) and tourist photographs.
b) Distribution data on hotel and Airbnb beds was normalised in order to eliminate the effect of different ranges in the variables so that distributions could be compared with each other.
c) Univariate spatial autocorrelation tools were used to identify the location and extent of spatial clusters of types of accommodation and tourist photographs.
d) Bivariate spatial autocorrelation tools were used to analyse spatial autocorrelation between accommodation types (hotels and Airbnb) and tourist photographs.
e) The rates of hotel and Airbnb beds per 1000 inhabitants were obtained in order to analyse pressure from tourism on the resident population.
f) Multiple regression models (Ordinary Least Squares [OLS]) were used to identify the driving mechanism underlying the different location patterns for hotels and Airbnb accommodation.

Aggregated data at census section level and density mapping are an initial visual approach to distribution of the accommodation offering, allowing the spatial patterns between Airbnb and hotel accommodation to be compared. The descriptive statistics enable measurements to be taken to determine the degree of concentration or dispersion of the types of accommodation. Data normalisation was used in order to map the degree of relative predominance of one type of offering over another in each of the census sections. To do this, the normalised densities of the Airbnb offering were deducted from the normalised densities of the hotels offered in each section.

Based on aggregated data by census sections, the location patterns were then analysed using spatial statistical indicators. Global Moran's I statistic was calculated to measure spatial autocorrelation based on feature locations and attribute values. Anselin Local Moran's I (LISA statistic) was used to identify local tendencies in the location of the different types of accommodation. Global and Local Bivariate Moran's I were used in order to measure spatial autocorrelation between variables and to identify spatial clusters in which the high values of one variable were surrounded by high values of the second (i.e. lagged) variable (high-high clusters) and so on. We chose to consider the spatial interaction between observations within a 1 km radius, that is, a typical 15-min walk, with a weight inversely proportional to the distance.

Two multiple regression models (OLS) were calculated using the normalised density of hotel and Airbnb beds, respectively, as dependent variables. The candidate independent variables were land use, the density of tourist photographs within a 1 km radius from the census tract centroid, distance to the city centre (i.e. Catalunya Square) and network distance to the beach.

5. Results

5.1. Distribution of tourism accommodation

Maps and descriptive statistics of the distribution of accommodation by census sections are shown in Fig. 3 and Table 4. The

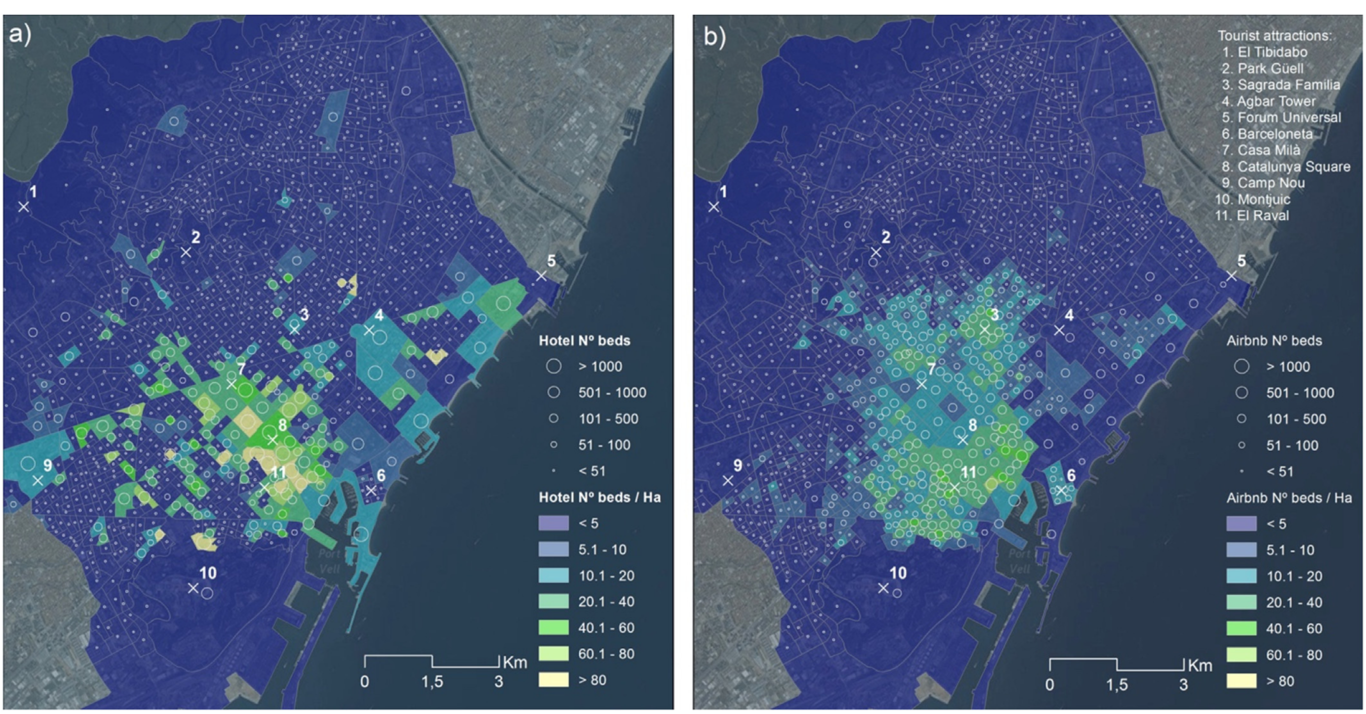

Fig. 3. Total number and density of beds, according to census sections: a) hotels, and b) Airbnb.

Table 4
Basic statistics on the distribution of number of beds offered by hotels and Airbnb according to census sections.

