Remedying Airbnb COVID-19 disruption through tourism clusters and community resilience☆

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ABSTRACT

Peer-to-peer (P2P) accommodation markets have been disrupted by the COVID-19 pandemic. However, little attention is paid to how to remedy the disruption in terms of P2P accommodation performance. This study empirically investigates the spatially heterogeneous COVID-19 disruptions in the Airbnb business and offers place-based remedying strategies through local resources, including tourism clusters and community resilience. Using real data on Airbnb operating performance and local resources in Florida, we employ spatial econometric models and visualization techniques to estimate the pandemic-disrupted Airbnb performance model. The results show that leisure and hospitality clusters and three resilience resources—social, community capital, and environmental—had spatially heterogeneous effects on Airbnb revenue and booking performance across Floridian counties during the pandemic. Furthermore, community resilience moderated the effect of tourism clusters on Airbnb performance across individual and subclustered counties. These findings enable P2P accommodation hosts and policymakers to adopt destination-specific remedying strategies to cope with the pandemic.

1. Introduction

The coronavirus (COVID-19) pandemic led to a 5.2 percent contraction in global GDP in 2020, although governments put extraordinary efforts into countering the downturn through fiscal and monetary policies (World Bank, 2021). The most disruptive hospitality player, Airbnb, was hit hard by this crisis. Airbnb projected that its revenue in 2020 would decline approximately 54% to $2.2 billion because of the global pandemic (Reuters, 2020). Given lockdown restrictions, Airbnb users have shifted from international travelers to entirely domestic travelers; previously, international Airbnb users constituted 80–90% of all Airbnb users in France, the Netherlands, and Denmark (Chadwick, 2020). Researchers have found that the tourism industry, especially international tourism demand, is vulnerable to external crises or disasters, such as political instability, economic conditions, and natural hazards (Okumus, Altinay, & Arasli, 2005).

Recently, researchers have explored the pandemic's impact on peer-to-peer (P2P) accommodation markets, mainly from the supply perspective. For example, Farmaki et al. (2020) found that host perceptions and responses to the pandemic are categorized into five types in a continuum of optimistic pessimist hosts. Zhang, Geng, Huang, and Ren (2021) also identified three types of postpandemic hosts: innovating entrepreneurs, unchanged diplomats, and quitting speculators. Furthermore, Xu, Huang, and Chen (2021) examined hosts' health and well-being by exploring their stress and coping strategies after the pandemic. From the demand perspective, Bresciani et al. (2021) investigated how the pandemic and the need for physical distance influence travelers' choices of different types of accommodation (i.e., Airbnb full flats vs. hotel rooms). Jang, Kim, Kim, and Kim (2021) examined how the interplay between tourists and destination attributes affects P2P accommodation consumption during the pandemic. However, more evidence needs to be applied to the topic of the P2P accommodation demand that has been disrupted by the pandemic. During the ongoing pandemic situation, a focus on the preliminary stage is essential to help P2P accommodation providers and local governments take short-term remedying actions during this crisis and build long-term localized resource development planning in advance of future crises.

Compared with other traditional accommodation markets, P2P

accommodation markets have emerged as a value cocreation platform to connect tourists with local and authentic experiences at a destination (Guttentag, 2015). Prior research has found that close proximity to leisure and hospitality suppliers might positively (Lee, Jang, & Kim, 2020) or negatively (Zervas, Proserpio, & Byers, 2017) influence P2P accommodation businesses. The colocation of complementary tourism businesses—so-called tourism clusters (Michael, 2003)—creates an overall tourism experience (Gutiérrez, García-Palomares, Romanillos, & Salas-Olmedo, 2017). Furthermore, in the face of a disaster or crisis, destinations need to not only develop economic resources (e.g., tourism businesses) but also reduce resource inequities and address their social vulnerabilities—so-called community resilience (Norris, Stevens, Pfefferbaum, Wyche, & Pfefferbaum, 2008). However, existing research on P2P accommodation disrupted by the pandemic has mainly focused on the role of a destination's or community's tangible resources, such as tourism clusters (Jang et al., 2021), and did not incorporate the impact of community resilience as a strategy for destination sustainability and recovery (Hall, 2017; Lin, Kelemen, & Kiyomiya, 2017). Hence, of paramount importance is assessing the role of a destination's immaterial (e.g., social responsibility) and material resources to better understand the pandemic's impact on P2P accommodation demand (e.g., Hassan & Soliman, 2021).

To fill these gaps, this study attempts to empirically examine the spatially heterogeneous effects of local resources on P2P accommodation performance during COVID-19 and offer destination-specific remedying strategies for P2P accommodation businesses that need to deal with the current pandemic. Specifically, this research investigates how two types of local resources—tourism clusters (i.e., leisure and hospitality) and community resilience (i.e., social, community capital, and environmental)—play independent and combined roles in attenuating pandemic-induced P2P accommodation disruption across destinations. As an empirical setting, we selected the U.S. state of Florida because it has widespread COVID-19 transmission, explosive Airbnb growth in rural areas (Florida Trend, 2018), and an array of natural disasters (FDEM, 2020), which have formed different levels of tourism specialization and resilience frameworks across Floridian counties. The results show that subcategories of tourism clusters and community resilience had independent and joint effects on Airbnb's performance across individual and subclustered counties during the pandemic.

This research contributes to a better understanding of the P2P accommodation market that is disrupted by or resilient to the pandemic by incorporating localized material (tourism clusters) and immaterial (community resilience) resources in the performance models. First, this study examines the spatially varying positive and negative effects of tourism clusters and community resilience on P2P accommodation performance during the pandemic. Hence, the findings of this study extend existing P2P accommodation research that primarily deals with hosts' responses to the pandemic and considers the role of material resources in pandemic-induced disruption. Second, this study identifies the interactive perspective of material and immaterial resources, which better explains how P2P accommodation businesses in some destinations are more resilient to the pandemic than those in other destinations. This finding advances the literature on destination resilience to disasters and crises based on the perspective of the sustainable livelihoods framework for tourism (SLFT), which includes core livelihood assets (e.g., human, economic, social, and natural capital), tourism- and nontourism-related activities and the vulnerability context (Shen, Hughey, & Simmons, 2008). Finally, spatial analytical methods allow P2P accommodation businesses and policymakers to understand the interplay among spatially referenced tourism clusters, resilience, and urban–rural destinations when understanding the complexity of COVID-19-induced P2P accommodation consumption.

2. Literature review

2.1. COVID-19 and P2P accommodation consumption

Tourists' decision making on P2P accommodation use during COVID-19 is likely to be complex from both individual and situational perspectives (Jang et al., 2021; Karl, Muskat, & Ritchie, 2020). Pandemic-induced perceived risk is likely to be a significant predictor of tourists avoiding a certain destination and using P2P accommodations. When tourists perceive that potential risks are larger than benefits, they may modify their trip to the destination. Past studies have shown that people normally avoid a trip to places with the spread of a viral infection to reduce their risk of acquiring the disease (e.g., Lau, Griffiths, Choi, & Tsui, 2009). In contrast, despite the virus, some domestic tourists may prepare health and safety procedures in conjunction with their trip (Reisinger & Mavondo, 2005) and voluntarily implement personal nonpharmaceutical intervention (NPI) measures to mitigate their perceptions of risk (Lee et al., 2012). Although perceived travel risk may negatively affect tourists' decisions to travel to destinations, it is unknown whether tourists, especially domestic tourists, intend to travel to a certain destination and further consume P2P accommodations during COVID-19.

From a situational perspective, tourists' consumption of P2P accommodations tends to be influenced by destination characteristics, such as material attributes (e.g., tourism clusters, Jang et al., 2021) and immaterial attributes (e.g., destination social responsibility, Hassan & Soliman, 2021). Extant studies have identified that the key advantage of P2P accommodations is the authentic local experience from interacting with hosts and other locals at the destination where tourists are staying and traveling (e.g., Mody, Suess, & Lehto, 2017). In addition to accommodation experience, which is central to tourists' overall destination memorability (Tukamushaba, Xiao, & Ladkin, 2016), the perception of destination localness is a source of authentication of tourists' consumption experience (Mkono, 2013). Hence, situational factors that P2P accommodation hosts cannot control but that may influence consumers' overall experiences need to be incorporated as antecedent or moderating variables into P2P accommodation consumption models (Mody et al., 2017; Walls, Okumus, Raymond, & Kwun, 2011). To date, little empirical research has explicitly examined the role of a destination's situational factors in shaping tourists' P2P accommodation demand during COVID-19.

2.2. Roles of tourism clusters and community resilience

According to the SLFT, a sustainable tourism livelihoods system includes local assets (e.g., human, social, and natural capital), tourism-related activities (e.g., tourism businesses), institutional arrangements (e.g., local governments), and vulnerability contexts (e.g., shocks) (Shen et al., 2008). A livelihood consists of the capabilities, assets, and activities for making a living to enable sustainable livelihoods to cope with and recover from disasters and crises and maintain or enhance local resources without undermining the natural resource base (Chambers, 1992). The SLFT inherently reveals the multisectoral character of real-life, requiring the integration of both material (e.g., tourism business activities) and immaterial (e.g., social capital) resources into a holistic crisis management framework (Tao & Wall, 2009). In this study, we apply the SLFT perspective to the context of P2P accommodation markets disrupted by COVID-19 and shed light on the role of tourism clusters (i.e., material resources) and community resilience (i.e., immaterial resources) in attenuating the negative impact of the pandemic on P2P accommodation demand.

Tourism clusters, which are defined as the specialization of tourism businesses within a particular destination, are crucial for the P2P accommodation business because they provide P2P accommodation consumers with localized tourism experiences (Chan, Lin, & Wang, 2012; Lee et al., 2020). Research has found that Airbnb hosts offer limited

services and must rely on other tourism products and services that can be served by a number of different firms (Gutiérrez et al., 2017). Tourism clusters can be classified into two categories of tourism industries: leisure (e.g., marinas and golf courses) and hospitality (e.g., hotels and restaurants) businesses (Lee et al., 2020). Furthermore, agglomeration researchers have suggested that the clustering of tourism businesses may increase benefits to members with each additional firm in a cluster—economies of agglomeration—or decrease benefits to members with each additional firm, mainly because a limit is surpassed—diseconomies of agglomeration (McCann & Folta, 2009). Potential sources of agglomeration economies include labor productivity, and those of agglomeration diseconomies include congestion costs (Kim, Williams, Park, & Chen, 2021). For instance, a high clustering of tourist attractions in a particular destination added value to the tourist experience before COVID-19 but was devoid of tourists when the pandemic outbreak occurred in March 2020 (Newman, 2020). Hence, it is imperative to provide empirical evidence on whether and how the effect of tourism clusters on P2P accommodation consumption during the pandemic is positive (i.e., agglomeration economies) or negative (i.e., agglomeration diseconomies) across industries (i.e., leisure and hospitality).

