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Tourism clusters and peer-to-peer accommodation

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ABSTRACT

This study examines the importance of tourism clusters in peer-to-peer accommodation. Based on a rich dataset of 112,748 Airbnb listings in Florida, one of the top U.S. tourism destinations, this study uses geographically weighted regression to explore the spatially heterogeneous effects of tourism clusters on Airbnb performance across individual counties (intraregional clusters) and neighboring counties (interregional clusters). The results indicate that overall tourism clusters, especially in the industries of accommodation and food services, lead to superior Airbnb performance, but the tourism clusters-Airbnb performance relationship varies across industry and region, confirming the existence of intraregional and interregional clusters. These findings can help Airbnb hosts and tourism policymakers in other regions implement localized tourism industry strategies for maximizing Airbnb performance.

Introduction

Tourism products and services are characterized by a network or cluster of tourism supply chains involving different service components (Zhang, Song, & Huang, 2009). Regional industry structure, such as the degree of industry clustering, influences a tourism firm's pricing and other business decisions, which in turn determine economic performance (Scherer & Ross, 1990). Clusters are defined as geographic concentrations of interconnected companies, specialized suppliers and customers, and associated institutions (Porter, 1998). Due to the localized nature of tourism experiences, tourism clusters result from the colocation of complementary tourism industries and firms in a given destination (Chan, Lin, & Wang, 2012; Michael, 2003) and further enable small enterprises to innovate incumbent tourism products (Novelli, Schmitz, & Spencer, 2006). Hence, Airbnb, the largest peer-to-peer accommodation sharing platform, emerged as a transformative innovation (Karlsson, Kemperman, & Dolnicar, 2017) and has been growing rapidly in an environment of tourism clusters through both collaboration and competition (Gutiérrez, García-Palomares, Romanillos, & Salas-Olmedo, 2017).

The phenomenal growth of Airbnb has motivated tourism researchers to better understand the nuances of the accommodation sharing economy. Previous research on Airbnb has adopted three levels of analysis: the individual/marketing level (e.g., host behavior, guest-host experience, and pricing decisions), the firm level (e.g., impacts on hotels and housing affordability), and the community/government level (e.g., social impact and regulation) (Cheng, 2016; Prayag & Ozanne, 2018; Sainaghi, Köseoglu, d'Angella, & Mehraliyev, 2019). For example, researchers have investigated the characteristics of peer-to-peer sharing transactions (Tussyadiah, 2015) and Airbnb's impact on the tourism industry (Fang, Ye, & Law, 2016) and tourist behavior (Tussyadiah &

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Pesonen, 2016). Researchers have also examined the spatial distribution of Airbnb supply and demand in a single city (Gutiérrez et al., 2017), large cities (Coyle & Yeung, 2017) and regions (Adamiak, 2018). However, little attention to date has been paid to the role of tourism clusters in the peer-to-peer accommodation sharing economy, especially at the community level (Sainaghi et al., 2019). Some scholars have indicated that the performance of Airbnb may be influenced by greater competition from the tourism and hospitality industries (Zervas, Proserpio, & Byers, 2017). Others have demonstrated that Airbnb can benefit more from proximity to hospitality and entertainment suppliers, which form the so-called tourism clusters, than hotels (Gutiérrez et al., 2017).

From the perspective of industry clusters, a large body of literature has been devoted to the role of tourism clusters in the regional economy and hotel performance (Chung & Kalnins, 2001). One stream of research has examined how the formation of tourism clusters is beneficial to regional economic growth (Nordin, 2003) and regional competitiveness (Jackson & Murphy, 2006). The other stream of research has focused on the horizontal clustering of hotels, such as how homogeneous or heterogeneous hotels produce agglomeration effects (Yang, Luo, & Law, 2014) and how hotels' colocation patterns result in competitive benefits (Alcácer & Chung, 2014). However, few studies examine whether prior theories related to tourism clusters can be applied in the context of the accommodation sharing economy. Furthermore, previous studies have mainly identified the clustering of aggregated tourism industries (Peiró-Signes, Segarra-Oña, Miret-Pastor, & Verma, 2015), although specific industries (e.g., hotels and restaurants) may form different clustering formats in one or multiple regions.

To fill the abovementioned gaps, this study attempts to address two major questions: (1) does the clustering of tourism industries influence the performance of peer-to-peer accommodation? and (2) does the relationship between tourism clusters and peer-to-peer accommodation performance vary across individual and neighboring regions? This study also observes the local composition of specific tourism industries, such as accommodation, food services, art, entertainment, and recreation. For the empirical research, the state of Florida in the U.S., one of the world's top tourism destinations, is selected as the study area because Floridian Airbnb listings appear to contribute positively to the hotel industry and to new employment in rural counties (Sunderland, 2019). This current study has collected rich data, including the location and performance of 112,748 Airbnb listings, the density of tourism clusters, and other socioeconomic factors across Florida counties. The findings on Floridian Airbnb listings have broad implications for Airbnb hosts and tourism policymakers, allowing them to reflect the intricate clustering-performance relationship in Airbnb marketing efforts and implement location-based tourism industry management.

Literature review

Tourism clusters

The concept of clusters of tourism industries and firms is rooted in industrial cluster theory, first introduced by Marshall (1890). In general, a cluster refers to a group of industries associated with specialized suppliers and buyers or connected by skills and technologies (Porter, 2000). Clusters of interrelated firms and institutions enhance innovation and performance in a particular industry, such as manufacturing (Shaver & Flyer, 2000), biotechnology (Folta, Cooper, & Baik, 2006), and hotels (Chung & Kalnins, 2001). Numerous studies have found that clusters influence firms' innovation activities (Jang, Kim, & von Zedtwitz, 2017) and industrial districts (Bellandi, 1996) across regions (Spencer, Vinodrai, Gertler, & Wolfe, 2010).

The theory of industry clusters has been applied to tourism research. Unlike a manufacturing industry cluster, a tourism cluster is composed of multiple industries because it is not structured by colocated tourism firms but instead is formed by relational dynamics created between different industries within the cluster (Cole, 2009). Michael (2003) described three forms of clustering activities: (1) horizontal clustering – the colocation of firms selling similar products using similar productive resources, (2) vertical clustering – the relative colocation of firms along an industry's value chain, and (3) diagonal clustering – the concentration of complementary firms, which supply separate products and services linked through the consumer's decision-making process.

When clustering activities are applied to tourism, destination management is often reflected at the regional level (Dredge, 1999; Sainaghi, 2006). Here, we define the destination region as a geographic region, such as a prefectural-level city (Yang & Fik, 2014) or county (Peiró-Signes et al., 2015), with a system that consists of a mix of tourism elements where each part depends on the others to attract, service, and satisfy tourists (Mill & Morrison, 1985). From the content perspective, the destination comprises two primary components: the attraction complex (i.e., individual attractions or objects that create a place of interest) and the service component (i.e., a diverse range of service facilities to support tourists) (Dredge, 1999). From the process perspective, the destination is shaped by operative activities that supply local product systems and support processes that connect various firms within the region (Sainaghi, 2006). Hence, destination management is likely to introduce the development of diagonal clustering in a region. Specifically, tourism destinations are explained by diagonal clustering because the colocation of complementary tourism businesses providing accommodation, hospitality, transportation, and activities creates an overall tourism experience (Jackson & Murphy, 2006; Michael, 2003).

Hence, tourism destinations are paramount to supporting the local peer-to-peer accommodation market because most hosts provide limited services (e.g., accommodation and household amenities) and rely on a number of different firms to provide other tourism and hospitality services (e.g., food and touristic activities) (Gutiérrez et al., 2017). Moreover, the local clustering of tourism industries within a destination region is likely to be crucial for the development and performance of Airbnb accommodations because they provide Airbnb users with location-specific experiences through synergistic interactions among tourism product components (Chan et al., 2012; Smith, 1994). Researchers have found that hotels located in a cluster with tourist-attracting businesses receive greater economic benefits than hotels less dependent on tourist-related businesses (Peiró-Signes et al., 2015). Although it is assumed that there is a positive relationship between tourism clusters and Airbnb performance, little or no empirical evidence has been provided through an explicit examination of this issue.

Tourism clusters and peer-to-peer accommodation performance

To assess the performance of peer-to-peer accommodation providers, numerous studies have been carried out using price and sales determinants of Airbnb listings. The price of Airbnb listings is determined by physical and host characteristics, online review ratings, location, and market competition (Chen & Xie, 2017; Gibbs, Guttentag, Gretzel, Morton, & Goodwill, 2018; Wang & Nicolau, 2017). Concerning the sales of Airbnb listings, Lee et al. (2015) found that room-specific attributes (e.g., price and household amenities) and social features (e.g., host responsiveness and review volume) are strongly associated with sales. Guttentag (2015) also examined how cost savings, household amenities, and local experience affect the demand for Airbnb listings. Recently, Abrate and Viglia (2019) examined the importance of the reputation factors of both hosts and households to maximizing the monthly revenue of Airbnb listings.