	Airbnb			Hotels		
	Total	Nº beds	Nº beds/ha	Total	Nº beds	Nº beds/ha
Count (Census sections):	*1061*	*1061*	*1061*	*1061*	*1061*	*1061*
Minimum:	0	0	0	0	0	0
Maximum:	175	616	64.0	48	2368	255.4
Sum:	14515	50969	6586.9	712	73158	6089.5
Mean:	13.7	48.0	6.2	0.7	69.0	5.7
Standard Deviation:	21.3	76.7	8.8	3.0	233.5	18.5
CV:	155.6	159.7	141.9	443.8	338.7	322.8
Nº Census sections > 100 lodgings			153 (14.4%)	153 (14.4%)		
Nº Census sections > 200 lodgings			50 (4.7%)	90 (8.5%)		

average number of Airbnb accommodation by census sections is 48, compared with 69 for hotels, with maximum values of around 600 lodgings for Airbnb and more than 2000 for hotels in some sections of the centre. The number of census sections with more than 200 lodgings is also much greater in the case of hotels (Table 4). The hotels are highly concentrated in the census sections comprising the Ramblas-Paseo de Gracia axis, certain areas dedicated to business and finance, like the Diagonal main street, or the coastal axis from the Barceloneta beach to the Forum. Outside these areas the availability is much lower. The differences in the distribution of Airbnb accommodation are not so marked, as shown by the coefficient of variation, which has much lower values for Airbnb than for hotels.

In order to compare the distribution of hotel and Airbnb accommodation by census sections, Fig. 4a and b shows the density of accommodation places with normalised data. This cancels out differences in the ranges of the two variables, thus making them comparable. In contrast to the marked concentration of hotels on the Ramblas-Paseo de Gracia axis, Airbnb accommodation is found in a concentric ring around the central hub of the city, the Plaza de Cataluña. The area it covers is much more extensive than that of the hotels and is occupied by traditional city centre residential districts, such as El Raval, La Barceloneta, La Ribera, the Gothic Quarter, and the area around the Sagrada Familia Church. In all these zones, the presence of Airbnb is greater in relative terms than that of hotels (Fig. 4c). As a result, the Airbnb accommodation contributes to increasing tourism pressure on the centre.

Spatial statistical analysis confirms the statistical significance of these location patterns. Global Moran's Index shows a strong positive spatial autocorrelation in both cases (positive Moran's Index and p-value = 0.00000) (Table 5), but it is higher for Airbnb than for hotels. Using Anselin Local Moran's I statistic, the spatial cluster distribution can be identified (Fig. 5). As expected, both cases show a clear concentration of HH clusters in the city centre and LL on the periphery. In the case of hotel accommodation, the HH clusters are located along the main Ramblas-Paseo de Gracia axis, around which LH outliers appear. These are central areas that have traditionally had a marked residential character but no hotel accommodation. In the case of Airbnb, the HH clusters extend through all the census sections in the city centre, including those that are residential in nature. In both cases, towards the outer edge of the central area is a belt of sections with values that are not significant, which would mark the limit of tourist accommodation in the central area. In the case of Airbnb, this belt is narrow and very clearly defined and is surrounded by LL census sections in all the periphery of the municipality. In contrast, in the case of hotels, the belt with not significant values is much more diffuse and extensive because of the presence of hotels on the axis of the Diagonal and in some peripheral census sections (census sections with not significant values or with HL outliers, which reduces the extension of LL clusters) The number of census sections according to types of cluster confirms that the distribution of Airbnb gives a greater positive spatial autocorrelation than that of hotels, with more census sections made up of types HH (258 for Airbnb vs. 81 for hotels) and LL (575 Airbnb vs. 392 hotels), and fewer outliers (33 vs. 77 LH clusters and 13 vs. 15 HL clusters).

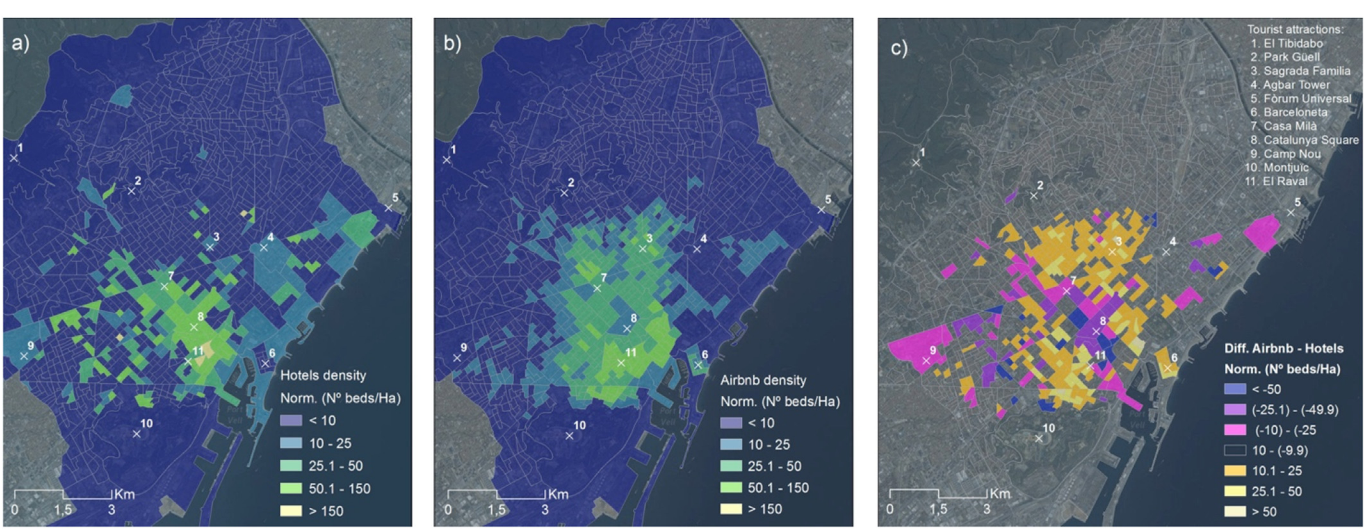

Fig. 4. Density of normalised distributions: a) hotels; b) Airbnb; c) differences.

