Why are hotel room prices different? Exploring spatially varying relationships between room price and hotel attributes

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ABSTRACT

Despite abundant research on modeling hotel room prices, traditional hedonic pricing models (HPMs) have failed to consider spatial variations in the relationships among hotel room price and attribute variables. This study demonstrates the utility of a spatial HPM (s-HPM) using a geographically weighted regression analysis of 387 hotels in the Chicago area. Specifically, this study explored spatial variations in modeling hotel room prices and further identified spatial clustering patterns of relationships between room price and hotel attributes across market segments. The findings reveal that the s-HPM successfully identified spatially varying relationships between room price and hotel attributes, such as site attributes – size, age, class and service quality – and situation attributes – distances to airports, highways and tourist attractions – across the study area. This study contributes to a better understanding of local patterns of modeling room prices, ultimately providing guidelines for effective location-based hotel room pricing strategies.

Keywords: hotel room prices; spatial hedonic pricing model; geographically weighted regression

1. Introduction

In recent years, discussions among tourism and hospitality scholars have increasingly attempted to address the fact that hotel room prices can be influenced differently by their site and situation attributes related to hotel location (Latinopoulos, 2018; Soler & Gemar, 2018). Site attributes refer to a hotel's physical or structural factors, such as size, class, age and service quality, while situation attributes refer to a hotel's outdoor environmental characteristics, such as proximity to airports, transportation stations and tourist attractions (Zhang et al., 2011a). Hedonic pricing models (HPMs) using ordinary least squares (OLS) regression have typically been employed to identify the determinants of hotel room prices (e.g., Chen & Rothschild, 2010; Monty & Skidmore, 2003; Schamel, 2012; Thrane, 2007; Zhang, Ye, & Law, 2011b). The HPM assumes that hotel room prices are a linear function of multiple site and situation factors (Zhang et al., 2011a; Zhang et al., 2011b).

However, the use of spatially referenced hotel attributes, such as site and situation attributes based on the hotel location, in a linear HPM may result in spatial effects, such as spatial dependence (i.e., spatial autocorrelation) and spatial heterogeneity (i.e., spatial non-stationarity). These spatial effects may not only violate the basic assumptions of OLS, including linearity, independence and homoscedasticity (Getis, 2007; Kim & Nicholls, 2016a), but also fail to explore important spatial variations in the relationships among the variables (Deller, 2010; Yang & Fik, 2014), which can lead to biased parameter estimates and misleading significance tests (Anselin, 1988). As noted by Gilbert and Chakraborty (2011), "the analysis of spatial data requires specialized techniques that are different from those used to analyze non-spatial data" (p. 274). Therefore, hotel room prices should be modeled using spatially explicit regression techniques that can account for geographic location and relevant spatial effects. Researchers have defined the spatial HPM (s-HPM) as an efficient type of HPM that addresses spatial non-stationarity, hence introducing less biased estimations of parameters (Kim, Phipps, & Anselin, 2003). Despite the importance of spatial effects, a few studies have recently used the s-HPM method to model hotel room prices (e.g., Zhang et al., 2011a; Latinopoulos, 2018; Soler & Germar, 2018).

The purpose of this study was therefore to demonstrate the utility of an s-HPM in the context of the tourism and hospitality market. To account for spatial effects, we employed an s-HPM using a geographically weighted regression (GWR) analysis, which has rarely been considered in previous hotel room price studies, via a case study of 387 hotels in the Chicago area, US. Specifically, this study (1) assessed whether the GWR-based s-HPM outperformed traditional HPMs, (2) explored important local variations (i.e., spatial heterogeneity) in modeling hotel room prices across the study area, and (3) identified market segment-based hotel room pricing strategies using the proposed GWR-based s-HPM. The findings of this study can help tourism and hospitality practitioners better understand local patterns in modeling hotel room prices, which is essential for facilitating the formulation of location-based hotel marketing strategies.

To the best of our knowledge, this is the first study to examine the feasibility of successfully implementing a location-based hotel room pricing strategy while taking into account spatially varying relationships between room price and hotel attributes. Following is a literature review on traditional (OLS-based) HPMs and s-HPMs. After the GWR-based s-HPM is introduced, the results of an empirical study of 387 hotels in the Chicago area are presented. Finally, based on the findings, methodological and practical implications for location-based room pricing strategies are discussed.