Among these determinants, location is known to be one of the most important attributes affecting the operating performance of accommodation providers (Peiró-Signes et al., 2015). The locational strategy of Airbnb listings is likely to extend beyond site attributes (e.g., distance to airport and city center) and market competition (e.g., number of hotels or Airbnb listings in the same area) because Airbnb listings within tourism clusters may perform better than those located outside clusters (Peiró-Signes et al., 2015). Researchers have also explored the spatial patterns of Airbnb listings to examine the demand elasticities (Gunter & Önder, 2018), the advantages of proximity to tourist attractions in urban cities (Gutiérrez et al., 2017), and the distribution of Airbnb supply across European cities (Adamiak, 2018). Therefore, the business structure and tourism environment of cities and regions support the rapid expansion of Airbnb listings in the selected destination (Gutiérrez et al., 2017) and the range of activities available in tourism destinations (Tussyadiah & Pesonen, 2016).

Nevertheless, there is no empirical evidence on whether Airbnb listings benefit from tourism clusters. Some studies have shown positive relationships between hotel clusters and performance because clustering allows hotels to improve both their efficiency and their chances of survival (Yang & Wong, 2012). Other studies have found that hotel clusters may lead to higher competition among hotels, ultimately resulting in lower performance (e.g., Baum & Haveman, 1997). Researchers have also shown that both positive and negative effects can occur simultaneously (Marco-Lajara, Úbeda-García, Sabater-Sempere, & García-Lillo, 2014) and that the combined effects can vary by industry (Cohen & Paul, 2005). A general consensus is that tourism clusters significantly affect the economic performance of tourism firms within a destination region. In particular, small tourism firms (e.g., Airbnb listings) rely heavily on regional tourism and hospitality services (e.g., attractions and restaurants) (Gutiérrez et al., 2017).

Given that a destination's attractiveness is based on the available combination of specialized regional tourism products and services, tourism clusters need to be decomposed into subcomponents. As Gunn (1994) and Dredge (1999) suggested, tourism clusters comprise two interdependent components: the attraction complex (e.g., museums and recreation facilities) and the service component (restaurants and shops). The attraction complex refers to any facility that tourists visit or contemplate visiting (i.e., a point of interest). As attraction complexes locate in one geographic location or in spatial clusters within the destination region (Dredge, 1999), the complementary nature of attractions may increase the overall appeal of the region where Airbnb listings colocate. The service component refers to any service facility necessary to support tourists within the destination region. While some service facilities (e.g., economy hotels) may have a competitive nature (Chen & Xie, 2017), other facilities (e.g., restaurants) tend to have a complementary nature (Önder, Weismayer, & Gunter, 2019). Therefore, we expect that tourism clusters – the diagonal clustering of tourism attractions and services that form a local destination setting – may have a significant influence in determining the operating performance of Airbnb listings within a destination region.

Spatial effects of peer-to-peer accommodation performance

The role of tourism clusters in peer-to-peer accommodation performance may vary across space due to the economic (e.g., GDP) and spatial (e.g., location) factors that explain the variability in tourism growth (Yang & Fik, 2014). Research on clustering in the hotel industry has found that low-cost hotels that are colocated with high-cost hotels within the same cluster perform better than those that are more separate (Canina, Enz, & Harrison, 2005; Chung & Kalnins, 2001). Researchers have also found that the choice of location for a hotel within a metropolitan city is determined by agglomeration economies from urbanization (being located within an urban setting with a concentration of overall economic activities) and localization (the local clustering of industries and firms and enhanced access to the local network) (Luo & Yang, 2016). Between these two forms, localization economies – the clustering of tourism industries and firms – lead to better growth in local tourism than urbanization economies (Cole, 2009; Yang & Fik, 2014). Therefore, it is assumed that peer-to-peer accommodation providers benefit from the local clustering of different tourism industries in a given region.

To investigate the geographical aspects of tourism clusters and measure regional peer-to-peer accommodation performance, two approaches – intraregional clusters (Sölvell, Ketels, & Lindqvist, 2008) and interregional clusters (Majewska, 2015) – are employed in this study. Intraregional clusters refer to geographical concentrations of industries and firms connected through the actor's activities within a single region (Capone, 2004; Porter, 2003), whereas interregional clusters are defined as the concentration of regions similar to one another in that they share a high level of a given relationship (Majewska, 2015). In the peer-to-peer accommodation setting, intraregional clusters are explained by a high concentration of a specific or of multiple tourism industries in one region, which may or may not affect peer-to-peer accommodation performance in that region. For instance, regions (e.g., coastal and mountain resorts) with a high density of restaurant businesses have become popular destinations for tourists using Airbnb listings (Adamiak, 2018). Interregional clusters are explained by spatial spillovers in terms of supply and demand: (1) one region's cluster of tourism industries (e.g., restaurants) can spread over into other regions through knowledge spillovers (Glaeser, Kallal, Scheinkman, & Shleifer, 1992),

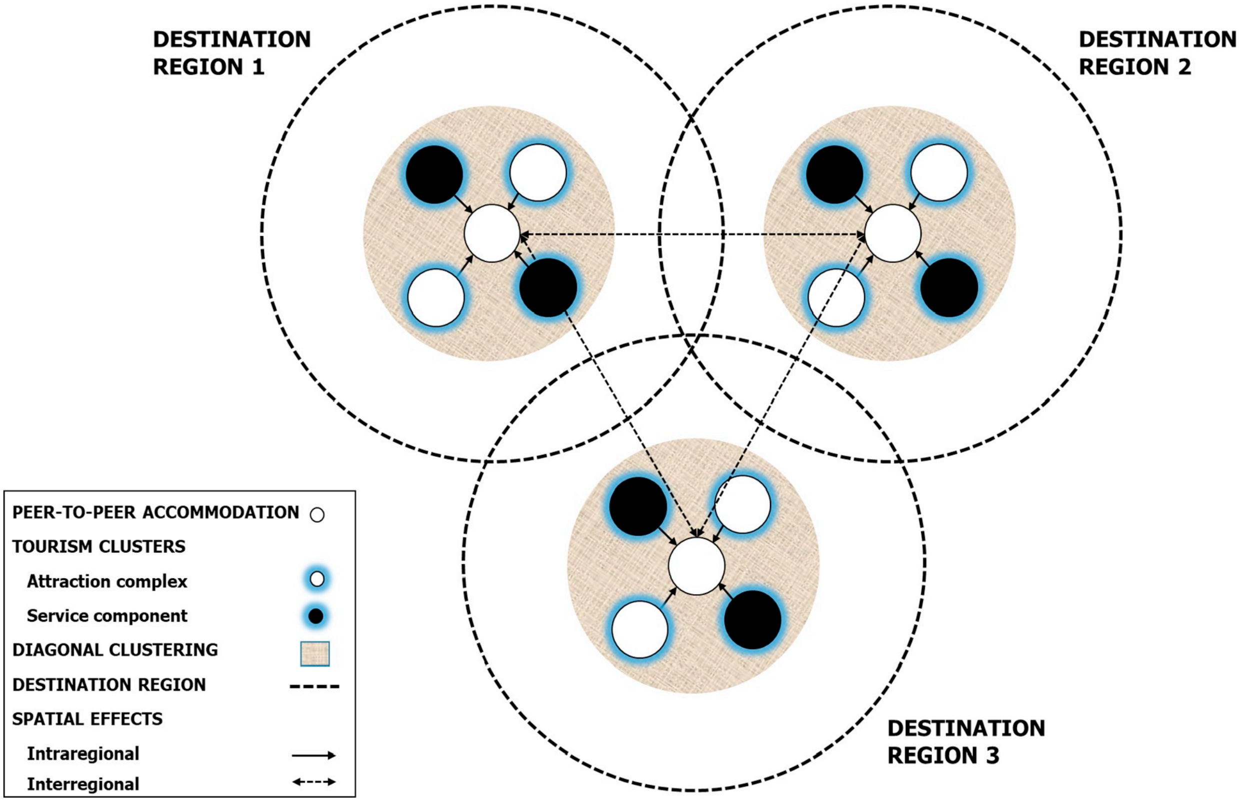

Fig. 1. Influence mechanism of tourism clusters and peer-to-peer accmommodation performance.

and (2) one region's tourism industries can influence peer-to-peer accommodation user flows to neighboring regions (Yang & Fik, 2014; Yang & Wong, 2012). Such spatial spillovers in tourism industries may affect peer-to-peer accommodation performance across multiple regions either positively or negatively. As such, empirical research needs to address two forms of spatial effects – intraregional clusters and interregional clusters – on the relationship between tourism clusters and peer-to-peer accommodation performance.

Given that tourism clusters affect peer-to-peer accommodation performance across space, we propose an influence mechanism showing the relationship between two components of tourism clusters, the attraction complex and the service component (Dredge, 1999; Gunn, 1994), and Airbnb performance. In addition, such relationships can vary across regions due to intraregional and interregional spatial effects. Fig. 1 describes the influence mechanism model within and across the destination region. This research attempts to quantify the spatial relationship between tourism clusters and Airbnb performance from both the overall and industry-specific perspectives.

