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**Article**

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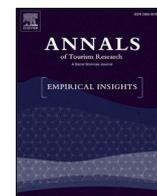
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# Spatial patterns and geographic characteristics of tourism-accommodation intensity hotspots in Kyoto city<sup>☆</sup>

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## ABSTRACT

The tourism intensity index can be used to determine the risk of overtourism. This study aimed to clarify the spatial patterns and geographic characteristics of tourism-accommodation hotspots in Kyoto City. This study calculated the tourism-accommodation intensity index as the ratio of the number of accommodation rooms to that of households. The results revealed that tourism-accommodation intensity hotspots emerged in neighborhoods near the periphery of the southeastern historical center. The hotspots emerged in neighborhoods where the number of rooms has exceeded that of households. Additionally, this study revealed that tourism-accommodation intensity hotspots were spatially associated with proximity to main stations and world heritage sites. This study's findings are useful for developing effective urban zones with total volume control in these neighborhood-units.

## 1. Introduction

Many tourist cities have suffered from touristification. Moderate touristification can bring economic benefits to tourist cities. However, excessive touristification has adverse social effects on residents and visitors, such as overtourism (UNWTO, 2018). Overtourism is caused by the overuse of a destination's resources, infrastructure, or facilities (Koens, Postma, & Papp, 2018). Therefore, overtourism poses a threat to sustainable tourism, which is based on resources, activities, and community traditions (Saarinen, 2006). One serious issue related to overtourism is tourism gentrification (González-Pérez, 2020). Tourism gentrification has caused the upscaling of real estate properties (Jover & Díaz-Parra, 2020) and the displacement of residents (Cocola-Gant, 2023). Displacement has been reported to have occurred in specific local neighborhoods (Sumka, 1979). However, in some tourist cities, displacement due to tourism gentrification correlates with population decline at the neighborhood level throughout the historical center (Kato & Takizawa, 2022). It has been reported that such population decline is caused by the transformation of houses into accommodations (Tanaka, Kato, & Matsushita, 2023). These areas with declining populations are thought to form hotspots because of disruptions to the appropriate balance between tourism accommodations and housing at the neighborhood scale.

This study's research question is as follows: Where are the hotspots with a disrupted balance between tourism accommodations and

housing? Many studies have analyzed uneven accommodation locations for hotels and short-term rentals (STRs). The clustering of hotels was found regardless of the area, such as in rural areas (Sánchez-Martín, Rengifo-Gallego, & Blas-Morato, 2019), or the scale, including the country level (Lee, Kang, Terry, & Schuett, 2018). STRs are also known to be spatially heterogeneous, formulating not only intraregional clusters but also interregional clusters (Lee, Jang, & Kim, 2020). An increasing number of accommodations are found in historical city centers (Álvarez-Herranz & Macedo-Ruíz, 2021; García-Amaya, Temes-Cordovez, Simancas-Cruz, & Peñarrubia-Zaragoza, 2021; García-Ayllon, 2018; Zhang, Chapple, Cao, Dennett, & Smith, 2020). Tourism clustering benefits regional industrial competitiveness (Jackson & Murphy, 2006). However, in Barcelona, STRs have begun to cluster not only in the historical center area but also in some peripheral areas near the new residential zone (Gutiérrez, García-Palomares, Romanillos, & Salas-Olmedo, 2017). On the basis of these results, Gutiérrez et al. (2017) concluded that accommodations caused tourism pressure on residents in some residential areas. As the results of these studies show, the ongoing debates on surrounding accommodation clusters have shifted from the accommodation itself to its relationship with residential areas. Nevertheless, a research gap exists regarding the geographic characteristics of hotspots in which the balance between tourism accommodations and housing is disrupted. These geographic characteristics can provide guidance about areas that should be the focus of urban planning efforts.

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This study aimed to clarify the spatial patterns and geographic characteristics of tourism-accommodation hotspots from the perspective of proximity to facility locations. This study analyzed the case of Kyoto City, one of the most famous tourist cities in the world. In this study, the tourism-accommodation intensity index was calculated as the ratio of the number of accommodation rooms to that of households. This study used the tourism-accommodation intensity index and conducted a hotspot analysis. The hotspot analysis revealed statistically significant spatial patterns of high values (hotspots) and low values (cold spots). The hotspot areas indicate zones with a loss of balance between accommodations and housing at the neighborhood scale. Additionally, policy-makers must identify areas at risk of becoming high-intensity tourism hotspots. Therefore, this study analyzed the geographic relationship between tourism-accommodation intensity and proximity to facility locations via OLS and multiscale geographically weighted regression (MGWR). The results reveal that policy-makers should develop urban planning zones that prevent the emergence of high-intensity tourism hotspots.

## 2. Literature review

### 2.1. Tourism-accommodation intensity index

This study used the tourism-accommodation intensity index. As the basis for this index, the tourism intensity index has been used in many studies. The tourism intensity index is similar to the tourism pressure index from the sustainable tourism perspective (Gogonea, Baltălungă, Nedelcu, & Dumitrescu, 2017; van der Borg, Costa, & Gotti, 1996). Using the tourism intensity index, Van der Borg, Costa and Gotti, (1996) analyzed seven European heritage cities and reported that tourism negatively affects the integrity of their heritage and the quality of life of their residents. Therefore, they asserted the necessity of measures to control the tourism intensity index by guiding visitor flow (van der Borg et al., 1996). The adverse effects of tourism on residents' satisfaction with living in high-intensity tourism areas have been reported (Lança, Silva, Andraz, Nunes, & Pereira, 2024). In addition, there is a direct relationship between tourism intensity and local deficits in the smallest and largest municipalities (Voltes-Dorta, Jiménez, & Suárez-Alemán, 2014). Therefore, the tourism intensity index has been used as an indicator to determine the risk of overtourism (Widz & Brzezińska-Wójcik, 2020). These studies suggest that urban policy-makers should control the tourism intensity index. Therefore, this study used the tourism-accommodation intensity index to analyze spatial patterns and geographic characteristics to determine urban planning zones that may prevent the emergence of high-intensity tourism hotspots.