Community resilience is defined as "a process linking a network of adaptive capacities (resources with dynamic attributes) to adaptation after a disturbance or adversity" (Norris et al., 2008, p. 127). Community, as an entity with shared geographic boundaries and fate, is composed of "built, natural, social, and economic environments that influence one another in complex ways" (Norris et al., 2008, p. 128). In the face of disasters and crises, individuals experience personal loss, and a community at large shares damages and disruptions to their various environments (Norris, Phifer, & Kaniasty, 1994). During COVID-19, tourists likely perceive resilient destinations as mutually beneficial for tourists and residents because resilience enhances the well-being of locals and tourists' experiences and offers tourists a safe environment and supportive trip experiences (Hassan & Soliman, 2021). Because SLFT suggests human, social, and natural capital as local livelihood assets (Shen et al., 2008), this study employs three resilience categories—social, community capital, and environmental—as immaterial local resources, whereas tourism clusters are regarded as tourism-related activities (i.e., material resources). Specifically, social resilience captures the demographic qualities of a community's population (e.g., physical and mental wellness), community capital resilience refers to the goodwill of local citizens to assist their neighbors and fellow citizens during emergencies, and environmental resilience relates to qualities of the environment that enhance the absorptive capacity of natural disasters (Cutter, Ash, & Emrich, 2014). This research attempts to investigate the category of community resilience that plays a critical role in attenuating the negative pandemic effect on P2P accommodation performance.

Although abundant research has studied tourism clusters and resilience management, researchers have primarily investigated two dimensions separately without capturing their intersectional effect in traditional and P2P accommodation markets. Regional science researchers argue that the configuration of material and immaterial resources can vary across communities. For example, greater income inequality may attract more skilled and specialized workers in urban U. S. counties but may weaken social cohesion, further hampering agglomeration economies (Fallah & Partridge, 2007). In addition, the concentration of economic activity can be associated with increasing social inequality and can further lead to congestion diseconomies that outweigh agglomeration benefits (Castells-Quintana & Royuela, 2014). Hence, during COVID-19, the concentration of leisure or hospitality businesses in a particular destination may lead to congestion diseconomies that further discourage tourists from traveling to the destination because of a virus infection. Conversely, if the destination is well equipped with high levels of social and environmental resilience, tourists may take their personal NPI measures, travel to this destination, and consume P2P accommodations. In this respect, this study attempts to examine the combined effect of tourism clusters and community resilience on P2P accommodation performance during COVID-19.

2.3. Place-based model for P2P accommodation performance

Scholars have agreed that an authentic local experience, as the key contributor to tourists' overall experience during P2P accommodation stays, includes social interactions with hosts, local residents, and communities (Cheng, 2016; Guttentag, 2015). P2P accommodation services have shifted their travel pattern by offering authentic social experiences to the local community (Cheng, 2016). The important role of the community has also been pronounced during the COVID-19 crisis because each community requires collective, unified action, such as social distancing. Thus, P2P accommodation research needs to go beyond focusing on individual (microlevel) psychological perceptions of the pandemic or state (macro)-level disruptions and examine community (meso)-level disruptions using objective data (Peters, 2020). In this study, we incorporate the destination and community terms in our empirical study and use the concept of the destination community—the location at which tourists spend their time and money and influence the development or degradation of the local environment (Singh, Timothy, & Dowling, 2003). Notably, tourism is closely linked to the social capital and well-being of destination communities (Moscardo, Konovalov, Murphy, & McGehee, 2013).

Given the uneven geography of the tourism industry (Lee et al., 2020) and resilience (Cutter, Ash, & Emrich, 2016) resources, we attempt to use spatial analytical methods to identify spatially heterogeneous effects of local resources on pandemic-induced P2P accommodation performance across destination communities. In the accommodation-sharing economy, a destination's tourism business structure and environment support the growth of tourism-related activities and Airbnb listings in that destination (Gutiérrez et al., 2017). Recently, it has been found that, although the clustering of hospitality businesses (e.g., hotels and restaurants) has a positive impact on Airbnb performance, the relationship between tourism clusters and Airbnb performance has spatial variations across Floridian counties (Lee et al., 2020). In addition to COVID-19 infections, actions to cope with the virus may disproportionately impact communities (Evelyn, 2020). More resilient communities are noted as being less vulnerable to disasters and crises than less resilient communities (Cutter et al., 2014). Specifically, overall resilience in urban areas is primarily driven by economic capital, whereas resilience in rural areas is influenced by social capital with considerable spatial variability (Cutter et al., 2016). In addition, resilience resources (e.g., human and social capital) are configured differently across urban, suburban, and rural areas (Dominiak, 2020). Recent studies on P2P accommodations have found geographical location to be a key attribute for P2P accommodation use (Cheng & Jin, 2019) because it offers tourists unique local experiences. Local experiences during P2P accommodation stays are more important in rural than urban areas, whereas locational benefits in terms of being close to shops and restaurants are deterrent in both urban and rural areas (Mahadevan, 2020).

These arguments indicate that a one-size-fits-all approach is not appropriate for boosting Airbnb businesses because of the multidimensional nature of community configurations (Cutter et al., 2016). Entrepreneurial researchers argue that combining community focus with neighboring communities (i.e., translocal embeddedness) to access new ideas and resources is important for entrepreneurial resourcefulness (Kloosterman, 2010). That is, P2P accommodation microentrepreneurs are likely to recognize and create unique opportunities and combine diverse resources by drawing on their embeddedness in the material and immaterial resources of other neighboring communities (Vlasov, Bonnedahl, & Vincze, 2018). To explore the spatially heterogeneous effects of local resources on P2P accommodation performance during COVID-19, we capture two types of spatial heterogeneity: individual and subcluster levels (e.g., Jang, Kim, & von Zedtwitz, 2017). Specifically, the
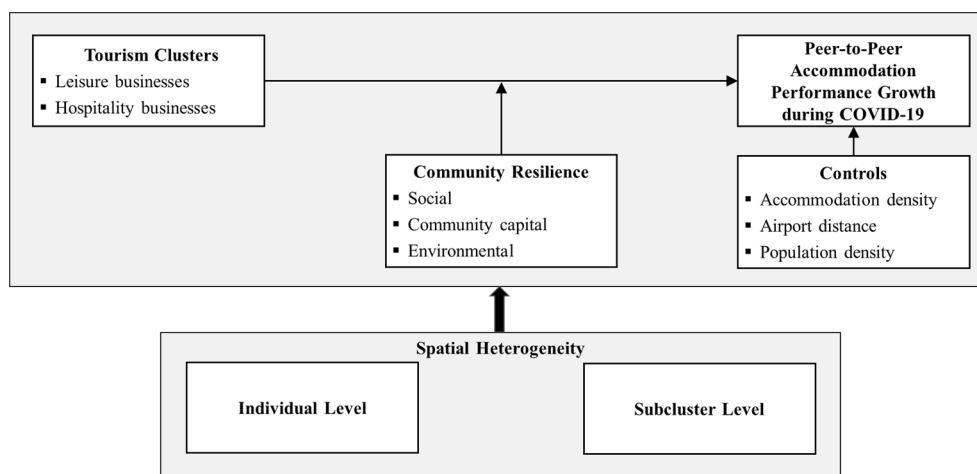
Fig. 1. Research model.

effect of local resources on P2P accommodation performance varies across each destination community. Furthermore, such individual effects may form subclusters because of the translocal embeddedness of local resources and P2P accommodations' entrepreneurial practices across neighboring local communities (Vlasov et al., 2018). Fig. 1 presents our research model that investigates the independent and joint effects of tourism clusters and community resilience on P2P accommodation performance during COVID-19 within and across communities.

3. Methods

3.1. Study area and variables

We chose the state of Florida as the empirical study area for several reasons. First, Florida, as one of the most popular tourism destinations, has shown rapid growth in Airbnb development and performance. More than 60,000 Airbnb listings in Florida received $1.2 billion in rent from 6.6 million guests in 2019, reflecting high growth relative to figures for 2018 (45,000 listings, $0.81 billion in rent, 4.5 million guests) and 2017 (40,000 listings, $0.45 billion in rent, 2.7 million guests). Second, the growth rate of Airbnb guests in rural Florida counties has nearly doubled beyond the growth rate in urban counties, indicating that an increasing number of Airbnb users intend to experience rural tourist attractions and not just urban destinations (Florida Trend, 2018). Third, Florida has an array of natural disasters (e.g., sea level rise, hurricane, flooding) that regularly affect local residents and visitors (FDEM, 2020). Finally, on March 1, 2020, Florida became the 7th U.S. state with a documented COVID-19 case and, on April 1, 2020, joined the list of states that limited their residents' movements and personal interactions outside the home. Such a natural setting enabled us to examine how tourism clusters and community resilience played a critical role in attenuating Airbnb disruptions across urban and rural areas during the early stage of COVID-19 (i.e., March 2020). As the destination community and the unit of analysis, this study employed Floridian County (N = 67) because county-level data are often used for measuring tourism clusters (Lee et al., 2020), community resilience (Cutter et al., 2008), COVID-19 infections (CDC, 2021), and destination-level P2P accommodation performance (Jang et al., 2021).

To measure the year-over-year operating performance of Airbnb listings, revenue and booking data for the two months (i.e., March 2019 vs. March 2020) were used in the empirical model because they are commonly used in Airbnb research (Lee et al., 2020; Yang & Mao, 2020). The focus of this study was on how the COVID-19 outbreak affected the growth rate of Airbnb's operating performance in March 2020 relative to March 2019. Because three datasets (COVID-19, tourism clusters, and community resilience) were collected on a county basis, performance

data of individual Airbnb listings acquired from AirDNA were merged at the county level. Finally, the year-over-year growth rates of the average Airbnb revenue-per-available-listing (RevPAL) and average Airbnb occupancy rate (OCR) for each county were defined as the dependent variables.

Regarding tourism clusters, two fields—leisure and hospitality—were considered to examine any independent and/or cooperative roles of the leisure and hospitality fields across destination communities (Hobson & Teaff, 1994). The former represents attraction-related businesses, and the latter represents service-related businesses (Lee et al., 2020). To measure the degree of specialization for a specific leisure or hospitality industry in a destination community, the location quotient (LQ) was used because it represents the relative agglomeration of the tourism industry in a county in relation to the entire population (Lazzeretti & Capone, 2006). The LQ can be specified as in Equation (1):

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

where s_{ij} is the share of tourism industry i's number of employees in county j relative to the total number of employees in tourism industry i, and s_{tj} is the share of county j's number of employees relative to the total number of employees in the overall U.S. economy. The North American Industry Classification System (NAICS) classifies the arts, entertainment, and recreation industries as NAICS 71 and accommodation and food services as NAICS 72. Whereas NAICS 71 belongs to the leisure industry, NAICS 72 belongs to the hospitality industry (Lee et al., 2020). Finally, the leisure and hospitality LQs for March 2020 were collected and used in the model.