Methods

Study area and variables

To explore spatial effects in the peer-to-peer accommodation performance model, we selected the state of Florida as the study area because it is one of the world's top tourism destinations. According to Visit Florida (2019), in 2018, Florida received approximately 124.7 million visitors (not including residents), and an estimated 14.3 million visitors came from Canadian and overseas markets. The statewide average hotel occupancy rate was 68.1%, and the average daily room rate was $152.82. The occupancy rates and revenue of Florida hotels have grown steadily, while over 45,000 Airbnb listings earned $810 million in income from approximately 4.5 million guest arrivals to the state in 2018 (Sunderland, 2019). Airbnb has also reported an increase in vacation rentals for senior hosts and in rural counties that lack hotels in Florida.

As an operating performance metric of Airbnb listings, revenue per available room (RevPAR) was used in the empirical model as is commonly done by researchers in the lodging industry (Canina et al., 2005; Chung & Kalnins, 2001; Marco-Lajara et al., 2014). Operating performance is measured based on the process of selling lodging services and includes the average daily rate (ADR), the occupancy rate, and RevPAR (Sainaghi, Phillips, & Corti, 2013). As researchers have investigated the influence of industry clusters on a firm's operating performance (Kukalis, 2010), it is critical to examine whether tourism clusters affect Airbnb operating performance. Thus, Airbnb RevPAR was used as a dependent variable by multiplying prices (average daily room rate: ADR) by sales

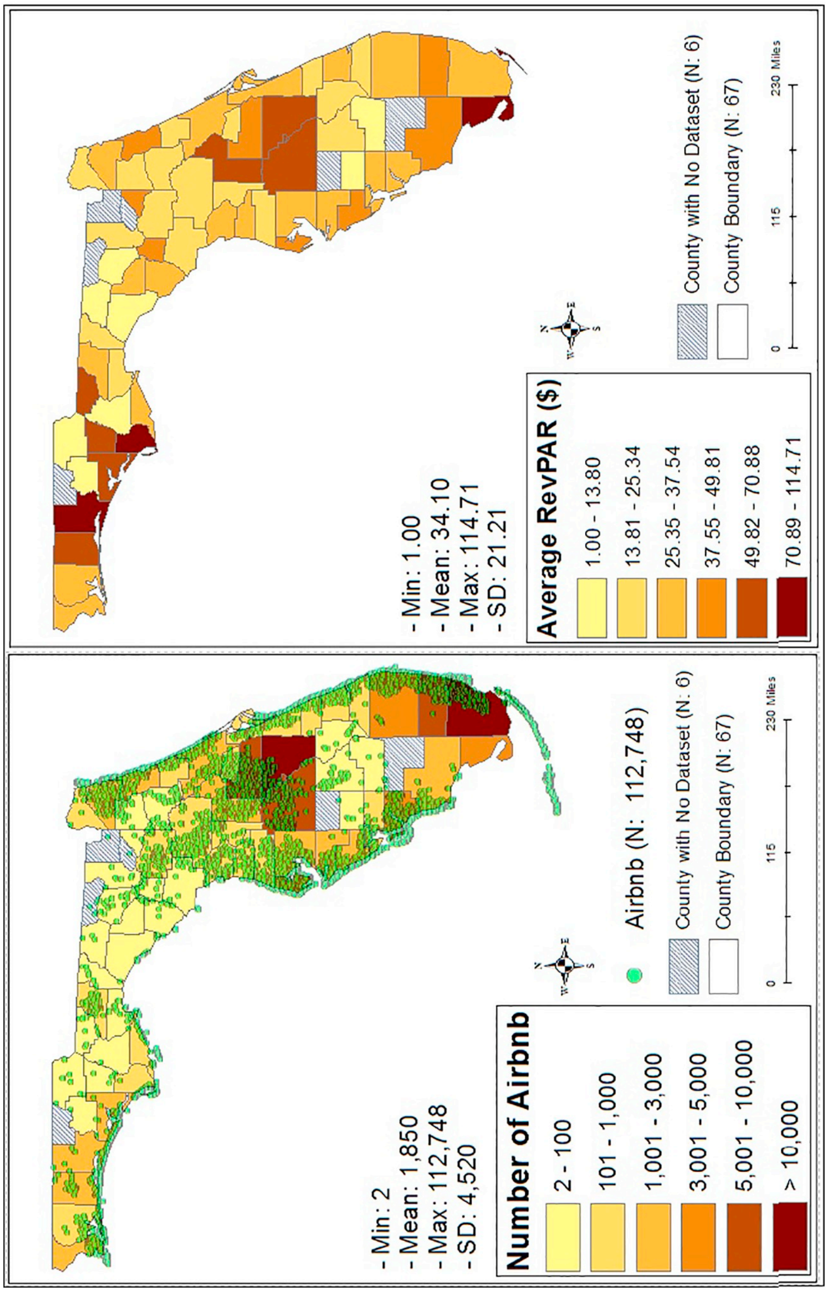

Fig. 2. Study area.

(occupancy rate) (Yang & Mao, 2020). The average Airbnb RevPAR for each county (i.e., region) in 2017 was thus defined as the final dependent variable. Fig. 2 exhibits the spatial distribution of 112,748 Airbnb listings and the average RevPAR across 61 counties in the study area (i.e., Florida).

To measure the degree of clustering for a specific tourism industry within a region, this study used the location quotient (LQ), which represents the relative specialization of the specific industry in a county with respect to the entire population (Hofe & Chen, 2006; Lazzeretti & Capone, 2006; O'Donoghue & Gleave, 2004). The regional tourism industry thus comprises the points of interest within a region, which also affect Airbnb pricing strategy (Önder et al., 2019). The LQ has been widely used to measure the ratio in the local, state, and national industry shares of productive activities in specific regions (Tian, 2013). Let $i = 1,2, \ldots, I$ denote industries and $j = 1,2, \ldots, J$ denote counties, specified as follows:

$$LQ_{ij} = \frac{S_{ij}}{S_{tj}} = \frac{\frac{x_{ij}}{x_{it}}}{\frac{x_{tj}}{x_{tt}}} \tag{1}$$

where x_{ij} indicates the number of employees in industry i in region j, x_{it} is the total number of employees in industry i in all regions t, x_{tj} is the total number of employees t in all industries in region j, and x_{tt} is the total number of employees t in the overall U.S. economy t. Thus, s_{ij} is the share of industry i's number of employees in region j relative to the total number of employees in industry i, and s_{tj} is the share of region j's number of employees relative to the total number of employees in the overall U.S. economy.

To infer the presence of a cluster, it is important to specify the concentration cutoff levels. Miller, Botham, Martin, and Moore (2001) and Tian (2013) suggested using an LQ above 1.25 for cutoff levels, whereas Malmberg and Maskell (2002) used an LQ above 3. To resolve the various cutoff criteria, researchers have used a standardized LQ, which identifies those locations with extraordinary LQ concentration values (O'Donoghue & Gleave, 2004; Peiró-Signes et al., 2015). Therefore, this study uses the standardized LQ to measure the clustering level of a specific tourism industry in each county, which is calculated as follows:

$$\text{Standardized } LQ_{ij} = \frac{LQ_{ij} - \overline{LQ_i}}{\text{std}\,(LQ_i)} \tag{2}$$

where std (LQ_i) and $\overline{LQ_i}$ are the standard deviation and mean of the LQ of industry i, respectively.

Finally, this study decomposed the tourism industry into multiple industries or categories, including service components (e.g., accommodation and restaurants) and attraction complexes (e.g., entertainment and recreation) (Dredge, 1999; Lazzeretti & Capone, 2006). In the International Recommendations for Tourism Statistics (IRTS, 2010), accommodation services, food and beverage services, cultural services, sports and recreation services, and various transportation services were listed as categories of characteristic tourism consumption products and activities. In the context of the U.S. tourism industries, the North American Industry Classification System (NAICS) classifies “Arts, Entertainments, and Recreation (NAICS 71)” and “Accommodation and Food Services (NAICS 72)” as level-1 industries. At level 2, NAICS 71 includes “Performing Arts and Spectator Sports (NAICS 711)”, “Museums, Historical Sites, Zoos, and Parks (NAICS 712)”, and “Amusement, Gambling, and Recreation (NAICS 713)”, while NAICS 72 includes “Accommodation (NAICS 721)” and “Food Services and Drinking Places (NAICS 722).” At level 3, the tourism industries coded into NAICS 71 and NAICS 72 are decomposed into 9 and 6 tourism industries, respectively. Fig. 3 illustrates the spatial distribution of county-level average LQ values for overall and specific tourism industries.