Table 5
Global Moran's I statistics.

	Hotels	Airbnb	Panoramio
Global Moran's Index	0.23	0.70	0.18
z-score	27.91	78.55	25.84
p-value	0.01	0.01	0.01

5.2. Areas visited by tourists

In order to analyse the main tourist areas, we mapped the density of photographs taken by tourists in terms of both absolute values (photographs/ha) (Fig. 6) and normalised values (Fig. 6b) to facilitate comparisons with the density of hotel and Airbnb

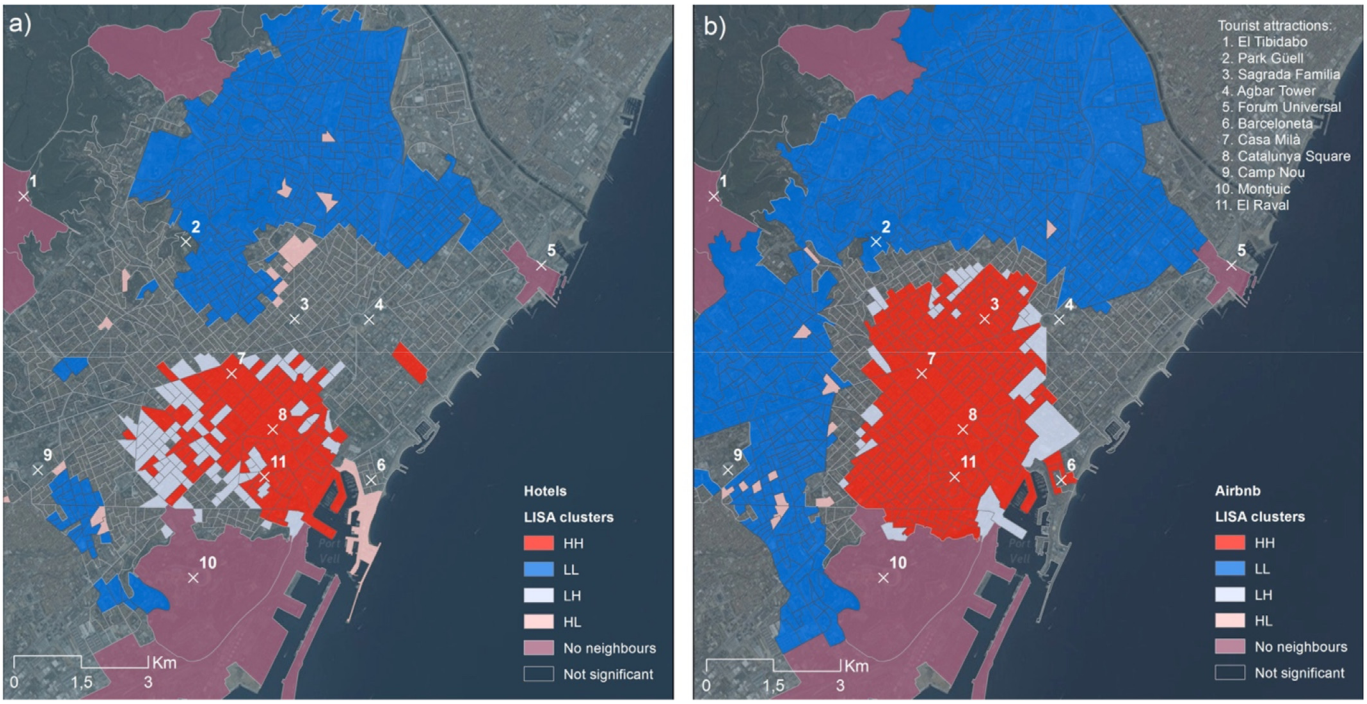

Fig. 5. Anselin Local Moran's I statistic (LISA): a) accommodation in hotels; b) accommodation in Airbnb. *No neighbours: Census sections larger than 2 km wide (without neighbours within 1 km from the centroid).