To measure three community resilience categories, the Baseline Resilience Indicators for Communities (BRIC) index was used because other resilience measurements focus mainly on place-specific (e.g., urban or rural) or dimension-specific (e.g., infrastructure sector) approaches (Cutter & Derakhshan, 2020). However, the BRIC measurement regards a community as an integrated system that influences crisis/disaster recovery and that consists of six different capitals: social, economic, community capital, institutional, housing/infrastructural, and environmental (Cutter et al., 2014). Each subresilience (e.g., social, community capital, environmental) index is scaled from 0 to 1, with 1 (0) meaning the highest (lowest) resilience among counties in that category. Once constructed, the overall BRIC score can be drawn from summing up six subindex scores, theoretically ranging from 0 to 6 for each county. Finally, the most recent BRIC indexes measured in 2015 were used as the variable of community resilience (Hazards & Vulnerability Research Institute, 2019). Although the 2015 data are not matched with the other variables' period (2020), the BRIC indexes in

Table 1
Operationalization of variables and data sources.

Variable	Operational definition	Source
Airbnb RevPAL growth	Year-over-year percentage change of average Airbnb RevPAL for each county	AirDNA
Airbnb OCR growth	Year-over-year percentage change of average Airbnb occupancy rate for each county	
Leisure	Location quotient of leisure industries (NAICS 71: Arts, Entertainment, and Recreation) for each county	US Bureau of Labor Statistics
Hospitality	Location quotient of hospitality industries (NACIS 72: Accommodation and Food Services) for each county	
Social	Social resilience index for each county	Hazards & Vulnerability Research Institute
Community capital	Community capital resilience index for each county	
Environmental	Environmental resilience index for each county	
Airbnb density	Number (in thousands) of Airbnb listings for each county	AirDNA
Airport distance	Distance (in miles) to the nearest airport from the county centroid	Florida Geographic Data Library
Population density	Number (in thousands) of population for each county	US Department of Labor

Note: RevPAL: Revenue per available listing; OCR: Occupancy rate; NAICS: North American Industry Classification System.

Florida showed relatively high stability during the 5-year period (from 2010 to 2015) (Cutter & Derakhshan, 2020).

This study controlled three variables that may influence current Airbnb performance. First, Airbnb density—the number of Airbnb listings for a given county—has been found to have a positive agglomeration effect on individual Airbnb listings (Xie, Kwok, & Heo, 2020). Whether the agglomeration effect can play a critical role in attenuating the negative effect of COVID-19 on Airbnb performance is worth identifying. Second, because transportation accessibility influences accommodation prices (Kim, Jang, Kang, & Kim, 2020), this study controlled the effect of the distance to the nearest airport from the county centroid (i.e., airport distance) on Airbnb performance. Finally, the inclusion of population density can control for the effect of the resident population on Airbnb performance because areas with a high population density likely have a wide virus spread, which may further decrease Airbnb consumption. Table 1 presents the operational definitions of all variables used in the model.

3.2. Data analysis

Multiple data analyses were conducted to measure both the aspatial and spatial effects among variables. First, we ran an ordinary least squares (OLS) regression to examine the global relationships among variables, as shown in Equation (2):

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \varepsilon \tag{2}$$

where y_i is the dependent variable that consists of Airbnb RevPAL growth (i.e., the growth rate of average Airbnb revenue) and Airbnb OCR growth (i.e., the growth rate of average Airbnb occupancy) in county $i \in \{1, 2, \cdots, n\}$; x_j is the jth explanatory variable; $j \in \{1, 2, \cdots, k\}$; β_j is the jth parameter estimate; and ε is the error term.

However, using spatially referenced county-level variables in OLS regression models might lead to biased estimation results from the spatial autocorrelation among variables (Lee, Kim, & Jang, 2021). Thus, a spatial Durbin model (SDM) was also employed to address this issue. The SDM is specified as follows:

Table 2
Descriptive statistics and correlation coefficients of variables.

Variable	Mean	Min	Max	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Airbnb RevPAL growth	0.083	−0.612	3.080	0.504	1.000									
(2) Airbnb OCR growth	−0.017	−0.359	2.281	0.380	0.649**	1.000								
(3) Leisure	1.055	0.000	6.300	1.017	−0.267*	−0.301*	1.000							
(4) Hospitality	1.164	0.000	3.660	0.641	−0.286*	−0.349**	0.477**	1						
(5) Social	0.626	0.510	0.704	0.041	−0.401**	−0.410**	0.215	0.322**	1					
(6) Community capital	0.306	0.191	0.375	0.038	0.008	0.154	−0.350**	−0.223	0.203	1				
(7) Environmental	0.636	0.550	0.771	0.034	−0.012	−0.002	0.071	0.262*	−0.229	−0.195	1			
(8) Airbnb density	6.433	0.006	79.447	12.657	−0.226	−0.240	0.274*	0.353**	0.275*	−0.486**	0.119	1		
(9) Airport distance	30.632	3.130	70.400	16.729	0.035	0.197	−0.342**	−0.167	−0.573**	0.007	0.243*	−0.234	1	
(10) Population density	0.337	0.010	3.034	0.499	−0.201	−0.186	0.346**	0.106	0.336**	−0.355**	−0.245*	0.358**	−0.512**	1

Note: According to Hazards & Vulnerability Research Institute, the US average scores of Social, Community capital, and Environmental are 0.665, 0.365, and 0.578.
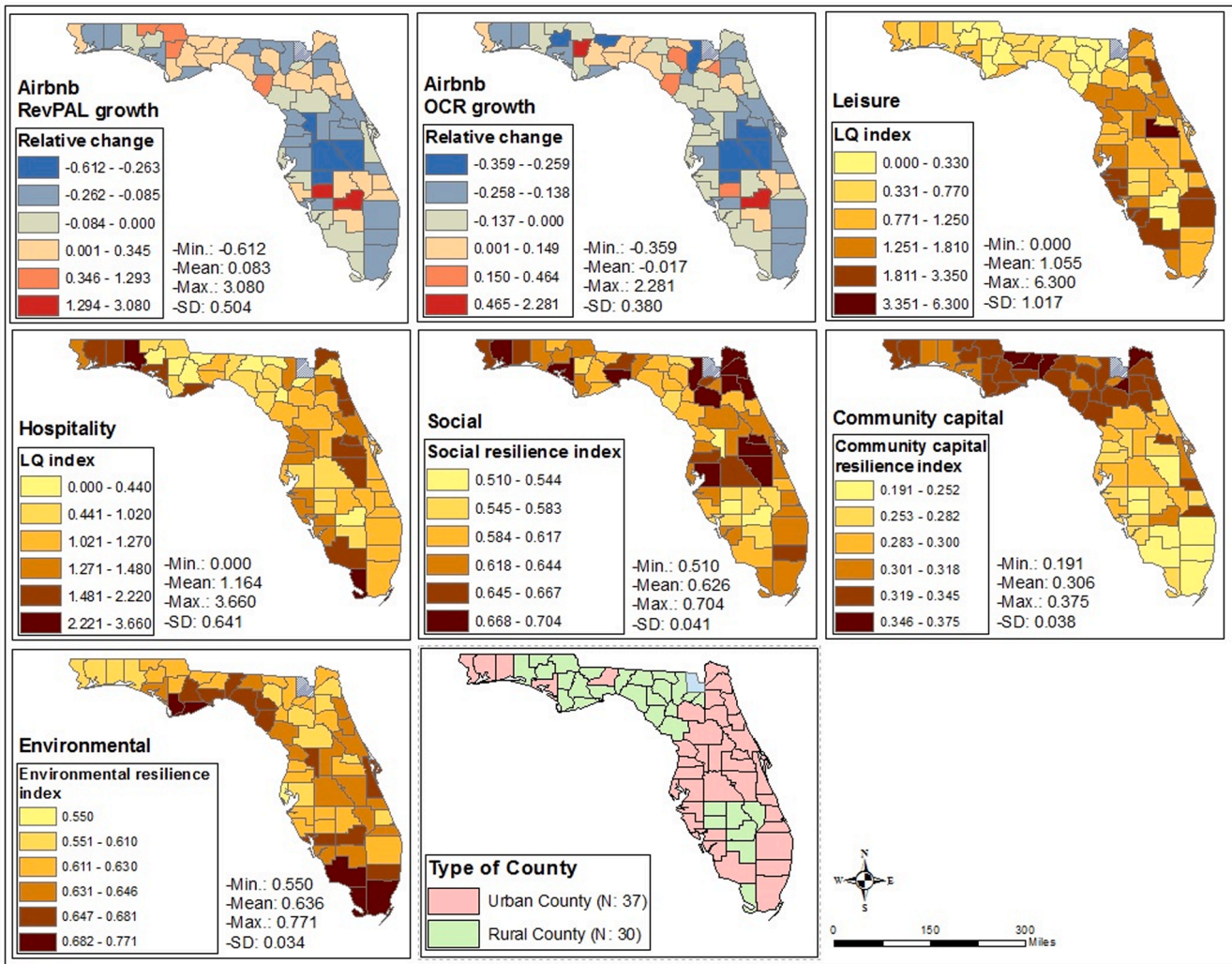* p < 0.05; ** p < 0.01.

Fig. 2. Spatial distribution of dependent and independent variables used in the model.

$$y_i = \sum_{j=1}^{k}(\rho_i W y_i + \beta_{ij} x_{ij} + W x_{ij} \theta_{ij}) + u_i + \varepsilon_i \tag{3}$$

where for an observation in county i, W is the spatial weight, which describes the spatial arrangement for n counties, ρ_i and θ_{ij} are the spatial parameters, u_i is spatial specific effects, and ε_i denotes the error term.

Next, a geographically weighted regression (GWR) was employed using the same set of variables to explore spatially heterogeneous relationships among variables. Unlike OLS and SDM methods, GWR explores the spatial variation in the relationships between georeferenced variables (Fotheringham, Brunsdon, & Charlton, 2000). GWR has been used as an explorative tool to detect spatial variability over the study area in tourism and hospitality research (Kim et al., 2020; Lee et al., 2020, 2021; Xu, Pennington-Gray, & Kim, 2019). The GWR model is shown in Eq. (4):

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{k} \beta_{ij}(u_i, v_i) x_{ij} + \varepsilon_i \tag{4}$$

where (u_i, v_i) refers to the coordinate at county i's centroid. The choice of bandwidth is critical for the spatial weighting function. The Gaussian kernel with a fixed bandwidth and a bisquare kernel with adaptive bandwidth are commonly used in GWR. The Gaussian kernel with a fixed bandwidth is suitable when the sample points are regularly distributed in the study area. If the sample points are not regularly

spaced, the bisquare kernel with adaptive bandwidth is desirable to accommodate this irregularity. We used a bisquare kernel function because of the geographically different size of county units based on previous regional studies (Lee et al., 2020; Xu et al., 2019). Furthermore, the GWR model fit was maximized when employing the bisquare kernel function compared with the Gaussian kernel function. The optimal kernel size is defined through an iterative optimization approach to minimize the corrected Akaike information criterion (AIC_c) (Fotheringham, Charlton, & Brunsdon, 1998).