This study controlled eight factors – Airbnb density, Airbnb tax, crime, food safety violation, median household income, population density, airport proximity, and beach accessibility – that may affect Airbnb operating performance. First, Airbnb listings tend to be influenced by Airbnb density – number of Airbnb listings for each county – either positively, due to the externalities generated within an industrial district (Canina et al., 2005; Chung & Kalnins, 2001), or negatively, with lower revenues due to higher competition (Baum & Haveman, 1997). It is important to better identify the existence of agglomeration or competition within tourism clusters (Peiró-Signes et al., 2015), as these can further influence the performance of Airbnb listings.

Second, Airbnb listings are likely to be influenced by laws concerning zoning, taxes, insurance, health and public safety, and employment that regulate commercial hotels (Tussyadiah & Pesonen, 2016). Although researchers have found that regulations related to tax collection obligations do not influence the supply of Airbnb listings (Yang & Mao, 2019), it is worthwhile to examine whether the county-variant tax rate on Airbnb listings influences Airbnb operating performance.

Third, crime is mainly a local issue, and it significantly affects house prices (Zabel, 2015) and the value of property at the local level (Linden & Rockoff, 2008). A high crime rate at a destination can have a negative impact on lodging businesses, such as driving a reduction in rental prices and thus profitability (Pope, 2008). Likewise, violent and property crime incidents can negatively influence accommodation providers' operating performance (Hua & Yang, 2017).

Fourth, as most Airbnb users try local cuisines (Airbnb, 2017), Airbnb provides food safety information – such as guidelines, trainings and general tips – to visitors and subscribers to their website (World Health Organization, 2020). Following this line of reasoning, the safety of local food at the destination is likely to affect not only tourism demand (Cohen & Avieli, 2004) but also Airbnb demand and performance.

Fifth, some researchers have found that neighborhoods with higher housing values and household incomes tend to have more Airbnb listings and that listing prices are likely to be higher (Jiao & Bai, 2020). Other researchers have reported that in London, there is a positive relationship between Airbnb offerings and housing prices but a negative relationship between Airbnb offerings and income (Quattrone, Proserpio, Quercia, Capra, & Musolesi, 2016). Hence, it will be valuable to examine the effects of median household income on Airbnb operating performance.

Sixth, population density is significantly correlated with the average price per person of Airbnb listings (Jiao & Bai, 2020) and the

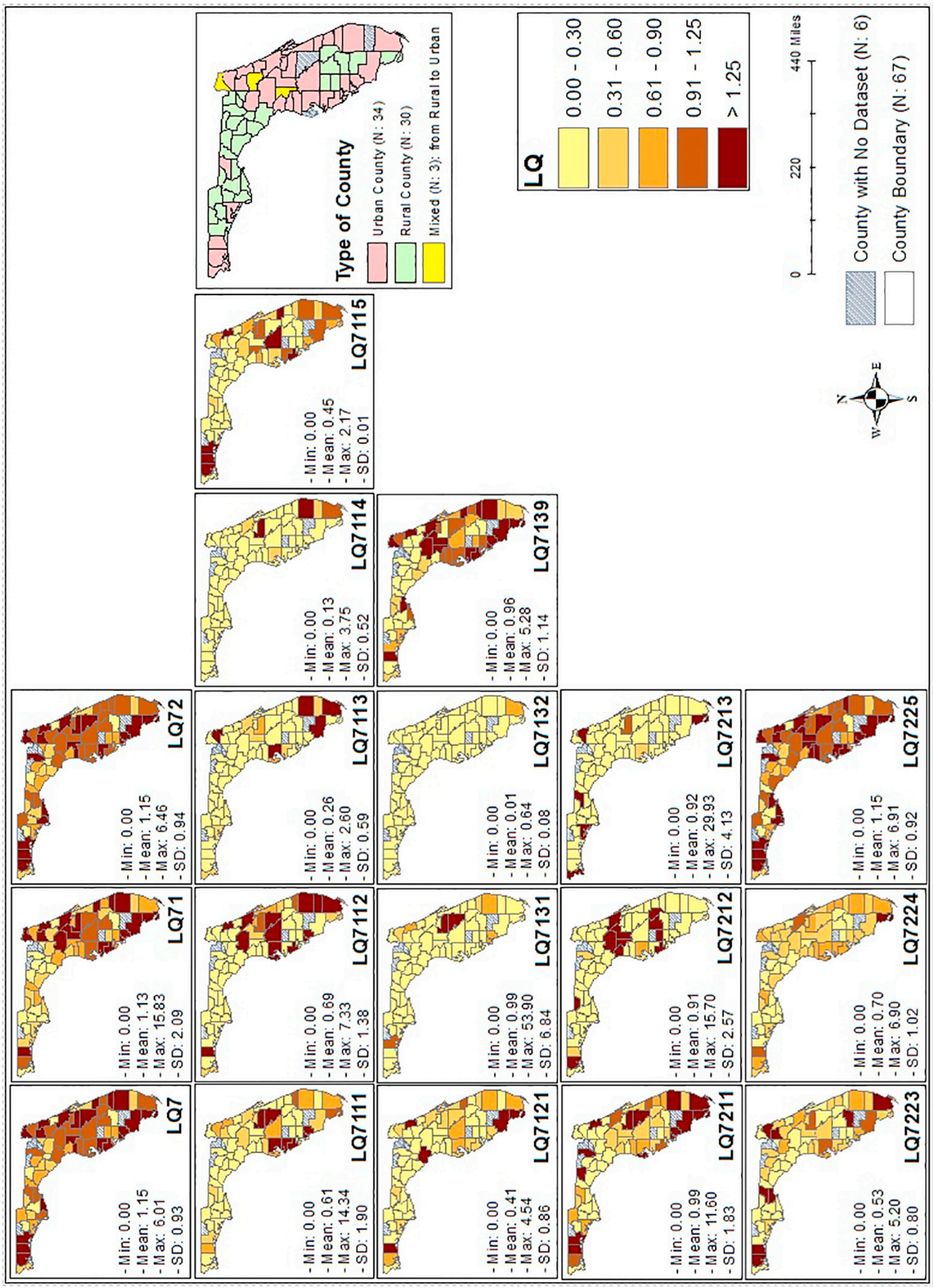

Fig. 3. Spatial distribution of LQ values for overall and specific tourism industries.

Table 1
Operationalization of variables, data sources, and tourism business establishments.

Variable	Operational definition (unit: county)	Source	Year	Number of business establishments in Florida	Average number of business establishments per county
Airbnb RevPAR	Average Airbnb revenue per available room	AirDNA	2017		
LQ7	LQ of NAICS 71 & 72 (tourism)	U.S. Bureau of Labor Statistics	2017	55,082	822
LQ71	LQ of NAICS 71 (arts, entertainment, and recreation)			10,536	157
LQ72	LQ of NAICS 72 (accommodation and food services)			44,546	665
LQ7111	LQ of NAICS 7111 (performing arts companies)			730	11
LQ7112	LQ of NAICS 7112 (spectator sports)			719	11
LQ7113	LQ of NAICS 7113 (promoters of performing arts and sports)			564	8
LQ7114	LQ of NAICS 7114 (agents and managers for public figures)			358	5
LQ7115	LQ of NAICS 7115 (independent artists, writers, and performers)			1482	22
LQ7121	LQ of NAICS 7121 (museums, historical sites, zoos, and parks)			464	7
LQ7131	LQ of NAICS 7131 (amusement parks and arcades)			352	5
LQ7132	LQ of NAICS 7132 (gambling industries)			78	1
LQ7139	LQ of NAICS 7139 (other amusement and receation industries)			5362	80
LQ7211	LQ of NAICS 7211 (traveler accommodation)			3958	59
LQ7212	LQ of NAICS 7212 (recreational vehicle parks and camps)			435	6
LQ7213	LQ of NAICS 7213 (rooming and boarding houses)			91	1
LQ7223	LQ of NAICS 7223 (special food services)			2609	39
LQ7224	LQ of NAICS 7224 (drinking places, alcoholic beverages)			2173	32
LQ7225	LQ of NAICS 7225 (restaurants and other eating places)			35,219	526
Airbnb density	Number (in thousands) of Airbnb listings for each county	AirDNA	2017		
Airbnb tax	Tax rate (in %) on Airbnb accommodations for each county	FDR	2017		
Crime	Total crime index (in hundreds) for each county	FDLE	2017		
Food safety violation	Average number of critical food safety violations for each county	FDHR	2016–2017		
Median household income	Median household income (in thousands) for each county	USDL	2017		
Population density	Number (in thousands) of population for each county				
Airport proximity	Distance (in miles) to the nearest airport from the county centroid	FGDL	2018		
Beach accessibility	Number (in hundreds) of beach access points for each county	FDEP	2017		

Note: LQ denotes standardized LQ. NAICS: North American Industry Classification System; FDR: Florida Department of Revenue; FDLE: Florida Department of Law Enforcement; FDHR: Florida Division of Hotels and Restaurants; USDL: U.S. Department of Labor; FGDL: Florida Geographic Data Library; FDEP: Florida Department of Environmental Protection.

intensity of Airbnb locations (Lagonigro, Martori, & Apparicio, 2020). Thus, population density is likely to account for the relationship between resident population and Airbnb performance because Airbnb expands tourism pressure over residential areas in a city (Gutiérrez et al., 2017).