In general, the tourism intensity index is calculated as the ratio of tourism accommodation establishments relative to the total resident population (Batista e Silva et al., 2018; European statistics, 2016; Manera & Valle, 2018; van der Borg et al., 1996). Many policy-makers use the tourism intensity index frequently. For example, in Portugal, the calculated tourism intensity index for each city is published online (TravelBI, 2024). Compared with the basic calculation method, some studies have adopted the tourism intensity index to divide the number of beds by the population (Cerezo-Medina et al., 2022; Vandarakis et al., 2023). In addition, some studies analyzed the tourism intensity index that is calculated using economic tourism revenue (Manera & Valle, 2018; Voltes-Dorta et al., 2014). Based on the calculation, the tourism intensity index has been improved with the latest data and analytical methods for more detailed analysis. For example, the spatiotemporal pattern of tourism was analyzed by a tourism intensity index to examine online booking services containing the precise location and capacity of tourism accommodations (Batista e Silva et al., 2018). In addition, a new tourism intensity index using high-resolution GPS data has been proposed as a tool for effective urban planning and tourism management (Mashkov & Shoval, 2023).

Based on the index, this study developed and used the tourism-

accommodation intensity index, which is the ratio of the total number of accommodation rooms to the number of households. The reason this study used the tourism accommodation intensity index rather than the tourism intensity index is related to traditional Japanese hotels (ryokans). Ryokans do not use beds. Instead of beds, ryokans use *futon*s, traditional Japanese bedding systems that typically lay mattresses, quilts, and pillows on the floor rather than placing them on a bed frame. In addition, many ryokans and accommodations are charged per room, not per bed. Therefore, an index based on the number of beds does not adequately reflect the proper tourism intensity in the context of Japanese traditional culture, especially in Kyoto. For these reasons, we calculate the tourism-accommodation intensity index using the number of rooms instead of the number of beds. The tourism-accommodation intensity index indicates the balance between accommodations and housing at the neighborhood scale. The tourism-accommodation intensity index contributes to the designation of zoning areas to monitor the tourism-accommodation intensity hotspots.

### 2.2. Spatial patterns of tourism accommodations

The location of accommodations has been studied for a long time. First, Yokeno (1968) proposed the location model of accommodations, which is a concentric land-use model based on the land-rent curve principle. In the concentric model of Yokeno (1968), accommodations located between the central business district and commercial land use zones. The concentric model was confirmed based on the average room rate (Shoval, 2006). In addition, accommodations closer to the center have higher average room rates, which tend to be five-star hotels (Shoval, 2006). This result was also found in the Alonso model of bid-rent analysis, which determined the types of hotels according to the distance from the city center (Egan & Nield, 2000). Large tourist hotels are located in periphery areas, unlike the city center, where five-star hotels are located (Egan & Nield, 2000). In addition, accommodations in the periphery are affected by railway stations (Arbel & Pizam, 1977). As a result, it was suggested that the location of accommodations should be based on a concentric circle model that takes into account the location of railway stations (Ashworth, 1989). Based on this model, there is a risk of emerging tourism-accommodation hotspots in the peripheral areas of the historic center.

To prevent the formation of tourism-accommodation hotspots, some municipalities have developed urban zoning plans to regulate the volume of STRs (von Briel & Dolnicar, 2021). In Barcelona, urban planning zoning (called PEUAT) divides the city into four zones, designating the historical center as Zone 1, which prohibits the opening of new accommodations to increase accommodation capacity, even if previous accommodations have shut down (Ajuntament de Barcelona, 2024). Zonal regulation in Barcelona is effective in decongesting accommodations from the historical center (Bei, 2025). The same urban planning zoning approach has been developed in Madrid and Donostia-San Sebastian (Calle-Vaquero, García-Hernández, & Mendoza de Miguel, 2020). However, in the case of Hoi An Ancient Town in Vietnam, World Heritage Site zoning was reported to cause a decline in population and local shops via the transformation of "museumification" (Jones, Bui, & Ando, 2022). Faced with such issues, we do not have clear evidence for determining where to designate zoning areas at the neighborhood scale. To specify these zoning areas, it is necessary to understand the geographic characteristics of accommodations. Therefore, this study also analyzed the geographic characteristics of tourism-accommodation hotspots.

The geographic characteristics of hotels and STRs have been studied in relation to accommodations. In geographic characteristic analysis, distance plays an important role (Benítez-Aurioles, 2018). In Beijing, for example, the location of hotels is associated with accessibility to subways and tourist sites (Yang, Wong, & Wang, 2012). In the United States, a strong spatial relationship between hotels and constructed amenity facilities has been reported (Lee et al., 2018). Additionally, the

distribution of upper-grade hotels is related to commercial facilities and the number of attractions in Hong Kong (Li, Fang, Huang, & Goh, 2015). Like hotels, STRs are located near subways in Seoul (Ki & Lee, 2019). In addition, in Barcelona, STRs benefit more than hotels from their proximity to sightseeing locations (Gutiérrez et al., 2017). However, in Boston, increased incidents of private conflict and social disorder have been reported due to the increase in listed accommodations (Ke, O'Brien, & Heydari, 2021). On the basis of the findings regarding facility types, this study analyzed the geographic characteristics of tourism-accommodation intensity hotspots with proximity to facility locations. The novelty of this study is the analysis of tourism-accommodation intensity instead of the number of listed accommodations. In previous studies, geographic characteristics have been analyzed via artificial intelligence technology (Chen & Wang, 2022) and geographically weighted regression (GWR) (Lagonigro, Martori, & Apparicio, 2020; Lee, Jang, & Kim, 2024). The advantage of this study's analysis method is the use of MGWR, which allows for a more nuanced analysis of spatial patterns.