Finally, we mapped local GWR coefficients and local R^2 to visualize the spatially heterogeneous effects of COVID-19, leisure clusters, hospitality clusters, community resilience, and other control variables on Airbnb performance growth. To analyze the spatial data, we employed advanced software programs, such as ArcGIS Pro, Stata (version 16.1), and GWR (version 4.09).

4. Results

4.1. Descriptive statistics

Table 2 reports the descriptive statistics and correlation coefficients for the variables used in the model. Fig. 2 visualizes the spatial distribution of these variables. In Florida, the average year-over-year growth rate of Airbnb RevPAL per county in March 2020 was 0.083, ranging from −0.612 to 3.080 and that of Airbnb OCR per county was −0.017 (mean), ranging from −0.359 to 2.281. Although the average Airbnb

Table 3
Estimation of OLS, SDM, and GWR models (DV: Airbnb RevPAL growth).

Variable	OLS (Model 1)	SDM (Model 2)	GWR (Model 3)			
			Min	Mean	Max	DIFF
Spatial weight		Queen contiguity	Kernel function using adaptive bi-square			
Leisure	−0.165**	−0.089**	−46.437	11.094	94.800	−6.621
Hospitality	−0.001	−0.021	−2.012	−0.070	5.638	−18.041
Social	−5.217**	−1.908**	−12.133	−0.515	2.532	−9.749
Community capital	−1.787	−6.402	−43.981	−0.156	48.426	−8.333
Environmental	0.061	1.548	−111.094	6.081	122.407	−15.291
Leisure × Social	2.574	6.100	−117.691	−17.561	20.143	−7.308
Leisure × Community capital	6.755	7.208	−28.320	17.185	97.570	−7.082
Leisure × Environmental	−0.097	−1.423	−202.166	−1.244	120.433	−8.710
Hospitality × Social	1.375*	4.354*	−28.336	11.378	69.658	−8.255
Hospitality × Community capital	1.481	−11.595	−84.336	−7.459	41.366	−7.855
Hospitality × Environmental	0.773	3.884	−127.211	2.977	122.663	−2.559
Airbnb density	−0.007	−0.015	−152.590	−4.761	124.096	−3.002
Airport distance	−0.014**	−0.012**	−0.438	−0.014	0.243	−9.633
Population density	−0.111	−0.046	−0.102	−0.024	0.018	−7.634
W × Leisure		0.134				
W × Hospitality		−0.271				
W × Social		0.983				
W × Community capital		−20.166				
W × Environmental		9.843				
W × Leisure × Social		−7.160				
W × Leisure × Community capital		14.715**				
W × Leisure × Environmental		−26.783				
W × Hospitality × Social		13.172				
W × Hospitality × Community capital		−33.184				
W × Hospitality × Environmental		−0.010				
W × Airbnb density		−0.046				
W × Airport distance		−0.032**				
W × Population density		−1.102**				
Intercept	4.470	5.231	−46.437	11.094	94.800	
R^2	0.471	0.483	0.485	0.501	0.526	
ρ		0.001				
$\sigma2$		0.070**				

Note: DIFF denotes difference of criterian value.
* $p < 0.10$; ** $p < 0.05$.

performance was positive, Airbnb listings in most (blue-colored) counties suffered negative growth rates (Fig. 2), meaning that Airbnb businesses in Florida were badly disrupted during the early stage of the COVID-19 outbreak. Concerning tourism clusters, the average leisure and hospitality LQs of Florida counties in March 2020 were 1.055 (from 0 to 6.300) and 1.164 (from 0 to 3.660), indicating that county-based tourism industry specialization in Florida was slightly higher than the U.S. county-level average (LQ: 1.0). Regarding community resilience, the average levels of social and community capital resilience in Florida were 0.626 and 0.306, respectively, which are lower than the U.S. average (0.665 and 0.365), but the average level of Floridian environment resilience was 0.636, which is higher than the U.S. average (0.578). Finally, correlation coefficients among independent variables were lower than 0.6, and the highest variance inflation factor (VIF) was 5.013 (Hospitality × Environmental), indicating the absence of multicollinearity in the final model.

4.2. Global model estimations

Tables 3 and 4 present the results of two types of global models (i.e., OLS regression model and SDM) using two dependent variables (i.e., Airbnb RevPAL growth and Airbnb OCR growth). The results of Model 1 reveal that, among the two types of tourism clusters, leisure clusters had a negative effect on Airbnb revenue performance ($\beta = -0.165$, $p < 0.05$), whereas hospitality clusters had no effect. This finding implies that a stronger dependence on leisure-related businesses and their employment caused more serious damage to Airbnb revenue during the COVID-19 crisis. Interestingly, social resilience had a negative effect on Airbnb revenue ($\beta = -5.217$, $p < 0.05$) for Model 1, whereas community capital resilience had a positive effect on Airbnb booking ($\beta = 1.202$, p

< 0.05) for Model 4. This finding indicates the differential role of resilience resources in the P2P accommodation business during the pandemic. Furthermore, the results show that social resilience played a crucial role in attenuating the negative effect of hospitality clusters on Airbnb revenue marginally (Model 1: $\beta = 1.375$, $p < 0.10$) and on Airbnb bookings significantly (Model 4: $\beta = 7.986$, $p < 0.05$).

The SDM results (Model 2 in Table 3 and Model 5 in Table 4) also confirmed the results of the OLS regression model. For example, leisure clusters had a negative effect on Airbnb revenue performance ($\beta = -0.089$, $p < 0.05$) for Model 2, whereas hospitality clusters also had no effect. In addition, social resilience had a negative effect on Airbnb revenue ($\beta = -1.908$, $p < 0.05$) for Model 2, whereas community capital resilience had a positive effect on Airbnb booking ($\beta = 0.683$, $p < 0.05$) for Model 5. This finding indicates significant effects of tourism clusters and community resilience on Airbnb performance across destination communities. Due to the significant spatial spillover effects of W*variables on Airbnb performance, the SDM estimated spatial feedback loop influences (Lesage and Fischer 2008), which identify the average effect of the independent variables on Airbnb performance of a county compared to its neighboring counties and vice versa (Kim et al., 2021). For example, the coefficient of the spatial spillover of *Leisure × Community capital* for Model 2 is 14.715, indicating a positive spatial spillover effect (Table 3). However, because these results do not reflect the marginal effects of X on Y, the estimations of the direct, indirect, and total effect of each variable on Airbnb performance can infer more accurate interpretations of the spillover effects (see the details in Appendix A).

Table 4

Estimation of OLS, SDM, and GWR models (DV: Airbnb OCR growth).

Variable	OLS (Model 4)	SDM (Model 5)	GWR (Model 6)			
			Min	Mean	Max	DIFF
Spatial weight		Queen contiguity	Kernel function using adaptive bi-square			
Leisure	−0.084	−0.126	−3.464	0.128	4.495	−6.081
Hospitality	−0.002	−0.031	−18.067	−1.780	1.083	−18.013
Social	−3.569	−0.898	−30.185	1.729	82.702	−9.786
Community capital	1.202**	0.683**	−105.391	39.624	651.792	−8.299
Environmental	0.940	0.201	−200.033	−14.707	20.025	−15.286
Leisure × Social	0.457	1.036	−52.805	8.786	120.529	−7.246
Leisure × Community capital	−1.035	0.404	−243.564	16.911	517.541	−6.707
Leisure × Environmental	1.130	−1.510	−208.038	−9.260	36.813	−8.732
Hospitality × Social	9.509**	7.986**	−21.064	5.182	61.926	−8.907
Hospitality × Community capital	0.468	5.417	−46.832	39.736	509.813	−7.859
Hospitality × Environmental	−0.084	−0.519	−84.375	−4.735	38.897	−2.597
Airbnb density	−0.005	−0.010	−0.316	0.037	1.058	−3.132
Airport distance	−0.002	−0.002	−0.060	−0.002	0.101	−9.612
Population density	0.154	0.066	−54.819	−4.054	1.446	−7.765
W × Leisure		0.010				
W × Hospitality		0.201				
W × Social		1.772				
W × Community capital		−15.970**				
W × Environmental		4.958**				
W × Leisure × Social		−7.239				
W × Leisure × Community capital		9.652**				
W × Leisure × Environmental		−10.453*				
W × Hospitality × Social		8.658				
W × Hospitality × Community capital		−28.773**				
W × Hospitality × Environmental		−2.808				
W × Airbnb density		−0.043**				
W × Airport distance		−0.013**				
W × Population density		−0.248				
Intercept	1.305	0.957	−111.869	−2.309	38.053	
R^2	0.549	0.575	0.521	0.594	0.657	
ρ		0.001				
$\sigma2$		0.033**				