Finally, because transportation hub and tourist attractions influence accommodation prices (Kim, Jang, Kang, & Kim, 2020; Zhang, Zhang, Lu, Cheong, & Zhang, 2011), this study examines the effects of airport proximity (i.e., distance to the nearest airport from the county centroid) and beach accessibility (i.e., number of beach access points for each county) on Airbnb performance. In addition to these control variables, this study initially considered other factors, such as hotel density (Chen & Xie, 2017), local tourism tax (Gooroochurn & Sinclair, 2005) and the consumer price index (Song & Wong, 2003), in the model but later excluded them due to multicollinearity issues.

Data regarding Airbnb listing locations and performance (i.e., ADR and occupancy rate) were acquired from AirDNA, a commercial sharing economy data company, and geographic data, such as county boundaries, were acquired from the Florida Geographic Data Library. Data related to the total crime index and critical food safety violations for each county were collected from Simply Analytics and the Florida Division of Hotels and Restaurants, respectively. Finally, demographic and socioeconomic data were collected from the U.S. Department of Labor. Table 1 presents all variables' operational definitions, data sources and types of business establishments included across the specific tourism industry (i.e., NAICS code) in Florida.

Data analysis

Determining both the aspatial and spatial effects of tourism clusters on Airbnb performance requires a sequence of multiple data analyses. First, a multiple linear regression analysis was employed to examine the global relationships among variables. The proposed ordinary least squares (OLS) regression model is shown in Eq. (3):

$$\mathrm{AirRevPAR}_i = \beta_0 + \beta_k\,\mathrm{LQ}_k + \beta_j\,\mathrm{CONTROL}_j + \varepsilon \tag{3}$$

where $\mathrm{AirRevPAR}_i$ refers to the average Airbnb RevPAR in county i; β_0 is the intercept parameter; LQ_k contains a set of explanatory variables capturing the values of the standard location quotient of each type of tourism industry; β_k is the regression coefficient for each explanatory variable; $\mathrm{CONTROL}_j$ includes a set of eight control variables; β_j is the regression coefficient for each control variable; and ε is the error term. To analyze the differential effects of overall and specific tourism clusters on Airbnb performance, three sets of LQ_k were applied: (1) one variable (LQ7); (2) two variables (LQ71 and LQ72); and (3) fifteen variables, including 9 industry LQs under LQ71 and 6 industry LQs under LQ72. However, the proposed OLS models could include potential endogeneity issues that lead to biased estimation results. To address this problem, a two-stage least squares (2SLS) approach was employed with two instrumental variables (IVs): unemployment rate (Pavlinek & Zenka, 2010) and poverty rate (Hasan & Quibria, 2004). The 2SLS regression analysis was performed for variables LQ7, LQ71 and LQ72 to avoid weakening the IVs when applied for variables representing the 15 disaggregated LQs.

Second, the same set of variables in Eq. (3) was used for running a geographically weighted regression (GWR) to explore spatial variations among variables. By applying GWR modeling, the spatial autocorrelation issues among spatially referenced variables could be considered, which could not be achieved through traditional OLS methods (Kim & Nicholls, 2016). GWR has been used to capture spatially varying relationships between variables in studies of tourism (Xu, Pennington-Gray, & Kim, 2019), hospitality (Kim et al., 2020), recreation (Kim & Nicholls, 2016, 2018), and marketing (Jang & Kim, 2018). The proposed GWR model is shown in Eq. (4):

$$\mathrm{AirRevPAR}_i = \beta_{i0}(u_i, v_i) + \beta_{ik}(u_i, v_i)\,\mathrm{LQ}_{ik} + \beta_{ij}(u_i, v_i)\,\mathrm{CONTROL}_{ij} + \varepsilon_i \tag{4}$$

where (u_i, v_i) is the coordinate of the centroid of county i, and $\beta_{ik}(u_i, v_i)$ is the local regression coefficient for the independent variable k in county i. When conducting GWR, a bisquare kernel function, which determines the specific number of neighbors used to maximize the model fit, was utilized due to the differing sizes of each county in the study area (Fotheringham, Charlton, & Brunsdon, 1998). The spatial weight (w_{ij}) for the bisquare function is estimated as follows:

$$w_{ij} = [1-(d_{ij}/b^2)] \text{ when } d_{ij} \le b,\ w_{ij} = 0 \text{ when } d_{ij} > b \tag{5}$$

where d_{ij} is the Euclidean distance from regression point i to Airbnb property j, and b is the threshold distance (Fotheringham et al., 1998). The spatial variability in the local coefficient for each independent variable was tested using rho values generated by the Monte Carlo significance test (Kim & Nicholls, 2018). An iterative statistical optimization was employed to minimize the corrected Akaike Information Criterion (AIC_c).

Finally, the values of the local coefficients and R^2 from GWR were mapped to visualize the effects of tourism clusters on Airbnb performance. Several software programs, including ArcGIS (version 10.4.1), STATA (version 15.0), R (version 3.4.4), GeoDa (version 1.10), and GWR4, were employed to analyze the spatial dataset.

Results

OLS regression models

Table 2 shows the descriptive statistics and correlation matrix for the variables considered in the full model. In Florida, the average Airbnb RevPAR per county is \$34.10, and the average standardized LQs vary across tourism industries, ranging from 0.01 to

Table 2
Descriptive statistics and correlation coefficients of variables.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Airbnb RevPAR	1.00											
(2) LQ7111	0.07	1.00										
(3) LQ7112	0.13	0.08	1.00									
(4) LQ7113	0.05	0.10	0.20	1.00								
(5) LQ7114	0.02	0.03	0.25*	0.55**	1.00							
(6) LQ7115	0.34**	0.30*	0.32*	0.23	0.22	1.00						
(7) LQ7121	0.35**	0.08	0.15	0.16	0.07	0.50**	1.00					
(8) LQ7131	0.06	0.09	0.03	0.12	0.33**	0.14	0.02	1.00				
(9) LQ7132	0.02	0.01	0.18	0.29*	0.24	0.11	0.06	−0.02	1.00			
(10) LQ7139	0.19	0.23	0.27*	0.24	0.09	0.62**	0.49**	−0.10	−0.03	1.00		
(11) LQ7211	0.56**	0.12	0.17	0.06	0.13	0.40**	0.70**	0.28*	0.08	0.36**	1.00	
(12) LQ7212	−0.11	−0.08	−0.01	−0.10	−0.07	−0.11	−0.13	−0.05	−0.05	0.01	−0.09	1.00
(13) LQ7213	0.32*	0.01	−0.05	−0.01	−0.04	0.05	0.57**	0.00	−0.03	0.08	0.67**	−0.08
(14) LQ7223	0.06	0.05	0.18	0.31*	0.13	0.38**	0.28*	0.10	0.14	0.43**	0.26*	−0.14
(15) LQ7224	0.36**	0.16	0.31*	0.09	0.08	0.40**	0.71**	0.06	0.06	0.45**	0.78**	−0.12
(16) LQ7225	0.35**	0.14	0.20	−0.02	−0.01	0.48**	0.41**	0.00	−0.02	0.65**	0.50**	−0.01
(17) Airbnb density	0.24	0.15	0.33*	0.33**	0.33**	0.24	0.17	0.15	0.86**	0.06	0.31*	−0.11
(18) Airbnb tax	0.02	−0.09	0.00	−0.12	−0.01	−0.07	0.20	0.20	−0.08	−0.13	0.23	0.19
(19) Crime	−0.07	−0.11	−0.07	0.07	0.12	−0.15	0.08	−0.10	0.09	−0.28*	−0.02	−0.02
(20) Food safety viloation	−0.17	−0.20	−0.07	0.07	0.00	−0.17	−0.03	−0.06	0.17	−0.15	−0.07	0.12
(21) Median household income	0.23	0.17	0.17	0.31*	0.18	0.55**	0.52**	0.07	0.01	0.56**	0.34**	−0.21
(22) Population density	0.07	0.15	0.48**	0.48**	0.29*	0.29*	0.06	0.22	0.26*	0.10	0.07	−0.14
(23) Airport proximity	−0.07	−0.19	−0.34**	−0.27*	−0.19	−0.26*	−0.07	−0.20	−0.09	−0.18	0.03	0.08
(24) Beach accessibility	0.21	0.11	0.49**	0.43**	0.37**	0.27*	0.25	−0.07	0.25	0.24	0.12	−0.17
Mean	34.10	0.61	0.69	0.26	0.13	0.45	0.41	0.99	0.01	0.96	0.99	0.91
Standard deviation	21.38	1.91	1.39	0.60	0.53	0.61	0.86	6.89	0.08	1.15	1.84	2.60