### 3. Materials and methods

#### 3.1. Case study

This study analyzed the case of Kyoto City. Fig. 1 shows a map and some images of the city of Kyoto. Kyoto City is one of the most famous tourist cities in the world. As of April 2024, the population of Kyoto City was approximately 1,375,000, and the number of households was approximately 737,000. Additionally, Kyoto City has an area of 827.9 km<sup>2</sup>. Kyoto City's historical center has been the capital of Japan for approximately 1200 years. There are fourteen UNESCO World Heritage Sites (WHs) in Kyoto City (UNESCO, 1994). Even more important than historical sites, however, is the culture that has taken root in the lives of local people (Kyoto City Government, 2021). The younger generation has preserved traditional culture, such as the Gion Festival (Brumann, 2009). To experience traditional culture, in April 2024, approximately 290,000 Japanese tourists and approximately 678,000 foreign tourists stayed overnight in Kyoto City (Kyoto City Tourism Association, 2024). This number of tourists was greater than that in 2019 before the COVID-19 pandemic. The increase in accommodations caused the increase in the number of tourists. According to the list on [booking.com](https://www.booking.com), there are over 3000 accommodation listings in Kyoto City, which is equal to or greater than in other tourist cities, such as Barcelona and Madrid

([Booking.com](https://www.booking.com), 2024).

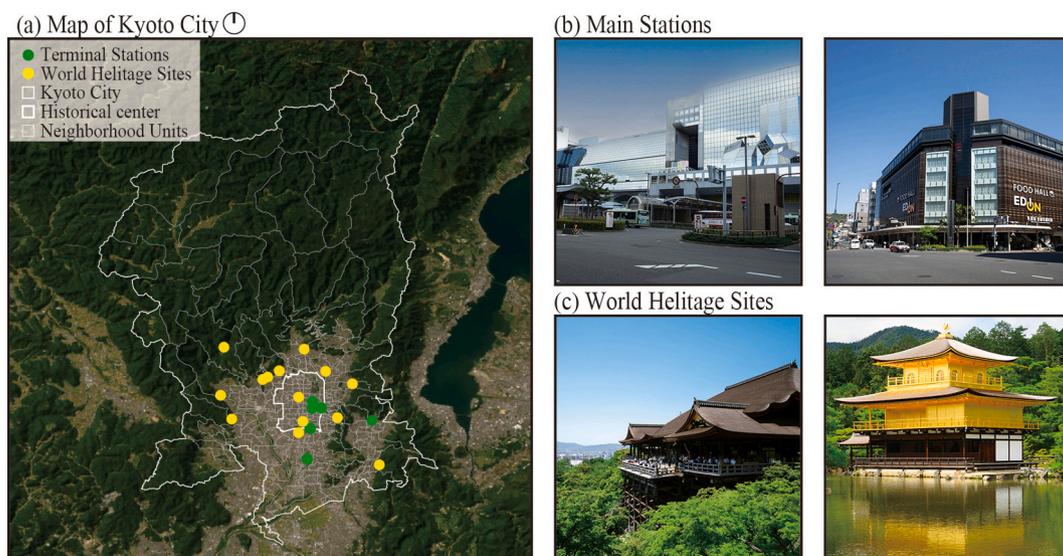
Like tourist cities worldwide, Kyoto City has suffered from a decline in population due to tourism gentrification in the historic center (Kato & Takizawa, 2022). The historical center of Kyoto City includes the Shimogyo, Nakagyo, and Kamigyo wards, which housed the capital area for approximately 1200 years. The population decline in the historical center is correlated with urban transportation from houses to accommodations (Tanaka et al., 2023). Tourism gentrification has also placed housing affordability at risk by increasing real estate prices (Yoshida & Kato, 2023). Population decline is a serious issue for maintaining traditional culture. Population loss due to tourism gentrification is perceived negatively by local communities (Kato, 2020). Therefore, local communities have addressed these issues by developing guidelines (Kato, 2022). With respect to these issues, the Kyoto City government has also developed regulations for accommodations that apply to the host's location (Sakuma & Kato, 2024). In addition to regulations, the Kyoto City government must regulate urban zones for accommodations in specific neighborhoods. Tourism-accommodation intensity hotspots' spatial patterns and geographic characteristics provide valuable insights into designating these zoning areas.

In this study, the analysis unit was the neighborhood-unit scale, which is the elementary school district scale. Neighborhood-units are neighborhoods based on elementary schools that are governed by local communities in aspects such as education, welfare, and disaster prevention (Kyoto City Library of Historical Documents, 2003). In Kyoto City, the neighborhood-unit scale is the basis on which communities make decisions about urban planning (Kato, 2022; Yoshida & Kato, 2023). Therefore, the neighborhood-unit scale was appropriate for this study.

The analysis period was 1 April 2024. Like other cities, Kyoto's tourism industry was affected by the COVID-19 pandemic (Kamino & Kato, 2024). However, by April 1, 2024, Kyoto City had recovered from the COVID-19 pandemic and was visited by many tourists (Kyoto City Tourism Association, 2024). The April 1 date was set to coincide with the release of household data from the basic resident register in Kyoto City (Kyoto City Statistics Portal, 2024).