Note: DIFF denotes difference of criterian value.
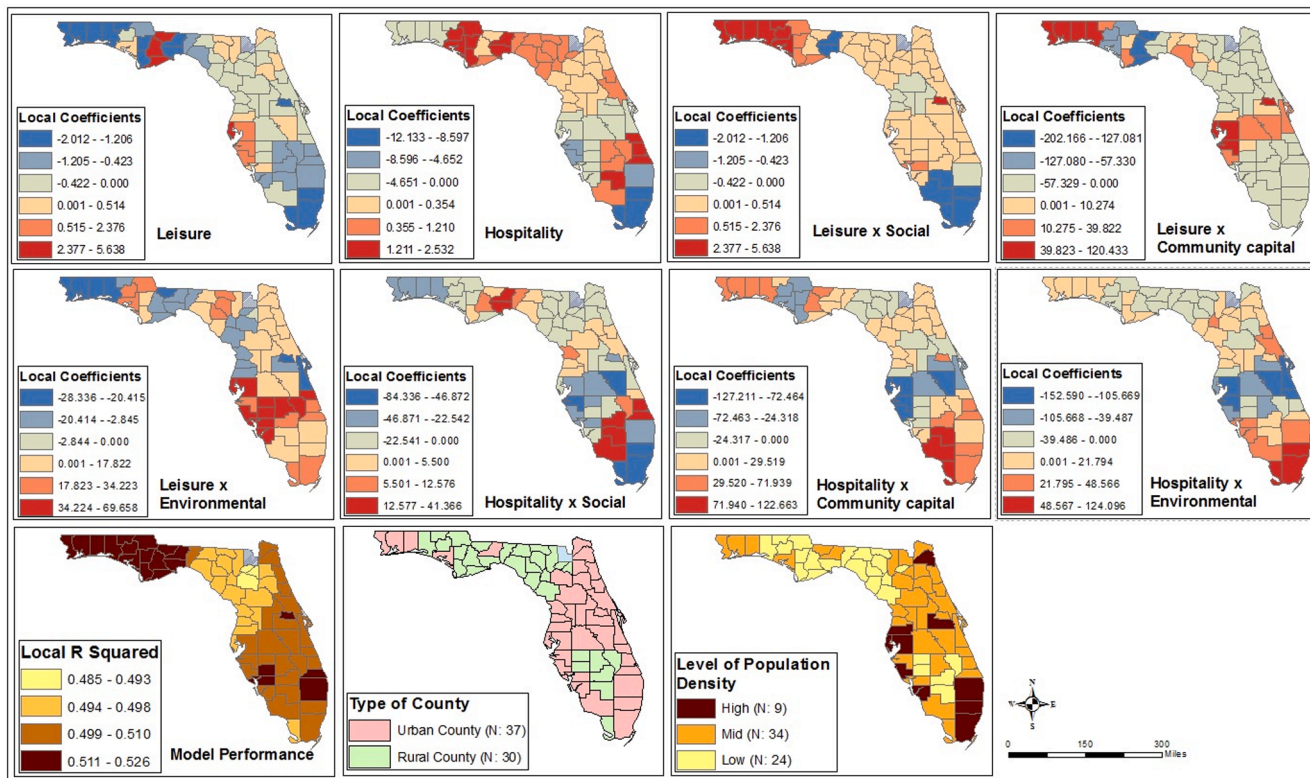
* $p < 0.10$; ** $p < 0.05$.

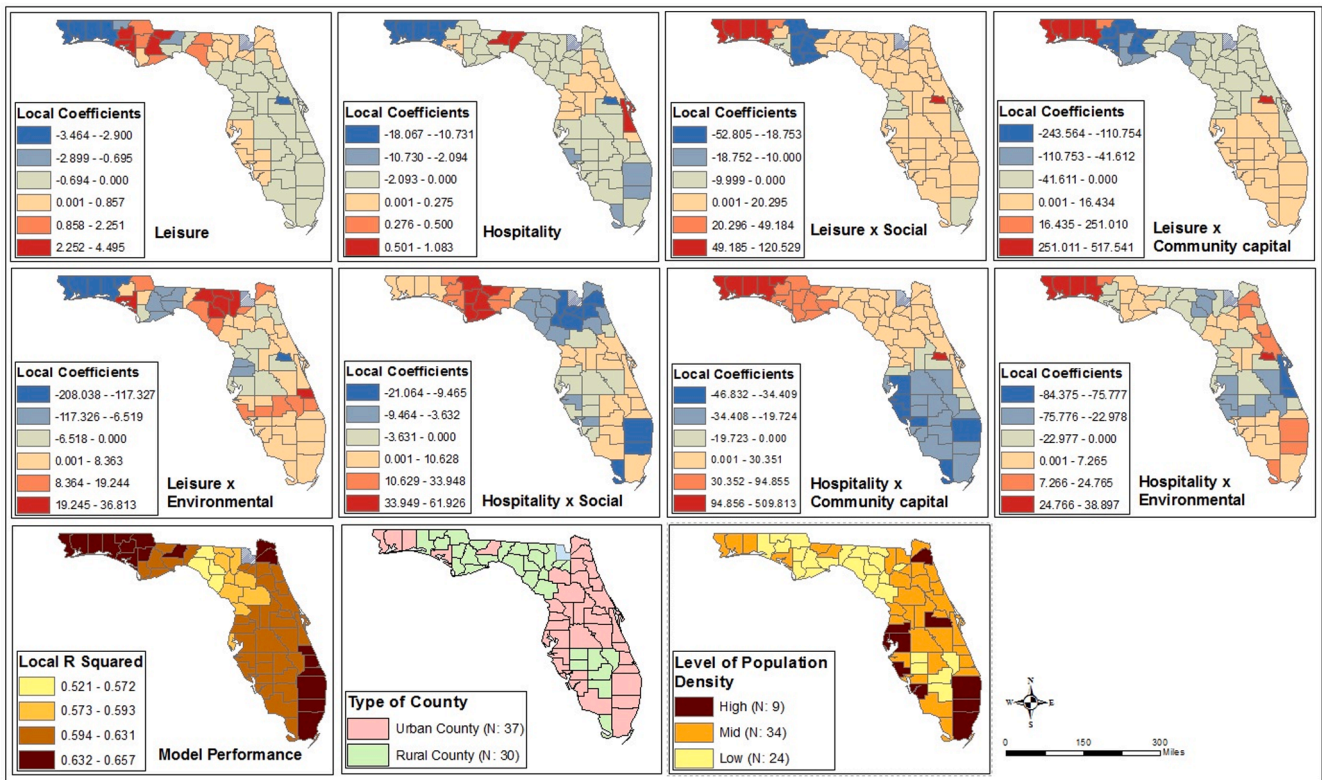**Fig. 3.** Spatial distribution of local GWR coefficients in Airbnb RevPAL growth model.

Fig. 4. Spatial distribution of local GWR coefficients in Airbnb OCR growth model.

4.3. Local model estimations

To examine the existence of spatial variability among local coefficients, we estimated the difference of criterion (DIFF) value, which identifies the difference of AICc between the fitted GWR and a model with the k-th coefficient fixed and all other coefficients kept as they are
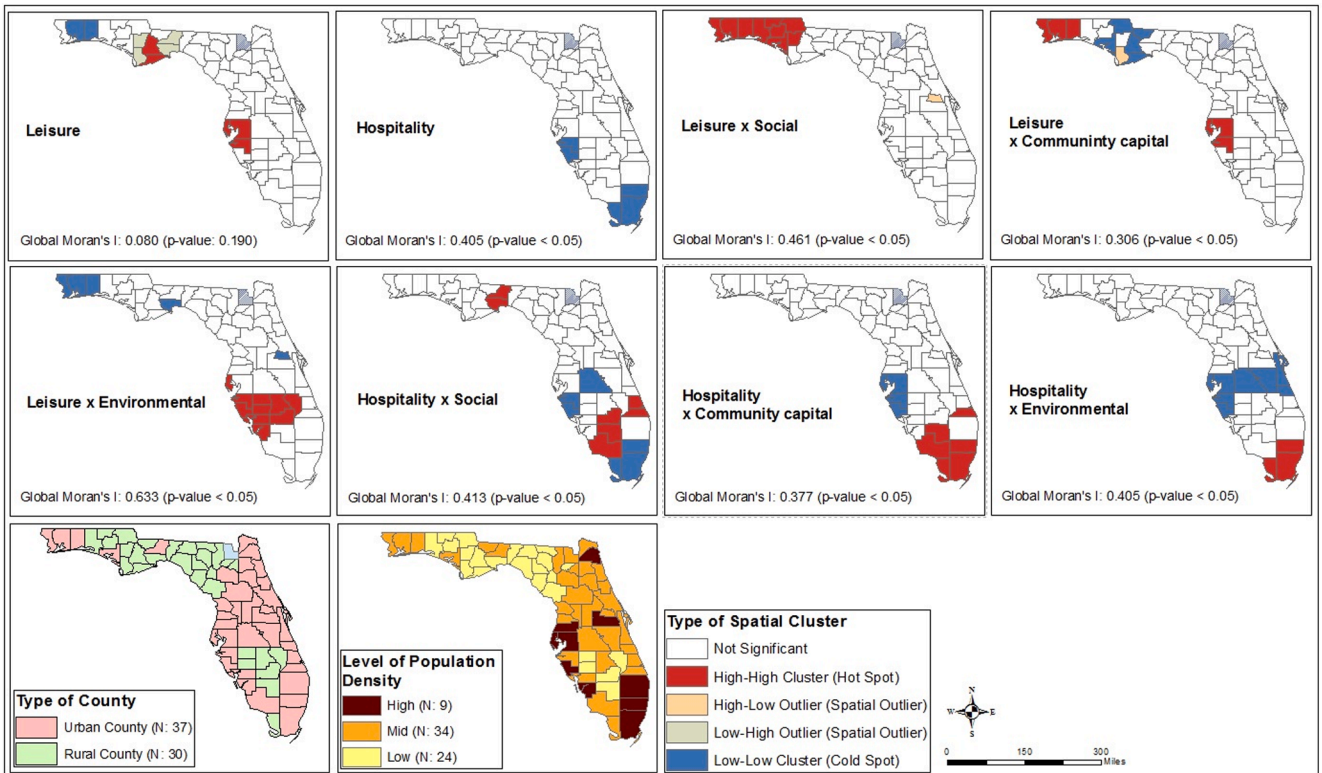

Fig. 5. Spatial distribution of clustered GWR-based local coefficients in Airbnb RevPAL growth model.
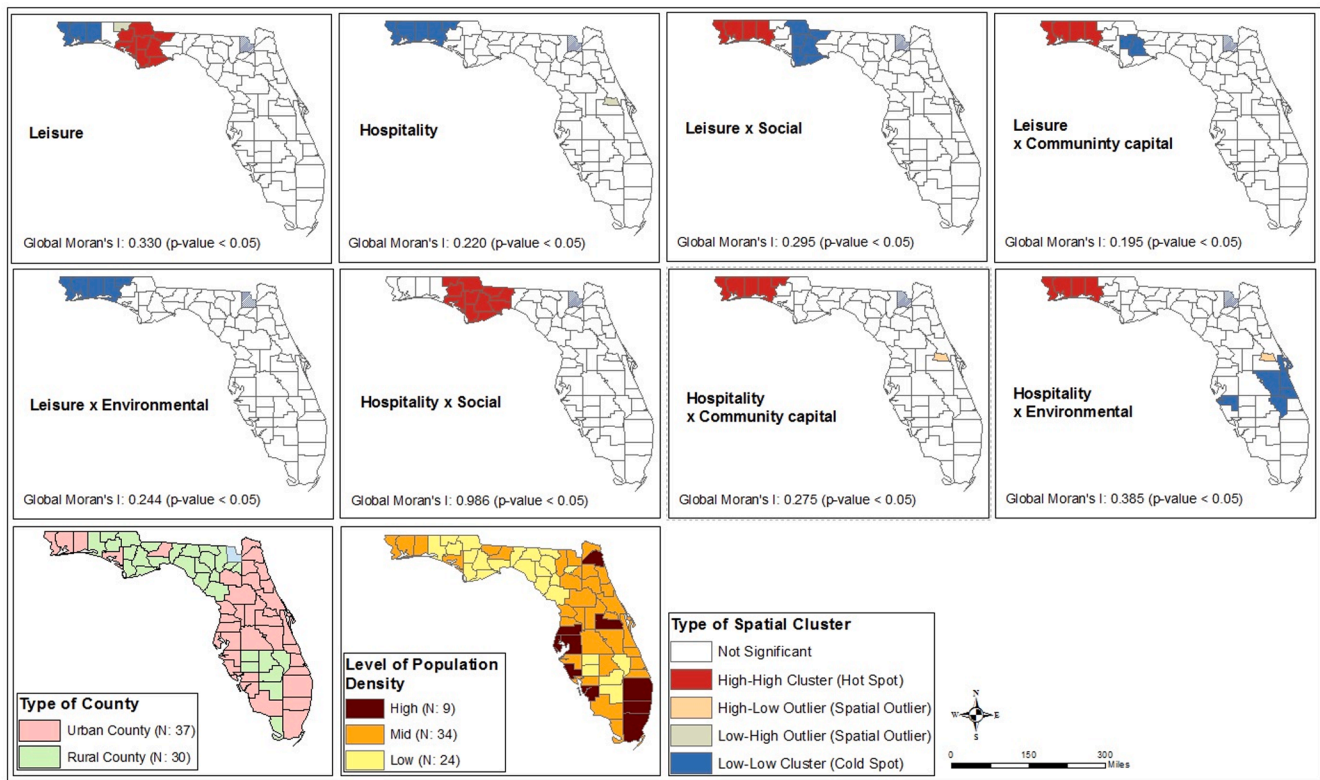
Fig. 6. Spatial distribution of clustered GWR-based local coefficients in Airbnb OCR growth model.