Variable	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(1) Airbnb RevPAR												
(2) LQ7111												
(3) LQ7112												
(4) LQ7113												

(continued on next page)

Table 2 (*continued*)

Variable	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(5) LQ7114												
(6) LQ7115												
(7) LQ7121												
(8) LQ7131												
(9) LQ7132												
(10) LQ7139												
(11) LQ7211												
(12) LQ7212												
(13) LQ7213	1.00											
(14) LQ7223	0.06	1.00										
(15) LQ7224	0.76**	0.40**	1.00									
(16) LQ7225	0.09	0.64**	0.51**	1.00								
(17) Airbnb density	0.04	0.18	0.18	0.08	1.00							
(18) Airbnb tax	0.37**	−0.07	0.19	−0.07	−0.09	1.00						
(19) Crime	0.22	−0.12	0.02	−0.21	0.04	−0.07	1.00					
(20) Food safety viloation	0.10	−0.07	0.01	−0.15	0.09	0.10	−0.02	1.00				
(21) Median household income	0.21	0.37**	0.45**	0.37**	0.14	−0.13	0.14	−0.18	1.00			
(22) Population density	−0.03	0.20	0.20	0.01	0.41**	−0.09	−0.02	0.06	0.34**	1.00		
(23) Airport proximity	0.10	−0.29*	−0.11	−0.04	−0.19	0.04	0.00	0.05	−0.45**	−0.51**	1.00	
(24) Beach accessibility	0.05	0.11	0.24	0.06	0.35**	−0.08	0.11	0.20	0.41**	0.52**	−0.42**	1.00
Mean	0.92	0.53	0.70	1.15	1.85	0.22	1.06	5.83	57.66	0.36	29.47	0.35
Standard deviation	4.16	0.81	1.03	0.92	4.56	0.27	0.27	1.59	9.53	0.51	16.27	0.54

* $p < 0.05$.
** $p < 0.01$.

1.15. Each county in Florida, on average, has 1850 Airbnb listings. As some correlation coefficients between independent variables were relatively high, the variance inflation factors (VIFs) for the independent variables were examined. The VIFs were below ten, indicating the absence of multicollinearity.

Table 3 presents the results of both the OLS regression and the GWR models, depending on the variables of the tourism clusters, which explain Airbnb performance across counties. The results revealed that the clustering of the overall tourism industry (LQ7) was positively related to Airbnb performance (Model 1), and in particular, that the clustering of tourism industries in accommodation and food services (LQ72) played a critical role in improving performance (Model 3). After addressing the endogeneity issue, the parameter estimates of the 2SLS approach confirmed that both LQ7 and LQ72 had statistically significant effects on Airbnb performance.

From the perspective of individual industries (Model 5), the tourism clusters-Airbnb performance relationship was positive for the independent artists clusters (LQ7115) and the restaurants clusters (LQ7225) but negative for the other amusement and recreation industries clusters (LQ7139) and the special food clusters (LQ7223). Furthermore, the disaggregated model (Model 5) also showed a better model performance (high R^2) than the aggregated models (Models 1 and 3). These findings demonstrate that although Airbnb listings benefit from the concentration of tourism industries overall, the relationship between two variables may vary depending on the type of industry.

GWR models

As shown in the results of the GWR models (Table 3), the local coefficients of tourism clusters were statistically significant in terms of the spatial variability across counties. From the aggregated perspective (Model 2), the clustering of the overall tourism industry (LQ7), on average, was positively associated with Airbnb performance ($\beta_{\text{GWR Mean}} = 5.570$). However, depending on the county, the positive effect can be smaller ($\beta_{\text{GWR Min}} = 4.737$) or larger ($\beta_{\text{GWR Max}} = 6.183$). Similar phenomena occurred in Model 4 for the art, entertainment and recreation clusters (LQ71) variable, which ranged from -25.342 to -0.356 ($\beta_{\text{GWR Mean}} = -3.910$), and the accommodation and food services clusters (LQ72) variable, which ranged from -3.735 to 15.623 ($\beta_{\text{GWR Mean}} = 7.741$). To provide a better understanding, Fig. 4 maps the spatial distribution of GWR-based local coefficients of the three variables across counties. Specifically, the clustering of accommodation and food services (LQ72) increased the performance of Airbnb listings located in the southern Floridian (red-colored) counties but decreased the performance of those in the mid-Floridian (blue-colored) counties.

From the disaggregated perspective (Model 6), the results showed that six variables for the industry-specific tourism clusters were statistically significant with spatial variability (Table 3). Fig. 4 further illustrates the existence of spatial variations in GWR-based local coefficients, which reveals that the effects of tourism clusters on Airbnb performance vary across individual counties ("intraregional clusters"). For the variables with (yellow-colored) positive coefficients (e.g., LQ7211: Traveler Accommodations), the positive effect was stronger across dark-colored counties than across light-colored counties, while for those with (blue-colored) negative coefficients (e.g., LQ7131: Amusement Parks and Arcades), the negative effect was stronger across dark-colored counties than across light-colored counties. Furthermore, some tourism clusters (e.g., LQ7121: Museums, Historical Sites, Zoos, and Parks) have mixed effects – positive in the red-colored counties located in the southern Floridian area and negative in the blue-colored counties in the northwestern area – on Airbnb performance.

From the perspective of interregional spillover, Fig. 5 shows a positive or negative relationship between the clustering of each specific tourism industry and Airbnb performance across neighboring counties ("interregional clusters"). Specifically, Airbnb listings located in the northwestern Floridian region were affected positively (i.e., hot spots) by the clustering of some tourism industries (e.g., LQ7225: Restaurant and Other Eating Places) but negatively (i.e., cold spots) by the clustering of other industries (e.g., LQ7121: Museums, Historical Sites, Zoos, and Parks). Fig. 6 illustrates how specific counties benefit from specific tourism industries (i.e., the clustering of positive GWR-based local coefficients). For example, the clustering of two tourism industries – independent artists, writers, and performers (LQ7115) and traveler accommodation (LQ7211) – leads to superior Airbnb performance in Madison and Taylor counties. In addition, seven counties (Franklin, Gulf, Jackson, Liberty, Okaloosa, Walton, Washington) benefit from the industry concentrations of eight tourism industries.

Finally, Table 3 also presents spatially varying local R^2 values across Model 2 (minimum: 0.343, mean: 0.379, maximum: 0.449), Model 4 (0.196, 0.384, 0.513) and Model 6 (0.302, 0.502, 0.677). These results imply that the GWR models employed in this study provided more accurate estimates with improved model performance than the corresponding OLS models. The spatial distribution of local R^2 is visualized in Fig. 4. These findings reveal that the exploratory power of the regional Airbnb performance model is not consistent for Floridian counties.

Discussion and conclusion

This study contributes to the understanding of the importance of tourism clusters in peer-to-peer accommodation by investigating whether the clustering of tourism industries affects Airbnb performance and how the relationship between tourism clusters and Airbnb performance varies across industries and regions. Using both aspatial and spatial econometric models in combination with GIS-based visualization techniques, this study has identified a set of tourism clusters that explain overall and spatially heterogeneous Airbnb performance across 61 Floridian counties in 2017. It is important for researchers and practitioners alike to utilize geospatial data and analytic techniques when implementing localized growth strategies to promote the peer-to-peer accommodation market.

As empirically demonstrated, Airbnb listings located in a region with tourism clusters enjoy greater economic benefits than those in a region with fewer colocated tourism-related businesses; this finding is in line with results from previous studies in the service and hotel industries (Lazzeretti, Boix, & Capone, 2008; Peiró-Signes et al., 2015). Although the overall relationship between tourism

Table 3
Estimates of OLS and GWR models using different sets of variables for tourism clusters.