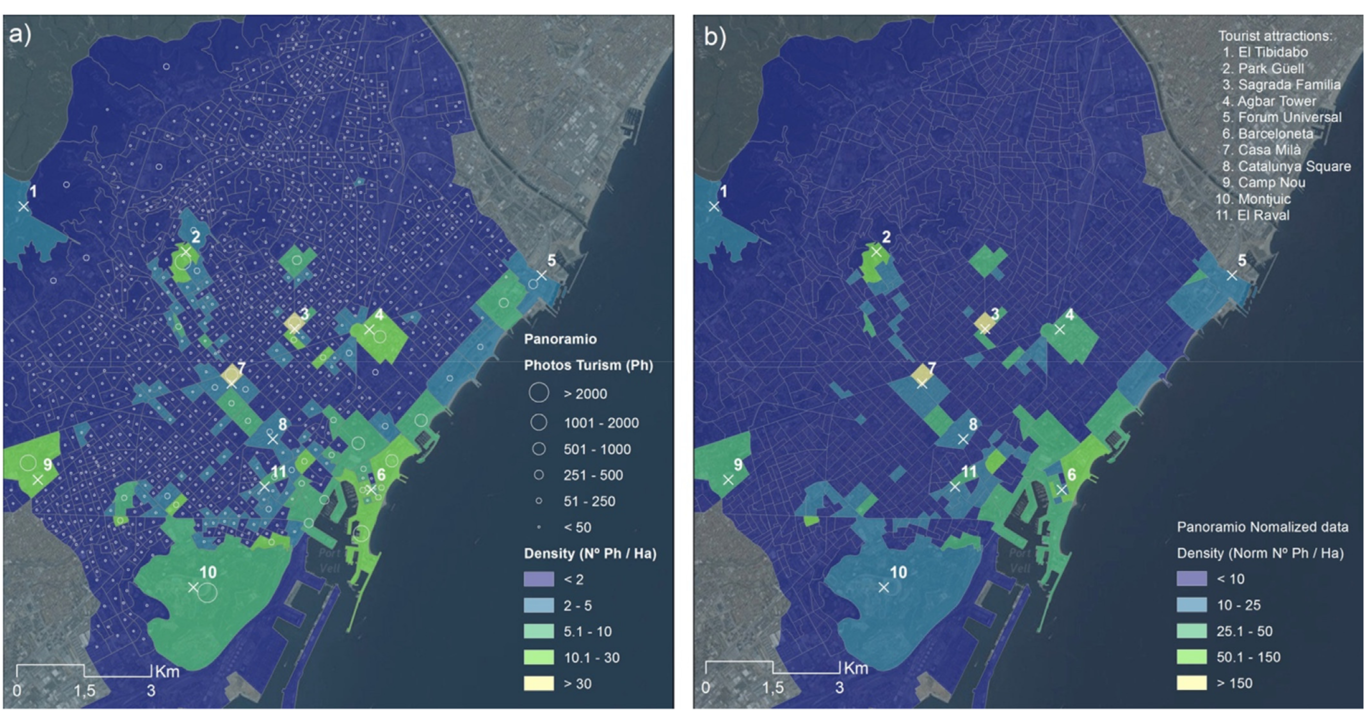

Fig. 6. Photographs taken by tourists: a) total number and density; b) normalized data.

Table 6
Basic statistics on the distribution of photographs taken by tourists according to census sections.

	Total photographs	Photographs/ha
Maximum:	3827	70.9
Sum:	26649	1176.8
Mean:	25.1	1.1
Standard Deviation:	161.2	3.3
CV:	641.8	300.8

accommodation. The photographs reflect the spatial distribution of the city's main sightseeing spots. The most photographed places, and consequently the most visited, are the Barcelona of Gaudi (the Sagrada Familia Church, Casa Batlló, Casa Milà, the Güell Park, and others), the Gothic Quarter in the historic centre, the port area and the beach, together with other tourist spots, such as Barcelona Football Club's Nou Camp stadium, the Torre Agbar and Forum buildings, or green spaces with scenic views like Montjuic and Tibidabo. This all shows a distribution of census sections that are dispersed throughout the city and have very high intensities, in which values exceed more than 2000 and even 3000 photos, compared to an average of 25 photographs per section (Fig. 6a and Table 6).

Moran's Index indicates a strong positive spatial autocorrelation in the distribution of areas, although with a lower value than in the case of Airbnb and hotels (Table 5). Calculation of Anselin Local Moran's I statistic (Fig. 7) shows two zones in which HH clusters are located, one in the area round Las Ramblas and the Gothic Quarter in the city's historic centre, and the other to the north of this, centred around the Sagrada Familia and including the Paseo de Gracia axis. Logically, in the more peripheral census sections away from the coast, the presence of tourists is diluted and LL clusters predominate.

5.3. Relations between the locations of different types of lodgings: hotels vs Airbnb

Relations between the location patterns of hotel and Airbnb accommodation can be analysed using bivariate autocorrelation indicators, both the Moran Index and LISA. The bivariate Moran Index shows a very high positive spatial autocorrelation between location of the hotels and the accommodation offered by Airbnb (Table 7). The mapped clusters are shown in Fig. 8.

The distribution of clusters shows a clear centre-periphery pattern. Type HH is located along the Ramblas-Plaza de Cataluña-Paseo de Gracia axis. These census sections have a large number of hotel places and are surrounded by sections with a high supply of