#### 3.2. Data

This study used three types of data. The household and accommodation dataset from 1 April 2024 was used to analyze the tourism-accommodation intensity index. The household data are the basic



**Fig. 1.** Map of Kyoto City. (a) Map of the city of Kyoto. (b) Pictures of main stations (Kyoto Station and Kawaramachi Station). (c) Pictures of world heritage sites (Kiyomizu temple and Kinkaku temple). In Fig. 1(a), the satellite photos were obtained via ArcGIS PRO 3.0, copyright ArcGIS World Imagery (Arc GIS, 2024).

resident register data, which are available online from the Kyoto City government (Kyoto City Statistics Portal, 2024). The basic resident register data comprises records of residents by city municipality to provide basic administrative services to residents (MIC, 2024). The Kyoto City government publishes only the household numbers of each neighborhood-unit every three months. This study used household data as of April 1, 2024.

Additionally, this study used the accommodation dataset published on the Rakuten Travel website (Rakuten Travel, 2024). Recent studies have focused on online booking services as effective data sources of detailed information on the accommodation supply (Batista e Silva et al., 2018; Le, Phan-Thi, Nguyen, & Nguyen, 2025). The Rakuten Travel website is a Japanese online booking service that handles most of the accommodations in Japan. The website lists accommodations according to the number of rooms. It primarily displays accommodations that can be reserved on the day of the visit. Therefore, this study conducted web scraping for the accommodation data listed on the Rakuten Travel website (Rakuten Travel, 2024). Web scraping extracted the name, address, and room counts of accommodations listed between March 29 and April 4, four days before and after April 1, 2024.

This study used facility location data to analyze the geographic characteristics that form tourism-accommodation intensity hotspots. The facility location data were geographic information system data with location data published by the Japanese government (MLIT of Japan, 2024). The seven types are WHSs, cultural properties, leisure facilities, main stations, bus stops, police stations, and city halls. The facilities were selected following previous studies (Ki & Lee, 2019; Lee et al., 2018; Li et al., 2015; Yang et al., 2012). In this study, the main stations are defined as railway stations used by an average of 50,000 people per day.

### 3.3. Statistical analysis

This study conducted three analyses. First, the tourism-accommodation intensity index was analyzed on the basis of the ratio of the number of accommodation rooms to the number of households in each neighborhood unit. The tourism-accommodation intensity index was calculated via Eq. (1).

$$\text{Tourism - accommodation intensity index} = \frac{N_{room}}{N_{household}} \quad (1)$$

where  $N_{room}$  is the total number of accommodation rooms in each neighborhood-unit, obtained from the Rakuten Travel website (Rakuten Travel, 2024).  $N_{household}$  is the total number of households in each neighborhood-unit, obtained from the basic resident register data (Kyoto City Statistics Portal, 2024).

Second, this study used the tourism-accommodation intensity index and estimated the tourism-accommodation intensity hotspots via the Getis-Ord  $G_i^*$  statistic. The Getis-Ord  $G_i^*$  shows where high- or low-value features are spatially clustered (Getis & Ord, 1992). For the hot-spot analysis, Getis-Ord  $G_i^*$  was calculated via Eq. (2). The conceptualization of spatial relationships was set as the inverse distance, where nearby neighboring features exert a greater influence on computing target features than do features that are far away.  $G_i^*$  indicates the Z score of the standard deviation. A Z score of 1.65 or + 1.65 corresponds to a 90 % confidence level; a Z score of 1.96 or + 1.96 corresponds to a 95 % confidence level; and a Z score of 2.58 or + 2.58 corresponds to a 99 % confidence level.

$$G_i^* = \frac{\sum_{j=1}^n w_{ij}x_j - \bar{X}W_i}{S\sqrt{\frac{nW_i^2 - (W_i)^2}{n-1}}} \quad (2)$$

$$\bar{X} = \frac{\sum_{j=1}^n x_j}{n} \quad (3)$$

$$S = \sqrt{\frac{\sum_{j=1}^n (x_j - \bar{X})^2}{n}} \quad (4)$$

$$W_i = \sum_{j=1}^n w_{ij} \quad (5)$$

where  $n$  is the total number of neighborhood-units.  $w_{ij}$  is the spatial weight between neighborhood-unit  $i$  and neighborhood-unit  $j$ .  $x_j$  is the attribute value (tourism-accommodation intensity, which is calculated via Eq. (1)) at neighborhood-unit  $j$ .  $\bar{X}$  is the mean of the attribute values (tourism-accommodation intensity), which is calculated via Eq. (3).  $S$  is the standard deviation of the attribute values (tourism-accommodation intensity), which is calculated via Eq. (4).  $W_i$  is the sum of the spatial weights for neighborhood-unit  $i$ , which is calculated via Eq. (5).

Third, this study used the ordinary least squares (OLS) and MGWR to analyze the geographic characteristics of tourism-accommodation hotspots. The OLS model was used to verify the results of the MGWR model. In the OLS and MGWR analyses, the dependent variable was set to the tourism-accommodation intensity (Getis-Ord  $G_i^*$ ) of each neighborhood-unit, which was calculated via Eq. (1). The explanatory variables were the nearest distances to the neighborhood-unit for each of the seven facilities. The confounding variable was the area of each neighborhood-unit, in reference to the previous analysis of Kyoto City (Sakuma & Kato, 2024). The units of area and nearest distance were ha and km, respectively. This research model's novelty is that the dependent variable is the tourism-accommodation intensity score rather than the number of listed accommodations.

The MGWR was calculated via Eq. (6). MGWR is a spatial regression analysis method that accounts for spatial heterogeneity by allowing each variable to operate at different spatial scales (Fotheringham, Yang, & Kang, 2017). Although GWR applies a single spatial scale to all explanatory variables to capture spatial variation, MGWR provides greater flexibility by allowing each explanatory variable to have its own spatial scale, facilitating a more nuanced analysis of spatial patterns. In this study, the neighborhood selection method was the golden search, which finds the optimal value by successively narrowing the range of values inside which the optimal value exists and comparing the optimization score of the model for each. The results indicate the coefficients' mean, standard deviation, min, medium, max, and significance. The model fit of the MGWR was verified by  $R^2$ , adjusted  $R^2$ , and the corrected Akaike information criterion (AICc).