Variable	Model 1 (OLS)	Model 2 (GWR)				Model 3 (OLS)	Model 4 (GWR)				Model 5 (OLS)	Model 6 (GWR)			
		Min	Mean	Max	SV		Min	Mean	Max	SV		Min	Mean	Max	SV
LQ7	6.610*	4.737	5.570	6.183	Yes										
LQ71						−1.153	−25.342	−3.910	−0.356	Yes					
LQ72						8.714*	−3.735	7.741	15.623	Yes					
LQ7111											−1.965	−3.532	−2.284	−0.611	
LQ7112											−1.424	−3.621	−0.221	0.772	
LQ7113											9.149	5.231	8.446	11.335	Yes
LQ7114											−7.246	−8.490	−4.426	3.542	
LQ7115											11.964*	5.306	7.421	12.368	Yes
LQ7121											−3.428	−4.167	−0.436	1.151	
LQ7131											−0.366	−1.238	−0.401	−0.075	
LQ7132											−110.405	−283.326	−183.228	−131.278	Yes
LQ7139											−6.756*	−7.001	−3.192	−0.267	Yes
LQ7211											4.527	0.263	3.002	5.672	
LQ7212											−0.080	−1.234	1.045	2.735	
LQ7213											1.652	1.224	1.902	2.734	
LQ7223											−9.392*	−48.391	−4.654	23.062	Yes
LQ7224											−3.947	−4.709	−1.256	−0.852	
LQ7225											11.942*	3.379	7.423	13.289	Yes
Airbnb density	0.912	0.771	1.367	2.607		0.824	−694.857	−7.473	374.116		2.412	−70.342	6.103	156.212	
Airbnb tax	5.219	1.665	3.166	6.984		4.381	−139.648	−12.105	132.224		−5.500	−60.306	4.842	35.714	
Crime	−2.015	−5.722	−1.225	6.675		−3.165	−351.548	−29.382	64.438		−11.935	−24.627	9.626	40.680	
Food safety violation	−2.379	−4.297	−1.813	−0.167		−2.358	−17.819	0.948	19.082		−2.659	−31.158	−2.051	11.636	
Median household income	0.035	−0.419	0.058	0.615		0.001	−7.179	−0.062	10.925		−0.199	−1.359	0.675	2.950	
Population density	−4.335	−14.478	−3.509	1.807		−3.509	−1205.753	44.345	1558.216		−7.601	−64.639	104.113	1581.467	
Airport proximity	0.064	−0.095	0.029	0.188		0.030	−8.183	−0.648	3.025		−0.260	−0.648	0.035	1.575	
Beach accessibility	8.842	−1.122	7.284	25.842		8.677	−422.867	−19.560	494.378		10.392	−57.689	32.038	369.556	
Intercept	34.284	−25.351	30.584	79.874		37.308	−578.792	64.833	743.282		70.146	−289.603	−23.873	156.751	
R^2	0.227	0.343	0.379	0.449		0.278	0.196	0.384	0.513		0.576	0.302	0.502	0.677	
Condition number		22.124	24.547	27.511			24.002	26.109	28.110			24.896	26.523	29.325	

Note: SV: spatial variability.
* $p < 0.1$.

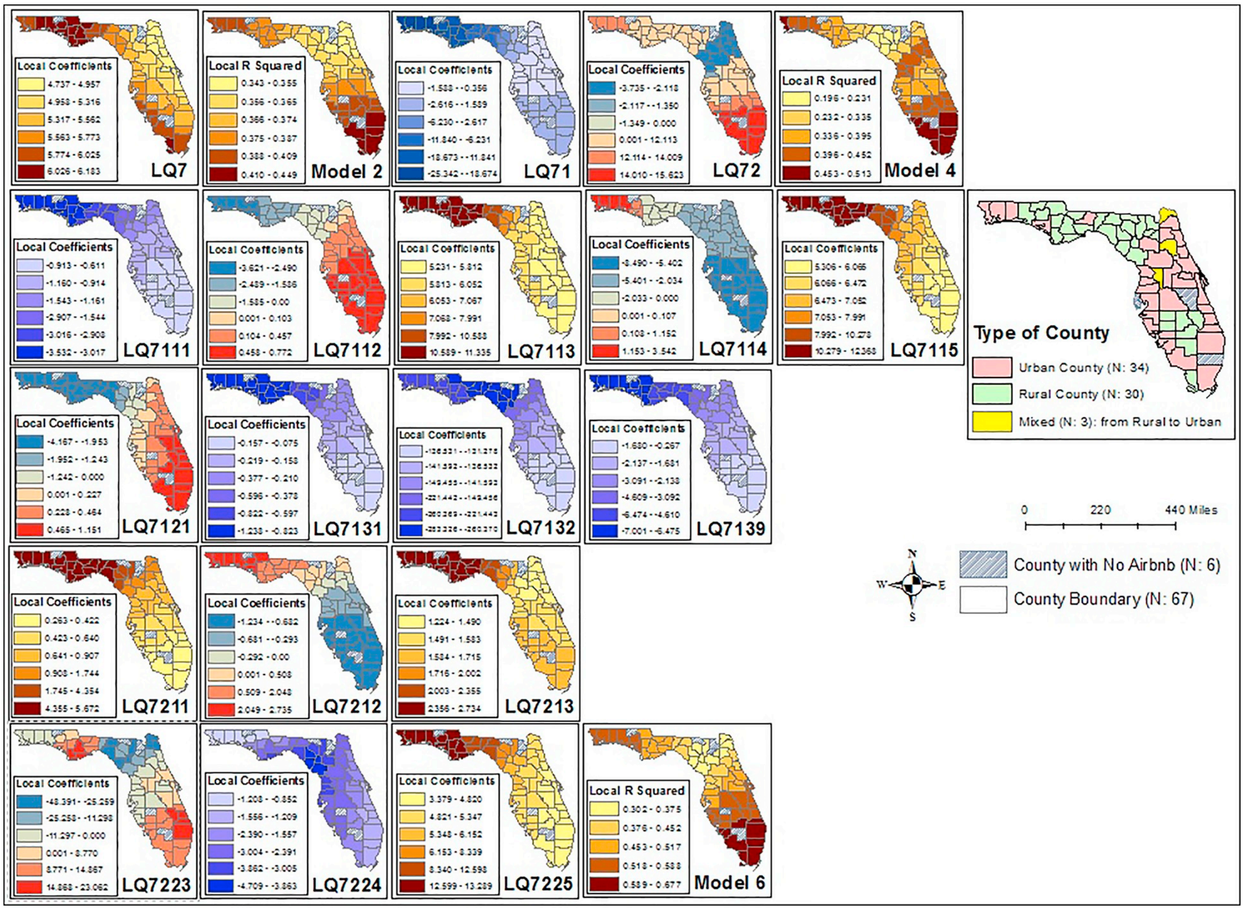

Fig. 4. Spatial distribution of GWR-based local coefficients ("intraregional clusters").

clusters and Airbnb performance is positive, the results show that the relationship varies across individual and neighboring counties. Such findings confirm that the effect of intraregional clusters (i.e., the combined effect of multiple tourism subindustries) varies county by county (Cohen & Paul, 2005), and both positive and negative effects occur across neighboring regions, which are known as interregional clusters (Yang & Fik, 2014).

Theoretical implications

Based on the empirical findings, this study formulates several theoretical implications for research on industry clusters and the accommodation sharing economy. The results offer evidence for the heterogeneous spatial relationship between tourism industries and peer-to-peer accommodation, thereby contributing to tourism cluster theory (Michael, 2003). Prior research on manufacturing industry clusters has mainly focused on firm-driven innovation activities based on knowledge spillovers among industries, leading to specialization externalities (Audretsch & Feldman, 2004) and diversification externalities (Frenken, Van Oort, & Verburg, 2007). However, this empirical study suggests that research on tourism clusters in peer-to-peer accommodation needs to pay substantial attention to localization economies – the local clustering of tourism industries and firms (Yang & Fik, 2014) that shapes the overall tourism experience (Dredge, 1999; Jackson & Murphy, 2006; Michael, 2003). To better measure the degree of tourism-related localization economies, this study employed LQs for specific industries across attraction complexes (i.e., art, entertainment, and recreation) and service components (i.e., accommodation and food services) in each county. This use of industry-specific LQs highlights the need for more research to identify both the individual and the combined effects of tourism clusters on accommodation providers' performance (Peiró-Signes et al., 2015).

Moreover, the finding of location-specific relationships between tourism clusters and Airbnb performance resonates with research finding that firms (e.g., Airbnb listings) benefit from tourism clusters across individual regions (intraregional clusters) and neighboring regions (interregional clusters). This finding suggests that both intra- and interregional tourism clusters (Majewska, 2015; Sölvell et al., 2008) should be incorporated when identifying localized patterns of peer-to-peer accommodation performance. In the case of Floridian Airbnb listings, although some regions have a high level of intraregional clusters in a specific tourism industry (e.g., spectator sports) (Fig. 3), the effect of intraregional clusters on Airbnb performance can be either positive or negative based on