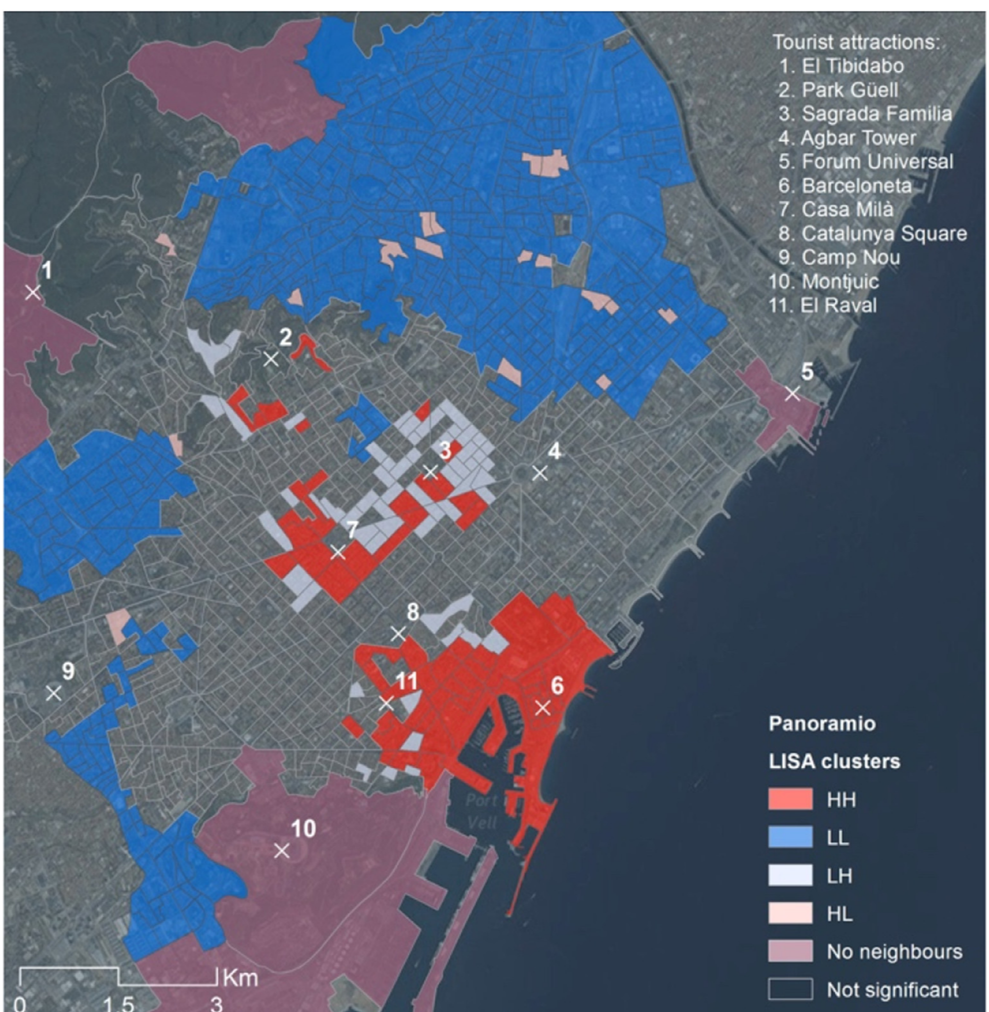

Fig. 7. Anselin Local Moran's I statistic (LISA) for the distribution of photographs taken by tourists.

Table 7
Bivariate Global Moran's I statistics.

	Hotels-Airbnb	Hotels - Panoramio	Airbnb - Panoramio
Global Moran's Index	0.32	0.08	0.18
z-score	57.70[a]	15.48[a]	25.,84[a]

[a] Significant at the 0.01 level.

Airbnb accommodation. Census sections of this type also appear in traditional residential districts in the centre, where some hotels are found in areas with a very strong Airbnb presence. Nevertheless, in these central residential districts LH census sections predominate, with a low number of hotel places and a high level of Airbnb accommodation. On the periphery, LL clusters prevail, that is, census sections with a low number of hotel places surrounded by sections with a low Airbnb presence. There are only a few cases of HL type census sections (high concentration of hotels and low presence of Airbnb), one example being the Diagonal axis.

5.4. Sightseeing spots and accommodation

Tourists tend to stay in places close to areas where the main sights and other tourist attractions are situated. Therefore, it is only to be expected that there is a strong spatial association between location of the accommodation (in hotels and with Airbnb) and the areas of the city that are of interest to tourists (photographs taken by tourists). Although the bivariate Moran's I confirms a very strong positive spatial autocorrelation in both cases, this is greater for Airbnb (Table 7), which suggests a better location of this type of accommodation with respect to the city's tourist attractions.

The bivariate LISA (Fig. 9) shows that the HH census sections are more numerous in the Airbnb-Panoramio relation than in the Hotel-Panoramio relation (102 vs. 50). These are census sections with a high density of lodgings surrounded by sections with a high density of photographs. In the case of hotels, HH are in the census sections of the Ramblas-Gothic Quarter, and around the Paseo de Gracia (with tourist sites at Casa Milà-La Pedrera and Casa Batlló). With respect to Airbnb, HH are located along these same axes, but they also extend in particular to the residential district of the Ensanche around the Sagrada Familia. With respect to hotels, these same census sections form part of type HL (low number of hotels in areas with a high number of photographs). There is a marked contrast between those results obtained for hotels and those for Airbnb in the census sections comprising the port, La Barceloneta and the beach. With respect to the relation between the hotels and the photographs, the appearance of HH census sections in the port and beach areas is due to the presence in this zone of hotels that are