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \quad (6)$$

where  $y_i$  is the value of the dependent variable at neighborhood-unit  $i$ .  $x_{ik}$  is the value of explanatory variable  $k$  at neighborhood-unit  $i$ .  $(u_i, v_i)$  are the spatial coordinates (longitude and latitude) of neighborhood-unit  $i$ .  $\beta_0(u_i, v_i)$  is the spatially varying intercept at neighborhood-unit  $i$ .  $\beta_k(u_i, v_i)$  is the spatially varying coefficient of explanatory variable  $k$  at neighborhood-unit  $i$ .  $\varepsilon_i$  is the error term at neighborhood-unit  $i$ .

## 4. Results

### 4.1. Basic statistics of tourism-accommodation intensity

Table 1 shows the basic statistics for the room, household, and tourism-accommodation intensity of neighborhood-units in April 2024. The average room, household, and tourism intensities were 252.07, 3335.18, and 0.16, respectively. Additionally, the standard deviations of the room, household, and tourism intensities were 637.20, 2224.85, and 0.49, respectively. The results indicate that the tourism-accommodation intensity in Kyoto City is not particularly high. Additionally, the median (IQR) of tourism-accommodation intensity was 0.01 (Q1: 0.00, Q3: 0.08). However, the maximum tourism-accommodation intensity was 5.31. The results indicate the possibility of extremely high local tourism-

**Table 1**

Basic Tourism-Accommodation Intensity Statistics of Neighborhood-Units in April 2024.

	Rooms	Households	Intensity
Average:	252.07	3335.18	0.16
Standard deviation:	637.20	2224.85	0.49
Max:	5414	12,027	5.31
Medium (IQR):	19 (Q1: 1, Q3: 213)	2995 (Q1: 1573, Q3: 4586)	0.01 (Q1: 0.00, Q3: 0.08)
Min:	0	21	0.00

intensive neighborhood-units.

Fig. 2 shows the tourism-accommodation intensity of each neighborhood unit in Kyoto City. Fig. 2(a) indicates that the tourism-accommodation intensity of most neighborhood-units ranged from 0 to 0.5, especially in the outskirts of the historical center of Kyoto. However, Fig. 2(b) shows that the neighborhood-units with high tourism-accommodation intensity were located in the southeastern part of the historical center of Kyoto City. These results suggest that hotspots may have emerged in the southeastern historical center area.

#### 4.2. Hotspots of tourism-accommodation intensity

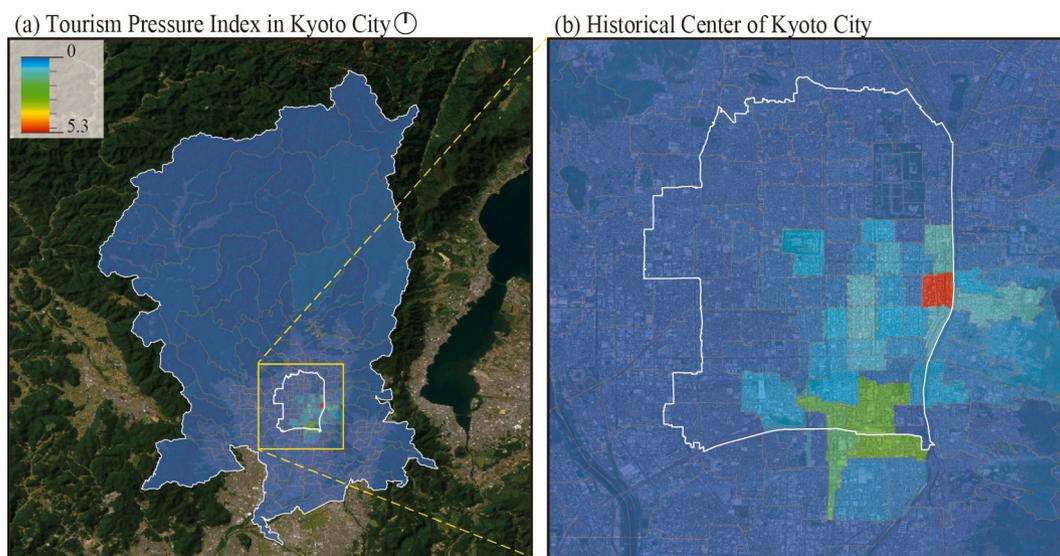
This study analyzed tourism-accommodation intensity hotspots via the Getis-Ord  $G_i^*$  statistic. Fig. 3 shows the hotspots of high tourism-accommodation intensity in Kyoto City. Fig. 3 shows two hotspots across six neighborhood-units near the periphery of the southeastern part of the historical center of Kyoto City: neighborhood-units of Rissei (5.31), Sannou (2.88), Kaizan (2.64), Annei (1.76), Kujo-Koudo (1.53), and Douda (1.02). Therefore, a hotspot emerged with a threshold tourism-accommodation intensity score of 1.0 in the city of Kyoto. This threshold of 1.0 means that the number of rooms has exceeded that of households based on Eq. (1). With respect to geographic characteristics, four neighborhood-units emerged as hotspots near Kyoto Station in the southern part of the historical center. Additionally, two neighborhood-units emerged as hotspots near Kawaramachi Station in the eastern part of the historical center. These results suggest that tourism-accommodation intensity hotspots tend to emerge near main railway stations.