in the fitted GWR (Latinopoulos 2018; Nakaya, 2015). If the DIFF value is greater than 2, the corresponding variable has no significant spatial variability and could be better predicted by a global term in the model. The last column of Table 3 reports that the DIFF values were below −2, revealing significant spatial variation in all local coefficients across Floridian counties.

Specifically, Model 3 reports that leisure clusters, on average, positively affect Airbnb RevPAL growth (β_{Mean} = 11.094); however, depending on the county, the relationship was negative (β_{Min} = -46.437) or more positive (β_{Max} = 94.800). A similar pattern existed for the Airbnb OCR growth model (Model 6), for which local coefficients ranged from −3.464 to 4.495 (β_{Mean} = 0.128). To provide a better understanding of the spatially varying coefficients, Figs. 3 and 4 map the spatial distribution of local GWR coefficients for eight variables of tourism clusters and their interactions with community resilience across counties in the Airbnb RevPAL growth model and the Airbnb OCR growth model, respectively. For example, leisure clusters had a negative effect on the operating performance of Airbnb businesses in some northwest Floridian (blue-colored) counties but a positive effect on those in other northwest (red-colored) counties. In addition, hospitality clusters had a positive effect on the revenue performance of Airbnb listings in some northcentral Floridian (red-colored) counties but a negative effect in southeast (blue-colored) counties. These findings reveal that the relationship between tourism clusters and Airbnb business performance varied across counties, and tourism clusters played a critical role in enhancing the performance of Airbnb listings, especially in rural and less populated counties. Similarly, three categories of community resilience had mixed (positive or negative) effects on Airbnb performance across Floridian counties.

Interestingly, the combined effects of both tourism clusters and community resilience on Airbnb performance varied depending on variable combinations and locations (Fig. 3). From the perspective of rural counties, the negative effect of leisure clusters on Airbnb revenue was attenuated by high levels of social resilience in northwest counties

and environmental resilience in southwest counties. In urban counties, community capital resilience attenuated the negative effect of leisure clusters on Airbnb revenue in northwest and central counties, and environmental resilience played a critical role in reducing the negative effect of hospitality clusters on Airbnb revenue in south counties. These results indicate that, from the perspective of Airbnb performance, some communities that rely heavily on leisure or hospitality clusters were vulnerable to external shocks, such as the COVID-19 pandemic, but might reduce this disruption with greater community resilience. In addition, compared with the OLS regression, the GWR improved the overall explanatory power of the Airbnb performance model (i.e., R^2 in Tables 3 and 4), and the two Airbnb performance models performed better in northwest Floridian (dark-colored) counties (Figs. 3 and 4). The results of GWR estimations imply that the effect of tourism clusters and community resilience on Airbnb performance varies across individual destination communities.

Finally, based on the obtained local coefficients, an application study to explore the subclustering of high or low local coefficients was performed using the global Moran's I statistic and local indicators of spatial association (LISA). In this study, the global Moran's I measures whether spatial dependence exists among the county-level coefficient of a focal location and coefficients of other neighboring locations (Li, Calder, & Cressie, 2007). LISA cluster maps can be classified into 5 types of spatial clusters: (1) high-high: hot spots; (2) high-low: spatial outliers; (3) low–high: spatial outliers; (4) low-low: cold spots; and (5) not significant (Jang & Kim, 2018; Jang et al., 2017). Figs. 5-6 illustrate the spatial distribution of hot and cold spots across variables. For example, Airbnb listings in the red-colored cluster of low- and mid-populated northwest counties benefitted from the combination of leisure clusters and social resilience that led to better revenue performance during COVID-19 (Fig. 5). In contrast, Airbnb listings in the cluster of densely populated South Floridian counties benefitted from the association of hospitality clusters with community capital resilience (Hospitality × Community capital: red-colored) but not from their association with social resilience

(Hospitality × Social: blue-colored). These results show the existence of spatial heterogeneity at the subcluster level in terms of the role of local resources in shaping P2P accommodation performance during COVID-19.

5. Discussion and conclusion

COVID-19 has heavily hit the tourism and lodging industry, especially small tourism businesses such as Airbnb listings that are vulnerable to crises and disasters. Using combined data on Airbnb performance and local resources in 67 Floridian counties over March 2019 and 2020, this study used spatial econometric models and GIS techniques and further examined the spatially heterogeneous effects of leisure clusters, hospitality clusters, and resilience resources (i.e., social, community capital, and environmental) on the growth rates of Airbnb and booking performance. The results of global regression models show that leisure clusters and social resilience negatively influenced Airbnb revenue, community capital resilience positively influenced Airbnb bookings, and social resilience attenuated the negative effect of hospitality clusters on both Airbnb revenue and bookings. In addition, the results of local regression models indicate that Airbnb listings in rural counties with a high specialization of leisure and hospitality businesses were less disrupted by COVID-19 than those in urban counties. Furthermore, although community resilience had mixed effects on Airbnb performance across counties, it moderated the spatially varying relationship between tourism clusters and Airbnb performance. For example, social (community capital) resilience attenuated the negative effect of leisure clusters on Airbnb revenue in some rural (urban) counties, whereas environmental resilience attenuated the negative effect of leisure (hospitality) clusters on Airbnb revenue in some rural (urban) counties. Such positive and negative relationships were heterogeneous across individual and subclustered counties, implying the existence of spatial heterogeneity in the Airbnb performance model.

5.1. Theoretical implications

Our study contributes to the literature on P2P accommodation and tourism crisis management by empirically investigating the spatially heterogeneous effects of destination-specific situational factors on P2P accommodation performance during COVID-19. First, our study reveals the importance of tourism clusters and community resilience to understand spatially heterogeneous P2P accommodation business disruptions and prepare for a future pandemic crisis (Jang et al., 2021). This finding implies that authentic local experience, as a key advantage for P2P accommodations (Mody et al., 2017), is embedded with tourism clusters and community resilience that accommodation hosts cannot control (Walls et al., 2011) during a disaster or crisis. This study extends the concept of SLFT to the context of the accommodation-sharing economy by identifying material (i.e., leisure and hospitality clusters) and immaterial (i.e., social, community capital, and environmental resilience) resources as sustainable livelihoods for P2P accommodation businesses during the pandemic crisis (Tao & Wall, 2009). In addition, exploring two situational factors that might influence tourists' P2P accommodation consumption during COVID-19 contributes to the P2P accommodation literature because recent studies have separately examined their effects (Hassan & Soliman, 2021; Jang et al., 2021).

Second, this study offers evidence for the spatially heterogeneous effects of tourism clusters on Airbnb performance during COVID-19, thereby extending tourism cluster theory (Michael, 2003). The empirical findings identified the existence of both economies and diseconomies of tourism business agglomeration across urban and rural destinations in terms of P2P accommodation performance. Prior studies have mainly focused on the positive role of tourism clusters (i.e., agglomeration economies) in P2P accommodation markets (Gutiérrez et al., 2017; Lee et al., 2020), which did not consider the pandemic context. This study filled this gap by showing that agglomeration

economies of leisure businesses enhanced Airbnb revenue in both rural and urban destinations (Fig. 5) but Airbnb bookings mainly in rural destinations (Fig. 6). Such mixed results can be explained by the complexity in tourists' decision making during the pandemic (Karl et al., 2020). Business tourists might intend to use Airbnb listings in urban destinations during the pandemic, whereas leisure tourists likely traveled to less populated rural destinations with leisure attractions (Jang et al., 2021). Conversely, agglomeration diseconomies of hospitality businesses disrupted Airbnb performance mainly in urban destinations (e.g., Miami-Dade County) to which business and leisure tourists often travel. The reason may be that a high clustering of hotels and restaurants in urban destinations was likely to increase congestion costs (McCann & Folta, 2009), spread the virus easily during the pandemic, and in turn discourage tourists from traveling to the destinations. This finding extends to the literature on agglomeration economies and diseconomies in the context of tourism clusters and P2P accommodation markets.

Finally, the combined effects of tourism clusters and community resilience resonate with research showing the importance of sustainable livelihoods in the form of material and immaterial resources across destination communities (Shen et al., 2008). Previous research has identified that overall community resilience is driven by different resilience resources, such as economic capital for urban resilience and community capital for rural resilience (Cutter et al., 2016). This study advances the resilience literature by showing the heterogeneous roles of specific resilience resources in P2P accommodation markets during the pandemic. Interestingly, the combination of leisure clusters with social resilience increased Airbnb performance in rural and less populated urban destinations, whereas the association of hospitality clusters with community capital resilience enhanced Airbnb performance in more populated urban destinations. This finding confirms that P2P accommodation consumers with greater social resilience, such as physical and mental wellness, are likely to travel to rural destinations than to urban destinations (Mahadevan, 2020; Mody et al., 2017). Furthermore, suburban areas often combine the features of rural communities, such as a higher level of trust (Dominiak, 2020) and community capital (e.g., local citizens' goodwill to assist their neighbors), and can remedy the pandemic-induced diseconomies of hospitality business agglomeration for P2P accommodations in urban destinations.