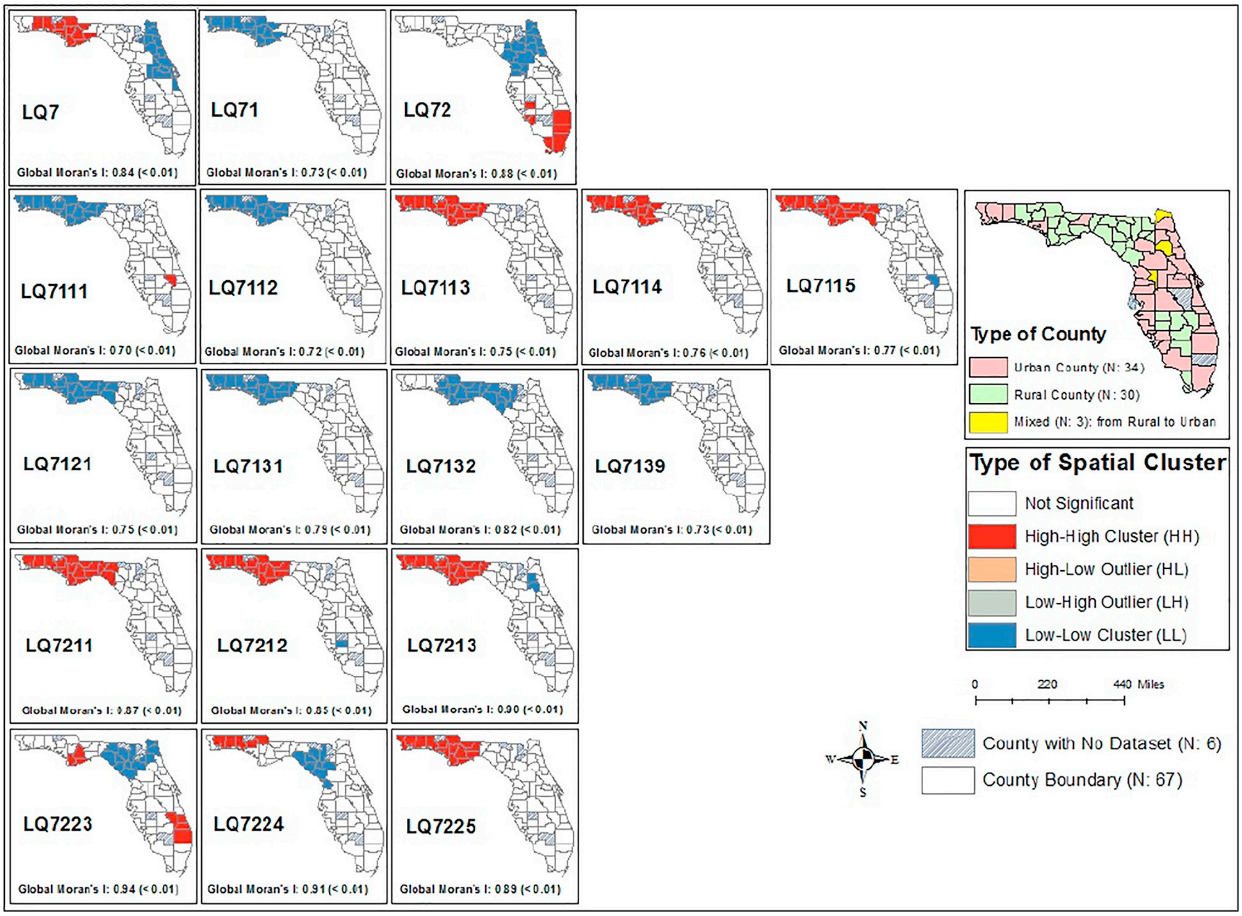

Fig. 5. Spatial distribution of clustered GWR-based local coefficients ("interregional clusters").

geography (Fig. 4). This finding implies that, in contrast to manufacturing, the tourism product is a set of different service components that form service networks (Yang, 2012) and that further require tourism firms to cluster together to offer an integrated tourism product (Pavlovich, 2003).

Finally, the identification of interregional clusters when considering Airbnb performance highlights the importance of spatial spillovers in the peer-to-peer accommodation market, in line with previous studies (Capone, 2004; Majewska, 2015; Porter, 2003). In the Floridian Airbnb context, the spatial spillover effects can be either positive or negative across industry and region. As shown in Fig. 5, Airbnb listings located in regions of northwestern Florida benefit from interregional clusters of traveler accommodation firms (LQ7211) but not from those of gambling industries (LQ7132). These findings may explain why some regions become hot-spot destinations for Airbnb accommodation users (Adamiak, 2018).

Practical implications

The current research findings provide several important implications for tourism practitioners. For the peer-to-peer accommodation market, this study suggests that accommodation hosts should take full advantage of tourism clusters in their own and neighboring counties to maximize their operating performance. Specifically, existing Airbnb hosts need to analyze the detailed components of the regional tourism industry, which consist of localized production and consumption (Jackson & Murphy, 2006), and reflect these components in their marketing activities, such as product offerings and communications with potential users. In addition, newly entering hosts should decide whether the location of their listing has the key element of being attractive to specific tourism industries because the tourist experience is highly dependent on the attractions in specific locations. In the Florida case, Airbnb listings in the southern region, which encompass an urban area, can internalize the benefits of concentrations in the industries of spectator sports (LQ7112) and museums, historical sites, zoos and parks (LQ7121). It is known that urban tourists exploit many facilities (e.g., public transportation, roads, and infrastructure) and services (e.g., festivals, historical areas and entertainment) (Ashworth & Page, 2011). In contrast, Airbnb listings in the northwestern region (i.e., a rural area) can utilize the clustering benefits in the industries of promoters of performing arts and sports (LQ7113) and independent artists, writers, and performers (LQ7115) because rural tourists tend to seek spiritual experiences from local agricultural products and cultural activities (Sharpley & Jepson, 2011).

County	Area	LQ7113	LQ7114	LQ7115	LQ7211	LQ7212	LQ7213	LQ7223	LQ7224	LQ7225
Bay	Urban	●	●	●	●	●	●			●
Calhoun	Rural	●	●	●	●	●	●			●
Escambia	Urban	●	●	●		●	●			●
Franklin	Rural	●	●	●	●	●	●	●		●
Gadsden	Rural	●	●	●	●	●	●			●
Gulf	Rural	●	●	●	●	●	●	●		●
Jackson	Rural	●	●	●	●	●	●		●	●
Jafferson	Rural	●		●	●		●			
Leon	Urban	●		●	●	●	●			●
Liberty	Rural	●	●	●	●	●	●	●		●
Madison	Rural			●	●					
Martin	Urban							●		
Okaloosa	Urban	●	●	●	●	●	●		●	●
Palm Beach	Urban							●		
Santa Rosa	Urban	●	●	●	●		●			●
St. Lucie	Urban							●		
Taylor	Rural			●	●					
Wakulla	Rural	●		●	●	●	●			●
Walton	Rural	●	●	●	●	●	●		●	●
Washington	Rural	●	●	●	●	●	●		●	●

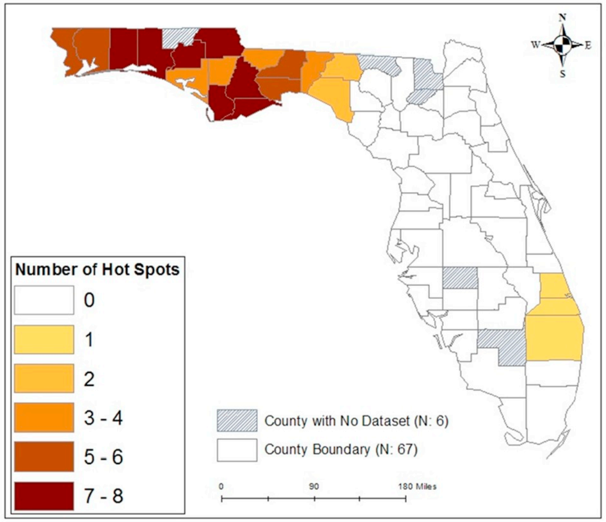

Fig. 6. Hot spot counties where Airbnb benefits from multiple tourism clusters.

From the tourism policy perspective, this study demonstrates how policymakers can plan and implement location-based tourism industry management to build synergistic interactions between established tourism industries and the accommodation sharing economy. Depending on the geographical context of individual and neighboring counties, the local government should understand how the concentration of one or multiple tourism industries leads to the development and profitability of peer-to-peer accommodation providers. As shown in Fig. 6, the empirical findings demonstrate that Airbnb listings located in northwestern Floridian counties (e.g., Gulf and Walton) – mostly rural areas – benefit from the local concentrations of eight tourism industries. Hence, local government agents can provide marketing support to local tourism businesses and Airbnb hosts by communicating the attractiveness of complementary tourism products to inbound tourists. This marketing support is of paramount importance to rural tourism firms because Airbnb-induced tourism can revitalize the already-declining agricultural and cultural industries and secure economic advantages for rural areas (MacDonald & Jolliffe, 2003).

Limitations and future research directions

Despite the significant theoretical and practical implications of this study, several limitations should be acknowledged. First, the findings of this study are limited to a single geographic area. Although Florida was studied due to the potential and current importance of Florida tourism and Airbnb developments, future research can collect the corresponding data (e.g., tourism clusters and Airbnb performance) from other regions and countries, therefore resolving the generalizability issue. Second, this study has focused on the overall performance of Airbnb listings without conducting a performance model according to the type of Airbnb accommodation, such as entire home, shared room, or private room. This study initially attempted to conduct those models but failed due to extensive missing data. However, further studies with updated data can determine how relationships between tourism clusters and Airbnb performance differ with regard to the type of Airbnb listings. Finally, this study did not consider the dynamic characteristics of the relationship between tourism clusters and Airbnb performance. From a long-term perspective, Airbnb development and performance can enable specific tourism businesses to grow or decline in specific regions. This limitation can be resolved by collecting and analyzing longitudinal data with advanced spatial econometric models.

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