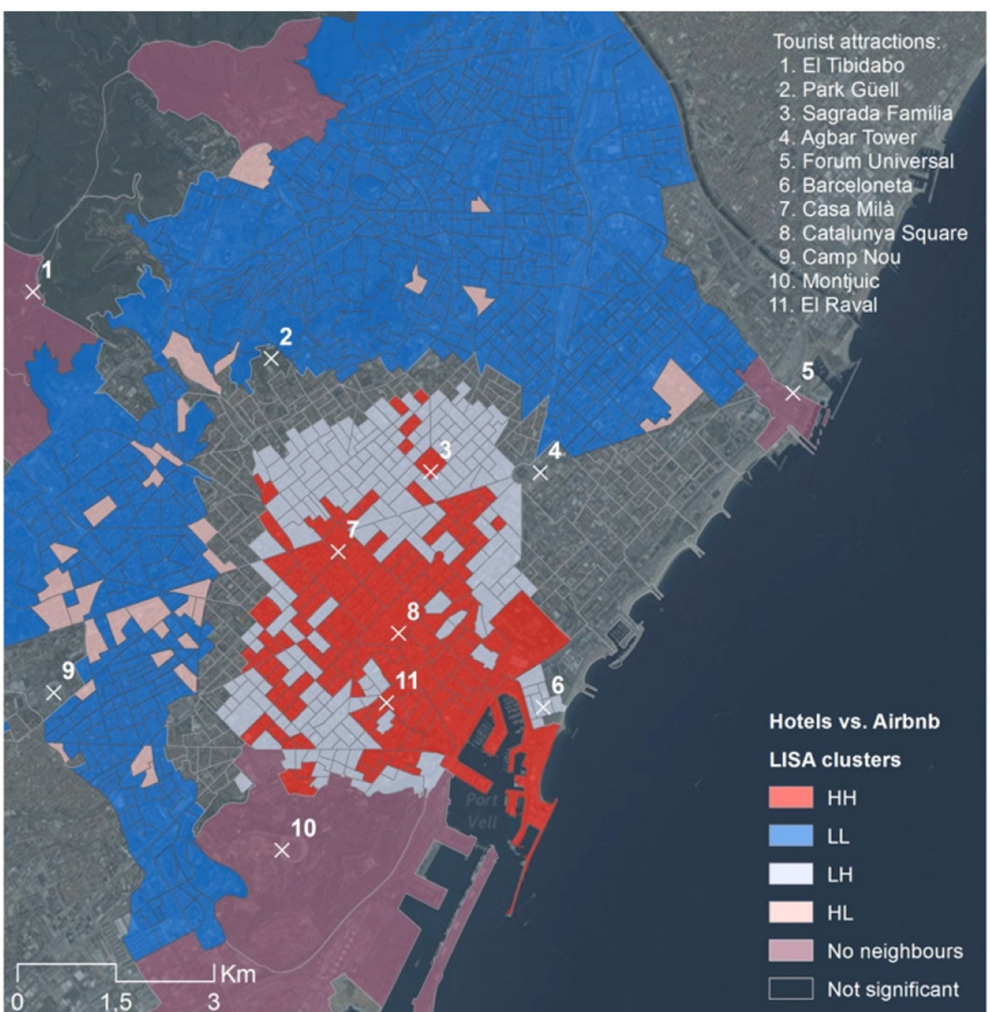

Fig. 8. Bivariate Anselin Local Moran's I statistic between offers of hotel and Airbnb accommodation.

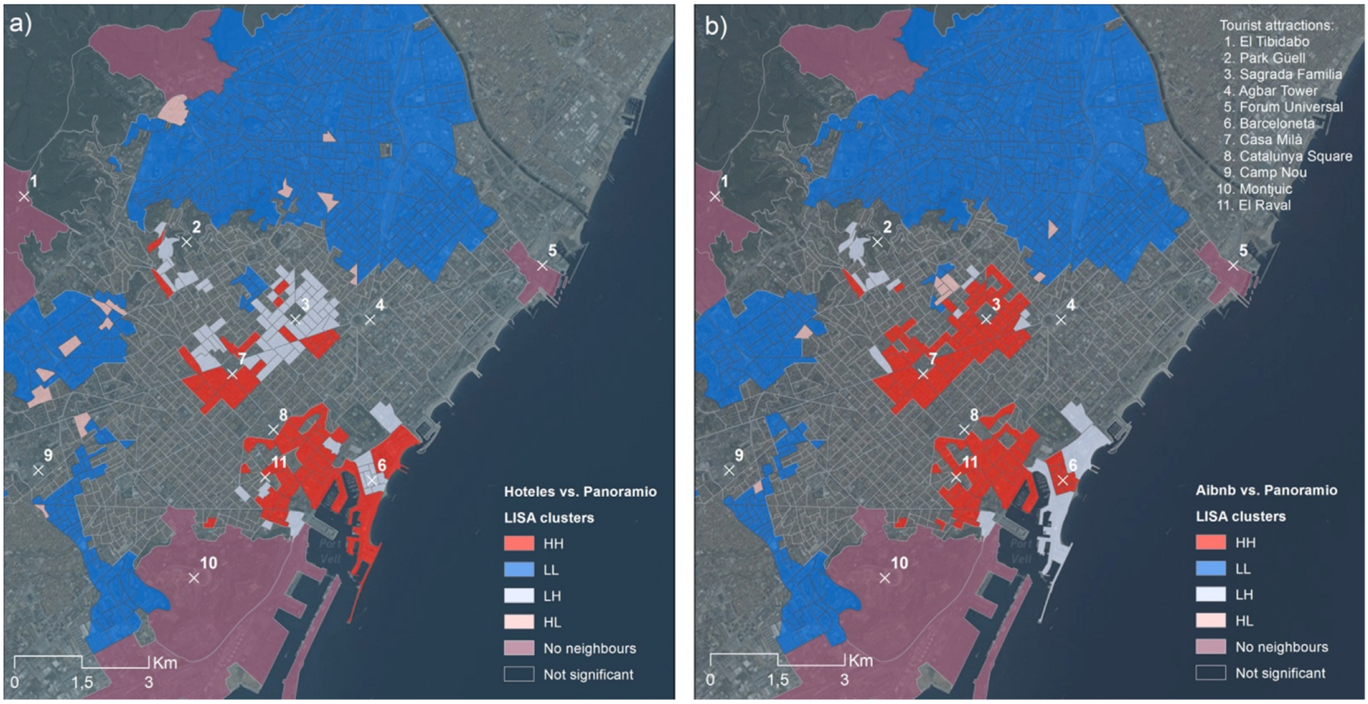

Fig. 9. Bivariate Anselin Local Moran's I statistic for hotels-Panoramio and Airbnb-Panoramio.

surrounded by much-photographed sites, with the exception of the traditional La Barceloneta district, which has no hotels and appears as HL. The opposite occurs in the case of Airbnb, since the LH census sections predominate in the port and beach zones, while La Barceloneta is HH. Around these central areas are census sections with values that are not significant. LL predominate in peripheral locations towards the outer edge, particularly in the case of Airbnb, while in that of hotels there is a greater presence of HL census sections due to hotels scattered in areas where few photographs are taken.

5.5. Driving mechanisms of Airbnb vs. hotel location patterns

Airbnb accommodation tends to be found in areas with well-defined characteristics. The model obtained for Airbnb therefore has a relatively high explanatory capacity (R2Adj: 0.55). By contrast, the driving mechanisms that explain the patterns of hotel location are much more complex, since hotels are located in a great variety of areas in different types of urban environment (Egan & Nield, 2000). This is reflected in a much smaller adjustment of the model, which only explains about 22% of their distribution (R2Adj: 0.22) (Table 8).

Airbnb is clearly linked to areas in the city centre that attract tourism (Table 8). The offer decreases with distance from the centre and from the beach (negative B coefficients) and the presence of industrial activity but increases with the proximity of sightseeing spots, and land use associated with the leisure, hospitality and entertainment industries. As expected, the presence of Airbnb is positively related to the existence of residential areas. Factors such as the presence of offices or commercial activities are not significant and remain outside the model.

Respecting the hotels, the independent variables in the model

Table 8
Multiple regression models (OLS).