5.2. Practical implications

Our empirical findings offer practical insights for stakeholders in the P2P accommodation economy. Specifically, this research suggests that Airbnb listings need to take full advantage of two types of situational factors (i.e., tourism clusters and community resilience) in their counties to attenuate the negative impact of COVID-19 on their revenue and booking performance. Airbnb hosts are encouraged to conduct a detailed analysis of specialized tourism clusters (e.g., leisure and hospitality) and the configuration of community resilience (e.g., social, community capital, environmental) that generate agglomeration (dis) economies and crisis management capacity, respectively, and reflect these components in their during- or post-COVID-19 marketing activities. For example, Airbnb hosts in rural destinations need to utilize the agglomeration economies of leisure resources (e.g., parks and beaches) and specific resilience factor(s) in their destinations in terms of product offerings and communication messages to potential guests. In addition, urban and rural Airbnb hosts could target business and bleisure (business and leisure) tourists, respectively, because tourists will more voluntarily implement personal measures to avoid viral infection on their trips to the destination (Jang et al., 2021).

From a policy perspective, local governments should take a place-based approach to manage the current pandemic crisis and prepare for a future crisis because a one-size-fits-all strategy cannot reflect the multidimensional nature of local resource configurations (Cutter et al., 2016). Depending on the geographical features of individual and neighboring communities, policymakers need to understand how the

Table A1

Impact measures: direct, indirect, and total effects in SDM coefficients.

Variable	DV (Airbnb RevPAL growth)			DV (Airbnb OCR growth)		
	Direct	Indirect	Total	Direct	Indirect	Total
Leisure	−0.199**	0.059	−0.141	−0.159	0.050	−0.108
Hospitality	−0.008	−0.292	−0.299*	−0.017	0.041	0.024
Social	−1.695**	0.278	−1.372	0.916	1.576	2.491
Community capital	−3.300	−4.234	−7.535**	2.397**	−10.698**	−8.301**
Environmental	3.324	7.117**	10.441**	0.159	3.531*	3.681**
Leisure × Social	6.712	−4.893	1.819	2.463	−3.824	−1.361
Leisure × Community capital	4.447	3.468	7.914**	−0.251	6.253*	6.002**
Leisure × Environmental	−2.064	−12.132**	−14.196*	0.333	−5.144	−4.811
Hospitality × Social	4.126	3.274	7.400	7.289**	1.101	8.390
Hospitality × Community capital	2.110	−4.189	−2.079	4.007	−12.582**	−8.575**
Hospitality × Environmental	0.841	−1.300	−0.459	−0.957	−1.069	−2.025
Airbnb density	−0.007	−0.006	−0.014	−0.007	−0.020**	−0.027**
Airport distance	−0.013**	−0.010**	−0.023**	0.001*	−0.007*	−0.006**
Population density	−0.119	−0.429**	−0.548**	0.079	−0.310	−0.232

combination of material and immaterial resources attenuates the negative impact of COVID-19 on the Airbnb business across individual and subclustered destination communities. For example, because northwest Florida has rich leisure resources (e.g., historical places, white beaches, national forests, and natural springs), Airbnb hosts could leverage the advantage of outdoor leisure clusters and resilience resources across neighboring counties. According to 2021 Airbnb search data, two northwest Floridian beaches (i.e., Cape San Blas and Grayton Beach) are among the top destinations for Airbnb users because the pandemic makes Airbnb users stay in unique and remote lodgings with plenty of privacy and outdoor space (Hayes, 2021). To maximize P2P accommodation consumption, this study suggests that each county in northwest Florida should be embedded with greater social resilience through a greater concentration of physicians and mental health supporting facilities. In addition, the findings of southeastern Florida (i.e., highly populated urban destinations) suggest that although diseconomies of hospitality agglomeration disrupted Airbnb revenue during COVID-19, greater environmental resilience attenuated the disruptions. For example, Greater Miami, as a resilient city, needs to enhance environmental resilience through urban forests, solar energy initiatives, and other climate change mitigation efforts (Caraway-Carlton, 2019), which can enhance the image of socially responsible destinations with potential tourists and Airbnb users.

5.3. Limitations and future research directions

Although the findings are insightful, several study limitations exist. First, because the empirical models are specific to the population of Floridian Airbnb listings, the findings of this study cannot be applied to other regions and countries. Future research can resolve the applicability issue by collecting and analyzing empirical data related to Airbnb performance, tourism clusters, and community resilience from other study areas. Second, this research focused on the early stage of the COVID-19 crisis and failed to capture how the relationship between local resources and Airbnb business performance evolved during the period. Future studies can resolve this limitation by collecting longitudinal data during the pandemic lifecycle. Third, although our SDM results showed the existence of both direct and (indirect) spillover effects of local resources on P2P accommodation performance, this study focused mainly on the spatially varying direct effects across individual and subclustered destinations. Future studies can explore the spatially heterogeneous spillover effects to identify where the competitive and complementary effects of local resources on P2P accommodation performance exist. Finally, due to a multicollinearity issue among variables, this study did not decompose tourism clusters and community resilience into detailed components. For instance, leisure subindustries (e.g., art, entertainment, and recreation) and other community resilience resources, such as economic, housing/infrastructure, and institutional

resources, can be included in the model. By using advanced modeling techniques, future studies can use decomposed resource components to explain the specific set of local resources that leads to better Airbnb performance during the pandemic.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Estimations of direct, indirect, and total effects in SDM coefficients

Table A1 shows the direct, indirect, and total effects of each variable on Airbnb revenue and booking performance. The direct effect measures the average effect of the change in independent variable (X) on dependent variable (Y), which includes the feedback via the neighboring county and back to the focal county. The indirect effect measures the average effect of the change in X of the focal county on the Y of neighboring counties. The total effect denotes the sum of the direct and indirect effects, which measures the average effect of the change in X of the focal county on the Y of all the focal and neighboring counties. For example, the direct effect of leisure clusters on Airbnb revenue was larger than the coefficient estimate (−0.199 vs. −0.089), implying the existence of feedback effect that passed via neighboring counties back to the focal county. Interestingly, the indirect effect of leisure clusters was positive (0.059) so that the total effect was smaller than the direct effect (-0.141), although both were statistically non-significant. This implies that there might be a decrease in Airbnb user traffic in a focal county with a high degree of clustering of leisure attractions, whereas neighboring counties with relatively lower leisure specialization might benefit from the spillover effect. In addition, both the direct and indirect effects of Hospitality × Social on Airbnb booking were positive (7.289 and 1.101), which lead to the positive total effect (8.390). This indicates that social resilience attenuated the pandemic-induced P2P accommodation market disruption across focal and neighboring counties.

References

Bresciani, S., Ferraris, A., Santoro, G., Premazzi, K., Quaglia, R., Yahiaoui, D., & Viglia, G. (2021). The seven lives of Airbnb. The role of accommodation types. *Annals of Tourism Research, 88,* Article 103170.

Caraway-Carlton, A. (2019). Miami's environment & sustainability. Greater Miami Convention & Visitors Bureau. (accessed April 14, 2021), [Retrieved from https://www.miamiandbeaches.com/about-gmcvb/miami-s-environment-sustainability].

Castells-Quintana, D., & Royuela, V. (2014). Agglomeration, inequality and economic growth. *The Annals of Regional Science, 52*(2), 343–366.

CDC (2021). Centers for Disease Control and Prevention. COVID data tracker. (accessed May 26, 2021), [Retrieved from https://covid.cdc.gov/covid-data-tracker/#county-view].

Chadwick, L. (2020). Coronavirus: Hotels and Airbnb plan 'fundamental shift' after COVID-19 lockdowns. (accessed July 01, 2020), [Retrieved from https://www.euronews.com/2020/05/08/coronavirus-hotels-and-airbnb-plan-fundamental-shift-after-covid-19-lockdowns].

Chambers, R. (1992). Sustainable livelihoods: The poor's reconciliation of environment and development. In P. Ekins, & M. Max-Neef (Eds.), *Real-life economics: Understanding wealth creation* (pp. 214–230). London: Routledge.

Chan, L.-Y., Lin, H.-L., & Wang, C.-L. (2012). Industry-region position and economic performance of travel and tourism service industry: An agglomeration perspective. *Asia Pacific Journal of Tourism Research, 17*(5), 562–576.

Cheng, M. (2016). Sharing economy: A review and agenda for future research. *International Journal of Hospitality Management, 57*, 60–70.

Cheng, M., & Jin, X. (2019). What do Airbnb users care about? An analysis of online review comments. *International Journal of Hospitality Management, 76*, 58–70.

Cutter, S. L., & Derakhshan, S. (2020). Temporal and spatial change in disaster resilience in US counties, 2010–2015. *Environmental Hazards, 19*(1), 10–29.

Cutter, S. L., Ash, K. D., & Emrich, C. T. (2014). The geographies of community disaster resilience. *Global Environmental Change, 29*, 65–77.

Cutter, S. L., Ash, K. D., & Emrich, C. T. (2016). Urban-rural differences in disaster resilience. *Annals of the American Association of Geographers, 106*(6), 1236–1252.

Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. *Global Environmental Change, 18*(4), 598–606.

Dominiak, J. (2020). Human and social capital in urban agglomeration and its changes in the core-peripheries pattern. The example of Poznań agglomeration. *City, Culture and Society, 23*, Article 100371.

Evelyn, K. (2020). 'It's a racial justice issue': Black Americans are dying in greater numbers from Covid-19. (accessed July 01, 2021), [Retrieved from https://www.theguardian.com/world/2020/apr/08/its-a-racial-justice-issue-black-americans-are-dying-in-greater-numbers-from-covid-19].

Fallah, B. N., & Partridge, M. (2007). The elusive inequality-economic growth relationship: Are there differences between cities and the countryside? *The Annals of Regional Science, 41*(2), 375–400.

Farmaki, A., Miguel, C., Drotarova, M. H., Aleksić, A., Časni, A.Č., & Efthymiadou, F. (2020). Impacts of Covid-19 on peer-to-peer accommodation platforms: Host perceptions and responses. *International Journal of Hospitality Management, 91*, 102663. https://doi.org/10.1016/j.ijhm.2020.102663

FDEM. (2020). Florida Division of Emergency Management. [Retrieved from https://www.floridadisaster.org/].

Florida Trend. (2018). Report: Rural Florida experiencing explosive Airbnb growth. (accessed July 01, 2020), [Retrieved from https://www.floridatrend.com/article/25460/report-rural-florida-experiencing-explosive-airbnb-growth].

Fotheringham, S. A., Brunsdon, C., & Charlton, M. (2000). *Quantitative geography: Perspectives on spatial data analysis*. London: Sage Publications.

Fotheringham, A. S., Charlton, M. E., & Brunsdon, C. (1998). Geographically weighted regression: A natural evolution of the expansion method for spatial data analysis. *Environment and Planning A, 30*(11), 1905–1927.