#### 4.3. Multiscale geographically weighted regression

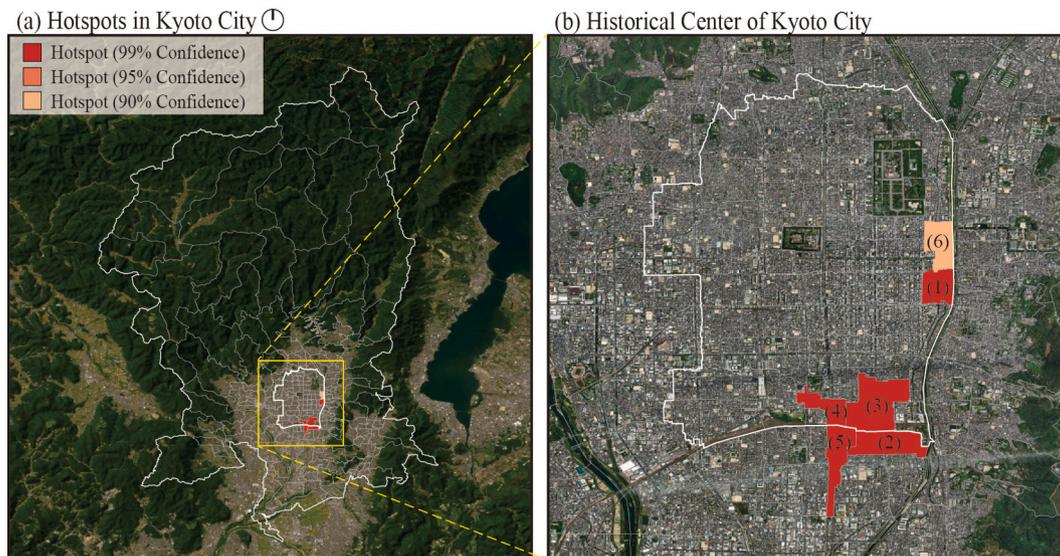
Table 2 shows the results of the OLS and MGWR models. In the OLS model, tourism-accommodation intensity was significantly correlated with three urban facilities: the proximity to WHSs was 16.72 (95 % CI ranged from 0.65 to 32.79); the proximity to main stations was -14.91 (95 % CI ranged from -22.03 to -7.79); and the proximity to city halls was -28.67 (95 % CI ranged from -53.70 to -3.65). Specifically, neighborhood units far from WHSs are likely to have high-intensity tourism-accommodation hotspots. Moreover, neighborhood-units closer to the main stations and city halls are likely to have high-intensity tourism-accommodation hotspots. However, the reliability of these results is problematic because the model goodness of fit for OLS was low ( $R^2 = 0.113$ ; adjusted  $R^2 = 0.080$ ; RMSE = 0.967).

In Table 2, the model fit for MGWR was slightly higher than that of the general regression models ( $R^2 = 0.367$ ; adjusted  $R^2 = 0.262$ ; AICc = 617.252). However, the model fit score was appropriately compared with the spatial patterns of accommodations analysis in previous studies (Ki & Lee, 2019; Lagonigro et al., 2020; Lee et al., 2020; Li et al., 2015; Sarkar, Pick, & Jabeen, 2023; Yang et al., 2012).

As shown in Table 2, tourism-accommodation intensity is significantly correlated spatially with proximity to main stations (227, 100 %) and WHSs (19, 8.37 %). Fig. 4 shows the distribution of coefficients for each main station and WHS. Table 2 shows that the main station coefficients are spatially negatively correlated with tourism-accommodation intensity (mean: -0.50 [min: -0.54, max: -0.48]). This result means that neighborhood-units closer to the main station are likely to have high-intensity tourism hotspots, which suggests that an imbalance exists between houses and accommodations in highly accessible neighborhood-units. Additionally, Table 2 shows that the WHS coefficients were spatially slightly and significantly correlated with tourism-accommodation intensity (mean: 0.23 [min: 0.20, max: 0.27]). This result indicates that neighborhood-units far from WHSs tend to be tourism-accommodation intensity hotspots. Notably, tourism-accommodation intensity was not significantly spatially correlated with proximity to city halls. Additionally, this study revealed that tourism-accommodation intensity was not spatially correlated with other urban facilities, such as cultural properties, leisure facilities, bus stops, city halls, or police stations.



**Fig. 2.** Tourism-Accommodation Intensity of Each Neighborhood-Unit. The left side (a) shows Kyoto city, and the right side (b) focuses on the historical center of Kyoto city. In Fig. 2, the satellite photos were obtained via ArcGIS PRO 3.0, copyright ArcGIS World Imagery (Arc GIS, 2024).



**Fig. 3.** Tourism-Accommodation Intensity Hotspots of Each Neighborhood-Unit. The left side (a) shows Kyoto city, and the right side (b) focuses on the historical center of Kyoto city. On the right side, (b) shows the neighborhood-units of (1) Rissei, (2) Sannou, (3) Kaizan, (4) Annei, (5) Kujo-Koudo, and (6) Douda. The satellite photos shown in Fig. 3 were obtained via ArcGIS PRO 3.0, copyright ArcGIS World Imagery (Arc GIS, 2024).

**Table 2**  
Estimation Results of OLS and MGWR Model Coefficients.

	OLS model		MGLW model			
	B	95 % CI	Mean	Min	Max	Significance
Proximity to WHS:	16.72*	0.65, 32.79	0.23	0.20	0.27	19 (8.37 %)
Proximity to cultural properties:	-6.16	-25.07, 12.74	-0.04	-0.06	-0.03	0.00 (0.00 %)
Proximity to leisure facilities:	3.03	-13.14, 19.21	0.04	0.02	0.05	0.00 (0.00 %)
Proximity to main stations:	-14.91**	-22.03, -7.79	-0.50	-0.54	-0.48	227 (100.00 %)
Proximity to bus stops:	12.88	-64.27, 90.03	-0.01	-0.03	0.02	0.00 (0.00 %)
Proximity to city hall:	-28.67*	-53.70, -3.65	-0.11	-0.12	-0.07	0.00 (0.00 %)
Proximity to police stations:	11.13	-28.62, 50.88	0.01	-0.03	0.03	0.00 (0.00 %)
Area (omitted variable):	0.00	0.00, 0.00	0.13	0.13	0.14	0.00 (0.00 %)
Intercept:	0.53**	0.28, 0.78	0.01	-0.51	1.28	28 (12.33 %)
R <sup>2</sup>	0.113		0.367			
Adjusted R <sup>2</sup>	0.080		0.262			
RMSE	0.967					
AICc			617.252			

Notes: B is the regression coefficient; SE is the standard error; 95 % CI is the 95 % confidence interval; \* is a p value <0.05; \*\* is a p value <0.01.