Independent variables	Airbnb OLS model					Hotel OLS model				
	B	Std. error	t	Sign.	VIF	B	Std. error	t	Sign.	VIF
Intercept	19761.3	3126.7	6.3	0.000000[a]	–	−446.42	1889.02	−0.236	0.813227	–
Distance to city centre	−1.550	0.363	−4.290	0.000024[a]	4.920					
Leisure and restaurants	0.037	0.005	8.130	0.000000[a]	1.609	0.078	0.010	8.047	0.000000[a]	1.944
Residential	0.002	0.001	3.362	0.000817[a]	2.313	−0.001	0.001	−1.847	0.06502	1.414
Industrial	−0.023	0.004	−5.464	0.000000[a]	1.532					
Shows/performances	0.243	0.030	8.048	0.000000[a]	1.529	0.184	0.054	3.428	0.000648[a]	1.278
Offices						0.020	0.005	4.366	0.000017[a]	2.191
Retail										
Tourist photographs	4.391	0.836	5.250	0.000000[a]	1.753					
Distance to the beach	−1.630	0.265	−6.149	0.000000[a]	2.419					
Number of Observations: 1061						Number of Observations: 1061				
Akaike's Information Criterion (AICc): 22868.2						AICc: 24271.21				
Multiple R-Squared: 0.56						Multiple R-Squared: 0.22				
Adjusted R-Squared: 0.55						Adjusted R-Squared: 0.22				
F-Statistic: 190.09 Prob(>F), (7,11) degrees of freedom: 0.000000[a]						F-Statistic: 75.75 Prob(>F), (4,11) degrees of freedom: 0.000000[a]				

[a] Significant at the 0.01 level.

obtained (Table 8) show that their presence decreases on land given over to residential use and increases in the presence of office and land dedicated to the leisure, hospitality and entertainment industries. Distance to the city centre and total number of photographs of the surrounds from Panoramio were not significant and not included in the model.

5.6. Pressure from tourism on residential areas

In order to analyse tourism pressure on residential areas, the number of places of accommodation (hotels and Airbnb) per 1000 inhabitants has been calculated according to census sections, excluding those sections that have hardly any population (<5 inhabitants/ha), such as green spaces or industrial zones (Fig. 10).

Fig. 11a highlights the tourism pressure exerted by hotels along the main hotel axis, where several census sections exceed 500 lodgings per 1000 inhabitants. Between this axis and the periphery there is an abrupt drop in pressure on residential areas from tourist accommodation. This drop is much more gradual in the case of Airbnb (Fig. 11b). The lodgings available through Airbnb extend over residential areas in the centre which have no hotels and where there were formerly no accommodation. Some census sections have more than 100 Airbnb places per 1000 inhabitants, reaching a maximum of almost 400 places per 1000 inhabitants. The pressure from this type of accommodation on the centre is intensified by the fact that Airbnb occupation levels are greater in the centre than on the periphery (see Section 3). Finally, Fig. 10c shows the total number of places for both types of accommodation (hotels and Airbnb). This map should be analysed with caution, since the level of occupation is higher for hotels than for Airbnb, but it illustrates the pressure exerted by tourism on the city due to Airbnb lodgings, with several census sections in which the number of places exceeds and even doubles the number of inhabitants (see also Table 9).

6. Conclusions

The eruption of P2P accommodation platforms in tourist cities has received very little attention from researchers, particularly in relation to the location of its lodgings and their possible impact on the city. The present study aims to close this gap with a contribution on the location of Airbnb accommodation offered in cities with mass tourism, related to hotel location and the most visited tourist attractions (locational advantages), and the resident population (tourism pressure), using Barcelona, a city with one of the highest numbers of tourists in Europe, as a case study.

The results of the study show that the distribution of the Airbnb accommodation offered in Barcelona has a clear centre-periphery pattern. Its listings tend to be concentrated in the city centre, where they cover a wider area than the main hotel axis as they also extend to very central residential districts that are not covered by hotel lodgings. Spatial autocorrelation analysis shows that the distribution of Airbnb is much simpler and more regular, from the HH clusters in the centre to the LL clusters at the periphery, incorporating a narrow band of not significant census sections, and with a scarcity of outliers. In contrast, hotels show more complex patterns, with less extension of HH and LL clusters and a greater extension of not significant census sections and outliers.

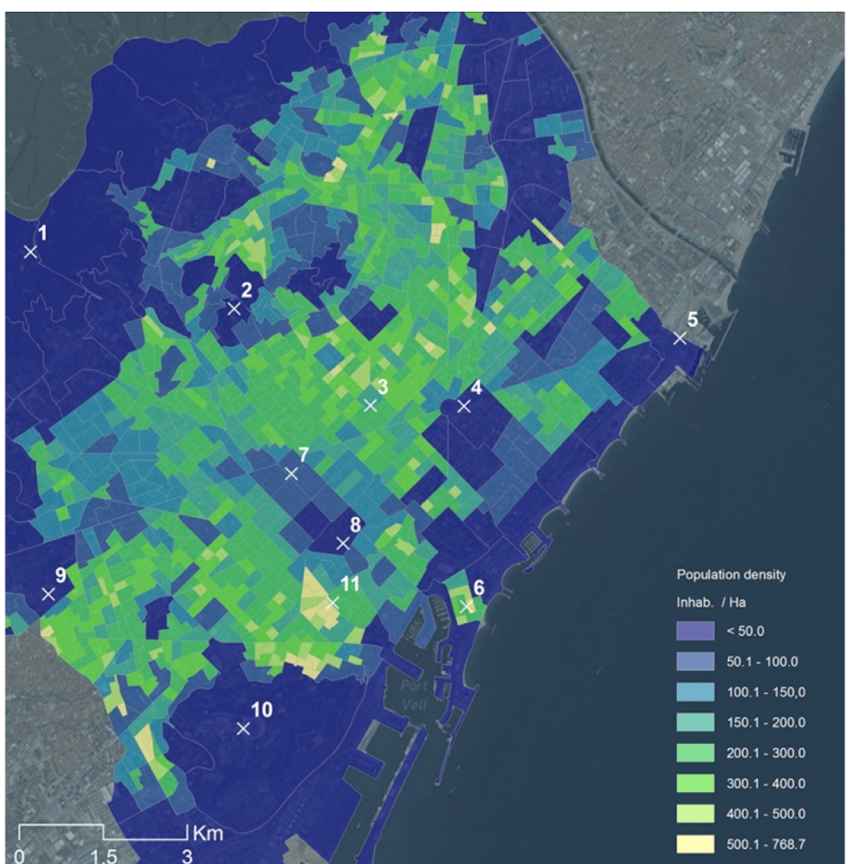

Fig. 10. Population density according to census sections (inhabitants/ha).