Gutiérrez, J., García-Palomares, J. C., Romanillos, G., & Salas-Olmedo, M. H. (2017). The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona. *Tourism Management, 62*, 278–291.

Guttentag, D. (2015). Airbnb: Disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism, 18*(12), 1192–1217.

Hall, C. M. (2017). Resilience in tourism: Development, theory, and application. In J. M. Cheer, & A. A. Lew (Eds.), *Tourism*. Resilience and Sustainability. Routledge.

Hassan, S. B., & Soliman, M. (2021). COVID-19 and repeat visitation: Assessing the role of destination social responsibility, destination reputation, holidaymakers' trust and fear arousal. *Journal of Destination Marketing & Management, 19*, 100495. https://doi.org/10.1016/j.jdmm.2020.100495

Hayes, K. (2021). Two Florida beaches rank as top destinations for Airbnb users this spring. Florida Politics. (accessed April 12, 2021), [Retrieved from https://floridapolitics.com/archives/412713-two-florida-beaches-rank-as-top-destinations-for-airbnb-users-this-spring/].

Hazards & Vulnerability Research Institute. (2019). Baseline Resilience Indicators for Communities (BRIC). BRIC 2015 County Scores. University of South Carolina, https://artsandsciences.sc.edu/geog/hvri/bric.

Hobson, J. S. P., & Teaff, J. D. (1994). Hospitality and leisure/recreation: Towards an understanding of an emerging partnership serving the tourism industry. *Journal of Hospitality and Leisure Marketing, 2*(1), 43–54.

Jang, S., & Kim, J. (2018). Remedying food policy invisibility with spatial intersectionality: A case study in the Detroit Metropolitan Area. *Journal of Public Policy & Marketing, 37*(1), 167–187.

Jang, S., Kim, J., Kim, J., & Kim, S. (2021). Spatial and experimental analysis of peer-to-peer accommodation consumption during COVID-19. *Journal of Destination Marketing & Management, 20*, 100563. https://doi.org/10.1016/j.jdmm.2021.100563

Jang, S., Kim, J., & von Zedtwitz, M. (2017). The importance of spatial agglomeration in product innovation: A microgeography perspective. *Journal of Business Research, 78*, 143–154.

Karl, M., Muskat, B., & Ritchie, B. W. (2020). Which travel risks are more salient for destination choice? An examination of the tourist's decision-making process. *Journal of Destination Marketing & Management, 18*, 100487. https://doi.org/10.1016/j.jdmm.2020.100487

Kim, J., Jang, S., Kang, S., & Kim, S.(. (2020). Why are hotel room prices different? Exploring spatially varying relationships between room price and hotel attributes. *Journal of Business Research, 107*, 118–129.

Kim, Y. R., Williams, A. M., Park, S., & Chen, J. L. (2021). Spatial spillovers of agglomeration economies and productivity in the tourism industry: The case of the UK. *Tourism Management, 82*, 104201. https://doi.org/10.1016/j.tourman.2020.104201

Kloosterman, R. C. (2010). Matching opportunities with resources: A framework for analysing (migrant) entrepreneurship from a mixed embeddedness perspective. *Entrepreneurship & Regional Development, 22*(1), 25–45.

Lazzeretti, L., & Capone, F. (2006). Identification and analysis of local tourist systems: An application to Italy (1996–2001). In L. Lazzeretti, & C. S. Petrillo (Eds.), *Tourism Local Systems and Networking* (pp. 25–42). (Amsterdam-New York: Elsevier).

Latinopoulos, D. (2018). Using a spatial hedonic analysis to evaluate the effect of sea view on hotel prices. *Tourism Management, 65*, 87–99.

Lau, J. T. F., Griffiths, S., Choi, K. C., & Tsui, H. Y. (2009). Widespread public misconception in the early phase of the H1N1 influenza epidemic. *Journal of Infection, 59*(2), 122–127.

Lee, C.-K., Song, H.-J., Bendle, L. J., Kim, M.-J., & Han, H. (2012). The impact of non-pharmaceutical interventions for 2009 H1N1 influenza on travel intentions: A model of goal-directed behavior. *Tourism Management, 33*(1), 89–99.

Lee, Y.-J., Jang, S., & Kim, J. (2020). Tourism clusters and peer-to-peer accommodation. *Annals of Tourism Research, 83*, 102960. https://doi.org/10.1016/j.annals.2020.102960

Lee, Y.-J.-A., Kim, J., & Jang, S. (2021). Intertemporal tourism clusters and community resilience. *The Professional Geographer*, 1–6.

Lesage, J. P., & Fischer, M. M. (2008). Spatial growth regressions: Model specification, estimation and interpretation. *Spatial Economic Analysis, 3*(3), 275–304.

Li, H., Calder, C., & Cressie, N. A. (2007). Beyond Moran's I: Testing for spatial dependence based on the spatial autoregressive model. *Geographical Analysis, 39*(4), 357–375.

Lin, Y., Kelemen, M., & Kiyomiya, T. (2017). The role of community leadership in disaster recovery projects: Tsunami lessons from Japan. *International Journal of Project Management, 35*(5), 913–924.

Mahadevan, R. (2020). Is there an urban-rural divide in the demand for peer-to-peer accommodation sharing? *Current Issues in Tourism*, 1–8.

McCann, B. T., & Folta, T. B. (2009). Demand- and supply-side agglomerations: Distinguishing between fundamentally different manifestations of geographic concentration. *Journal of Management Studies, 46*(3), 362–392.

Michael, E. J. (2003). Tourism micro-clusters. *Tourism Economics, 9*(2), 133–145.

Mkono, M. (2013). Using net-based ethnography (netnography) to understand the staging and marketing of 'Authentic African' dining experiences to tourists at Victoria Falls. *Journal of Hospitality & Tourism Research, 37*(2), 184–198.

Mody, M. A., Suess, C., & Lehto, X. (2017). The accommodation experiencescape: A comparative assessment of hotels and Airbnb. *International Journal of Contemporary Hospitality Management, 29*(9), 2377–2404.

Moscardo, G., Konovalov, E., Murphy, L., & McGehee, N. (2013). Mobilities, community well-being and sustainable tourism. *Journal of Sustainable Tourism, 21*(4), 532–556.

Nakaya, T. (2015). Geographically weighted generalised linear modelling. In Brunsdon, & Singleton (Eds.), Geocomputation: A practical primer. London, UK: Sage Publishing.

Newman, J. (2020). The Coronavirus has emptied tourist sites and the images are haunting. (accessed April 13, 2021), [Retrieved from https://www.townandcountrymag.com/leisure/travel-guide/g31483152/empty-cultural-landmarks-coronavirus/].

Norris, F. H., Stevens, S. P., Pfefferbaum, B., Wyche, K. F., & Pfefferbaum, R. L. (2008). Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *American Journal of Community Psychology, 41*, 127–150.

Norris, F., Phifer, J., & Kaniasty, K. (1994). Individual and community reactions to the Kentucky floods: Findings from a longitudinal study of older adults. In R. Ursano, B. McCaughey, & C. Fullerton (Eds.), *Individual and community responses to trauma and disaster: The structure of human chaos* (pp. 378–400). Cambridge: Cambridge University Press.

Okumus, F., Altinay, M., & Arasli, H. (2005). The impact of Turkey's economic crisis of February 2001 on the tourism industry in Northern Cyprus. *Tourism Management, 26*(1), 95–104.

Peters, D. J. (2020). Community susceptibility and resiliency to COVID-19 across the rural-urban continuum in the United States. *Journal of Rural Health, 36*(3), 446–456.

Reisinger, Y., & Mavondo, F. (2005). Travel anxiety and intentions to travel internationally: Implications of travel risk perception. *Journal of Travel Research, 43*(3), 212–225.

Reuters (2020). Airbnb warns 2020 revenue can fall by half amid COVID-19 hit: The Information. (accessed July 01, 2020), [Retrieved from https://www.reuters.com/article/us-airbnb-outlook/airbnb-warns-2020-revenue-can-fall-by-half-amid-covid-19-hit-the-information-idUSKCN21Q35D].

Shen, F., Hughey, K. F. D., & Simmons, D. G. (2008). Connecting the sustainable livelihoods approach and tourism: A review of the literature. *Journal of Hospitality and Tourism Management, 15*(01), 19–31.

Singh, S., Timothy, D. J., & Dowling, R. K. (Eds.). (2003). *Tourism in destination communities*. Wallingford: CABI.

Tao, T. C. H., & Wall, G. (2009). Tourism as a sustainable livelihood strategy. *Tourism Management, 30*(1), 90–98.

Tukamushaba, E., Xiao, H., & Ladkin, A. (2016). The effect of tourists' perceptions of a tourism product on memorable travel experience: Implications for destination branding. *European Journal of Tourism, Hospitality and Recreation, 7*(1), 2–12.

Vlasov, M., Bonnedahl, K. J., & Vincze, Z. (2018). Entrepreneurship for resilience: Embeddedness in place and in trans-local grassroots networks. *Journal of Enterprising Communities: People and Places in the Global Economy, 12*(3), 374–394.

Walls, A. R., Okumus, F., Wang, Y.(., & Kwun, D.-W. (2011). International journal of hospitality management an epistemological view of consumer experiences. *International Journal of Hospitality Management, 30*(1), 10–21.

World Bank. (2021). Global Economic Prospects. (accessed March 15, 2020), [Retrieved from https://www.worldbank.org/en/publication/global-economic-prospects].

Xie, K. L., Kwok, L., & Heo, C. Y. (2020). Are neighbors friends or foes? Assessing Airbnb listings' agglomeration effect in New York City. *Cornell Hospitality Quarterly, 61*(2), 128–141.

Xu, X.(., Huang, D., & Chen, Q. (2021). Stress and coping among micro-entrepreneurs of peer-to-peer accommodation. *International Journal of Hospitality Management, 97*, 103009. https://doi.org/10.1016/j.ijhm.2021.103009

Xu, Y.-H., Pennington-Gray, L., & Kim, J. (2019). The sharing economy: A geographically weighted regression approach to examine crime and the shared lodging sector. *Journal of Travel Research, 58*(7), 1193–1208.

Yang, Y., & Mao, Z. (2020). Location advantages of lodging properties: A comparison between hotels and Airbnb units in an urban environment. *Annals of Tourism Research, 81*, 102861. https://doi.org/10.1016/j.annals.2020.102861

Zervas, G., Proserpio, D., & Byers, J. W. (2017). The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. *Journal of Marketing Research, 54*(5), 687–705.

Zhang, M.o., Geng, R., Huang, Y., & Ren, S. (2021). Terminator or accelerator? Lessons from the peer-to-peer accommodation hosts in China in responses to COVID-19. *International Journal of Hospitality Management, 92*, 102760. https://doi.org/10.1016/j.ijhm.2020.102760

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