## 5. Discussion

### 5.1. Hotspots in Kyoto City

This study investigated the spatial patterns and geographic characteristics of tourism hotspots from the perspective of proximity to facility locations in Kyoto City. In this study, the tourism-accommodation intensity index was calculated as the ratio of the number of accommodation rooms to that of households. The results revealed that tourism-accommodation intensity hotspots emerged across six neighborhood-units near the periphery of the southeastern part of the historical center. This result differs from the hotel's location model, which assumed a concentric circle model in previous studies (Shoval, 2006; Yokeno, 1968). Four neighborhood-units emerged as hotspots near Kyoto Station in the southern part of the historical center. Additionally, two neighborhood-units emerged as hotspots near Kawaramachi Station in the eastern part of the historical center. The results for these peripheral hotspots differed from those in Barcelona (Gutiérrez et al., 2017; Lagonigro et al., 2020) but were the same as those in Madrid (Álvarez-Herranz & Macedo-Ruiz, 2021; Martínez, Sequera, & Gil, 2024). The hotspots indicate neighborhood-units with a disrupted balance between the number of residences and the number of accommodations. The

hotspots emerged with a threshold tourism-accommodation intensity score of 1.0, indicating that the number of rooms has exceeded that of households in these areas. On the basis of these spatial patterns, the Kyoto City government must develop urban planning zoning that prevents these hotspots from emerging. This policy will help prevent population decline and preserve the culture of local residents.

Additionally, this study revealed via MGWR analysis that the locations of tourism hotspots were significantly associated with proximity to main stations (mean: -0.50 [min: -0.54, max: -0.48]) and WHSs (mean: 0.23 [min: 0.20, max: 0.27]). This result means that neighborhood-units closer to main stations are more likely to have tourism-accommodation intensity hotspots. The result of this study confirmed the previous research that indicated the location of hotels near railway stations in periphery areas (Arbel & Pizam, 1977; Ashworth, 1989). The geographic characteristics of proximity to stations or subways are the same as those of hotels in Beijing (Yang et al., 2012) and STRs in Seoul (Ki & Lee, 2019). However, this study clarified the spatial correlation between tourism hotspots and main stations rather than ordinary stations in Kyoto City. Moreover, neighborhood-units that are far from WHSs tend to have tourism-accommodation hotspots. Notably, the geographic characteristics of the WHSs in Kyoto City differ from those in other tourist cities because many cities tend to have many STRs

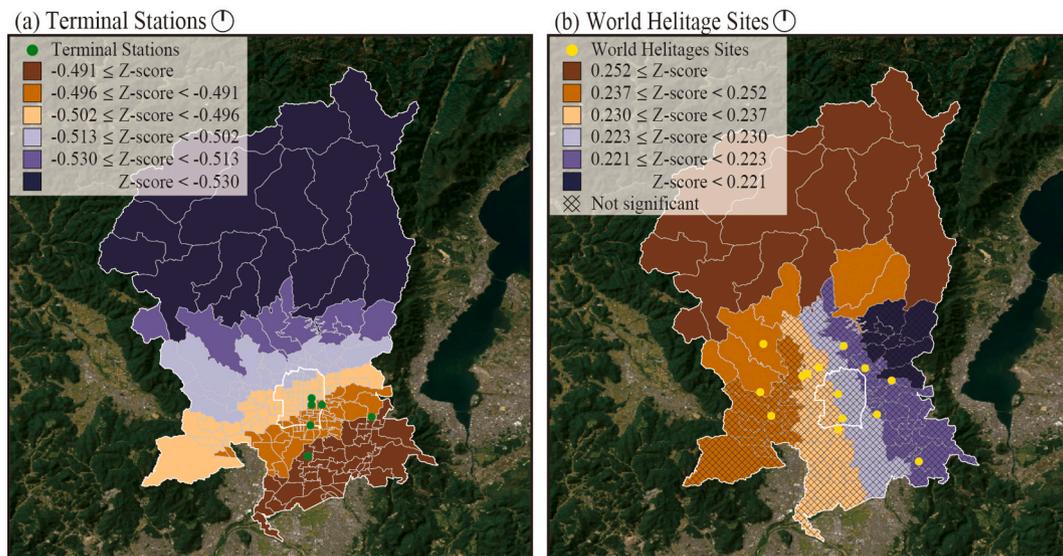


Fig. 4. MGWR Model Coefficients of Significant Variables. The left side (a) shows the coefficients of the main stations, and the right side (b) shows those of the world heritage sites. The satellite photos shown in Fig. 4 were obtained via ArcGIS PRO 3.0, copyright ArcGIS World Imagery (Arc GIS, 2024).

(Gutiérrez et al., 2017) and hotels (Yang et al., 2012) in areas close to WHSs. The results suggest that the urban planning regulations in Kyoto City are effectively implemented in areas close to world heritage areas. Therefore, the Kyoto City government must develop urban planning zoning to prevent the emergence of tourism-accommodation intensity hotspots near main stations.