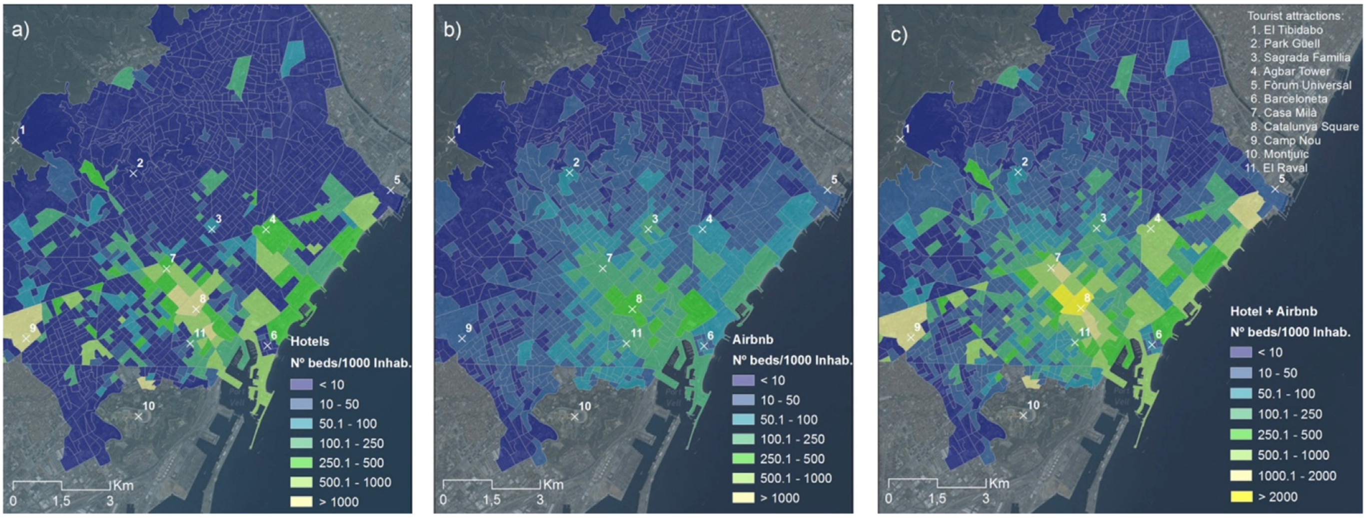

Fig. 11. Tourism pressure on residential areas: a) Hotel beds per 1000 inhabitants; b) Airbnb beds per 1000 inhabitants; c) Hotel beds + Airbnb beds per 1000 inhabitants.

Table 9
Basic statistics on the distribution of the beds offered by hotels and Airbnb per 1000 inhabitants according to census sections.

	Hotel beds/1000 inhabitants	Airbnb beds/1000 inhabitants	Hotel + Airbnb beds/1000 inhabitants
Maximum	1796.1	391.7	2148
Sum	46079.3	31941.6	78021
Mean	43.4	30.1	73.5
Standard Deviation	150.0	45.9	180.6
CV	345.4	152.5	245.6

Bivariate spatial autocorrelation analysis reveals a close spatial association between the Airbnb accommodation offered and that of hotels. The centre-periphery patterns shown by the results of this analysis are very clear. The axis of hotels in the centre (cluster HH) gives way to a band dominated by Airbnb (LH), a second band of not significant values and finally a peripheral area dominated by LL clusters, with some HL outliers (areas with a concentration of hotels but not Airbnb).

It is assumed that tourists tend to stay in the proximity of the places they wish to visit (Arbel & Pizam, 1977). This would explain the configuration of hotel districts in city centres (economies of location). Analysis of the bivariate autocorrelation between the accommodation and the sightseeing spots (tourists' photographs geolocated on Panoramio) confirms a close spatial association between both variables (accommodation and places visited). However, the differences between the two maps are generally to Airbnb's advantage. The results suggest that Airbnb benefits in greater measure than hotels from proximity to the most visited places in the city, probably because of its greater facility for expansion in already built-up areas.

Analysis of the driving mechanisms of Airbnb location patterns confirms its stronger relationship with areas in the city centre that attract tourism. Proximity to the city centre and the beach, the presence of sightseeing spots in the vicinity, and activities related to leisure, hospitality and entertainment are all factors explaining its presence. In contrast, hotel accommodation is located in areas of much greater diversity, as identified in previous literature (see Shoval, 2006).

Finally, the relation between accommodation places and the resident population shows that new residential areas are being added to the traditional areas of strong pressure from tourism along the city's main tourist axis, and Airbnb clearly contributes to that pressure. It is in these census sections where problems have arisen, involving the coexistence of the new Airbnb lodgings and the resident population.

Airbnb is changing the tourist accommodation model in a way that, currently, creates conflict in cities with mass tourism (Pearce, 2001). San Francisco, New York, Berlin, Barcelona and others are trying to control expansion of this type of rental through inspections to ensure that apartments are not functioning illegally and that taxes are paid. In this way, not only are more taxes collected but Airbnb's competitive advantage over traditional accommodation is reduced, thereby reducing its prospects for further expansion.

Acknowledgments

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