Finally, no spatial correlations were observed between tourism-accommodation intensity hotspots and proximity to other urban facilities, including cultural properties, leisure facilities, bus stops, city halls, or police stations in Kyoto City. Interestingly, proximity to city halls was correlated with tourism-accommodation hotspots in the OLS model but not the MGWR model. The result indicates that city halls had no spatial relationship with tourism-accommodation hotspots. In addition, this study revealed that the tourism-accommodation index was not correlated with leisure facilities, although such correlations have been documented in other tourist cities (Lee et al., 2018; Li et al., 2015). This result suggests that few tourists visit leisure facilities because Kyoto City has many WHSs. In addition, tourism-accommodation hotspots were not statistically significantly correlated with proximity to bus stops or police stations in Kyoto City. The results in Kyoto City were the same as those in Seoul (Ki & Lee, 2019). Understanding the relationships among these unrelated urban facilities is valuable in the development of urban regulatory zoning.

## 5.2. Theoretical and practical implications

This study's main theoretical contribution is its clarification of the geographic characteristics of the areas in which tourism-accommodation hotspots form. Like other tourist cities such as Barcelona and Madrid, Kyoto City has excess accommodations, which caused tourism gentrification (Kato & Takizawa, 2022; Tanaka et al., 2023; Yoshida & Kato, 2023). Several studies have analyzed uneven accommodation distributions, with a focus on STRs in tourist cities (Álvarez-Herranz & Macedo-Ruiz, 2021; García-Amaya et al., 2021; Garcia-Ayllon, 2018). Recent studies have discussed the issue of STR locations extending beyond the historical center to the peripheral areas where people live (Gutiérrez et al., 2017; Ki & Lee, 2019). In these peripheral areas, it is important to consider the balance between accommodation and housing and account for the tourism capacity of the area rather than simply the number of accommodations. The collapse of this balance could lead to a population decline in these areas that goes beyond simple displacement (Kato & Takizawa, 2022; Tanaka et al., 2023). As shown in

other studies, this study also confirmed that unbalanced areas are on the periphery of historic centers. However, our results revealed that these hotspots are distributed unevenly in the peripheral areas of the historic center. The novelty of our findings is our highlighting of the peripheral areas near the main stations. The results of this study could be generalized to tourist cities that face problems caused by excessive accommodation growth.

Regarding practical implications, our findings support the effectiveness of urban planning zoning policies. Tourist cities worldwide have implemented regulations of accommodations to ensure the sustainable growth of the tourism industry with a balanced market (Bei & Celata, 2023). These regulations are also designed to reduce the negative effects of tourism on neighborhood communities (Nieuwland & van Melik, 2020). Such regulations include licensing requirements, license fees, location zoning, guest days, violation fines, and taxation (von Briel & Dolnicar, 2021). Many cities in Spain, including Barcelona, have implemented zoning for accommodations (de la Calle-Vaquero, García-hernández, & de Miguel, 2021). Therefore, the Kyoto City government should define zones for those neighborhood-units that are close to the main stations in the historical center. The results of this study show the effectiveness of regulating the total volume of accommodations on the basis of the tourism-accommodation intensity index. In Kyoto City, hotspots emerged in neighborhood-units where the tourism-accommodation intensity exceeded 1.0, the same as PEUAT conducted in Barcelona. Therefore, designated zoning areas would be an effective policy for neighborhood-units close to the historical center's main stations to ensure that the total number of rooms in accommodation facilities does not exceed the number of households.

## 5.3. Research limitations

This study has three research limitations. The first limitation concerns the explanatory power of the MGWR model. This study's model fit was appropriately compared with the spatial patterns of accommodations analysis in previous studies (Ki & Lee, 2019; Lagonigro et al., 2020; Lee et al., 2020; Li et al., 2015; Sarkar et al., 2023; Yang et al., 2012). However, according to the regression analysis results, the model fit in this study has weak explanatory power. Future research should explore models that incorporate other types of facilities. The second limitation is the risk of sampling bias. The number of accommodation rooms does not directly indicate the number of tourists. However, it is difficult to estimate the number of tourists in Kyoto City, which can be accessed from

various cities by land. Future research should calculate tourism-accommodation intensity on the basis of the number of tourists using smartphone GPS data. The third limitation is the generalizability of this study. This study analyzed one famous tourist city worldwide, Kyoto City. Like other tourist cities, Kyoto City has many WHSs and excess accommodations. However, the results of this study may not always be generalizable to cities in other situations. Therefore, comparative studies involving other cities are needed in the future.

## 6. Conclusion

Regardless of the research limitations, this study reached valuable conclusions. The study concluded that tourism-accommodation intensity hotspots have emerged near the periphery of the southeastern part of the historical center of Kyoto City. The hotspots emerged with a threshold tourism-accommodation intensity score of 1.0, meaning that the number of rooms exceeded the number of households. Additionally, this study revealed via MGWR analysis that tourism-accommodation intensity hotspots were associated with proximity to main stations. This result means that neighborhood-units closer to main stations are more likely to have tourism-accommodation intensity hotspots. The formulation of tourism-accommodation hotspots near main stations in peripheral areas could be generalized to tourist cities that face problems caused by excessive accommodation growth. The findings are important for developing effective urban zones in neighborhood-units that are close to main stations on the periphery of historical centers to ensure that the total volume of rooms in accommodations does not exceed the number of households.

## CRedit authorship contribution statement

**Haruka Kato:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

## Declaration of competing interest

Haruka Kato reports that financial support was provided by the Telecommunications Advancement Foundation Research Grant and JSPS KAKENHI (23K26284). If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Data availability

This study used three types of open-source datasets. The household data are the basic resident register data available online from the Kyoto City government ([Kyoto City Statistics Portal, 2024](#)). The accommodation dataset is published on the Rakuten Travel website ([Rakuten Travel, 2024](#)). The facility location data were geographic information system data with location data, which the Japanese government published ([MLIT of Japan, 2024](#)).

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