2. Literature review

2.1. Hedonic pricing approach in the hotel industry

Since Rosen (1974) proposed the theory of hedonic prices in the context of a competitive market, the HPM has commonly been applied to explain the variations in the market prices of residential properties that reflect the value of local environmental attributes (Freeman, 2003). The HPM assumes that the price of a marketed good is related to a bundle of its attributes or characteristics (Rosen, 1974). Under the hedonic price framework, a hotel room is a composite and heterogeneous product (Zhang et al., 2011a). Thus, the price of a hotel room is based not only on the characteristics of the hotel site, such as the hotel's size, age, class, and service quality (i.e., site attributes), but also on the characteristics of the location, such as the proximity to downtown, highways, tourist attractions, and airports (i.e., situation attributes). Multiple empirical studies employing different HPMs have indicated that the key determinants of hotel room prices include the hotel's star rating (Bull, 1994; Israeli, 2002; Latinopoulos, 2018; Zhang et al., 2011a), age (Bull, 1994; Zhang et al., 2011a), size (Coenders, Espinet, & Saez, 2003; De La Pena, Nunez-Serrano, Turrion, & Velazquez, 2016; Hung, Shang, & Wang, 2010; Lee & Zhang, 2012; Soler & Germar, 2018; Zhang et al., 2011a), class (Zhang et al., 2011b), service quality (Monty & Skidmore, 2003; Thrane, 2007; Zhang et al., 2011b), and proximity to tourist attractions (Carvell & Herrin, 1990; Santana-Jiménez, Sun, Hernandez, & Suarez-Vega, 2015; Zhang et al., 2011a), downtown (Bull, 1994; Lee & Jang, 2011; 2012; Soler & Gemar, 2018), airport (Lee & Zhang, 2011; Soler & Gemar, 2018), and transportation stations (Thrane, 2007; Zhang et al., 2011a).

Previous HPM approaches can be classified into the following three categories based on their techniques: (1) linear HPMs; (2) log-linear HPMs; and (3) s-HPMs (see Table 1). Linear HPMs are most commonly used to model hotel room prices. An OLS multiple regression analysis is typically employed to examine the influences of diverse site and situation determinants on hotel room prices. Carvell and Herrin (1990) used a linear HPM to measure the impacts of hotel amenities (e.g., food sales, gift sales, concierge service, gym, valet dry cleaning service, free local calling service, complimentary breakfast, and AAA rate) and proximity to a tourist attraction (e.g., Fisherman's Wharf) in San Francisco. Israeli (2002) also used a linear HPM to measure the impacts of the star rating, hotel brand (e.g., corporate affiliation) and location on room prices in 215 hotels in Israel. Recently, Zhang et al. (2011b) employed a linear HPM to investigate the influence of hotel class, size, location, cleanliness, and service quality on hotel room prices in New York City.

[Insert Table 1 about here]

Because using logs in a linear model is more effective for estimating heteroscedastic or skewed distributions and achieving a better model performance (Woodridge 2009), log-linear HPMs have also been used to model hotel room prices. Bull (1994) used semi-log and log-linear hedonic models to examine the influence of the star rating, hotel age, motel facilities (e.g., restaurant), hotel scenic view (e.g., riverside) and proximity to downtown on room prices in Ballina, Australia. Thrane (2007) employed a semi-log hedonic model to assess the influence of hotel brand, hotel amenities (e.g., mini-bar, free parking, restaurant, hairdryer, room service, and beds) and proximity to transportation stations on hotel room prices in Oslo, Norway.

Finally, s-HPMs represent another methodological approach for modeling hotel room prices. These models require consideration of spatial autocorrelation (spatial dependence) or the neighborhood effects of spatially referenced site and situation attributes. For example, Lee and Jang (2011) used an s-HPM to examine the dual effects of proximity to airports and central business districts (CBDs) in the US. Zhang et al. (2011a) employed a GWR-based s-HPM to measure the influence of hotel size, star rating, hotel age, and proximity to tourist attractions and transport hubs on hotel room prices in Beijing, China. Using a framework of bounded price competition, Lee and Jang (2012) also investigated the effects of hotel concentration on hotel room rates in downtown Chicago. Santana-Jimenez et al. (2015) used an s-HPM to estimate the quantitative influences of the rural environment on rural lodging room prices in Spain and Taiwan. Recently, by using a GWR-based s-HPM, Latinopoulos (2018) evaluated the effect of sea view on hotel prices in Halkidiki, Greece, and Soler and Gemar (2018) measured the effects of hotel category, size, location and other service attributes on room prices in Malaga, Spain.

2.2. *Traditional HPMs and spatial effects*

Traditional HPMs have commonly been conducted using OLS, which is a linear regression method used to model a dependent variable's association with a set of independent variables (Zhang et al., 2011a). OLS is based on the following two basic assumptions: (1) the observations are independent of one another and (2) there is a stationary relationship among the variables, i.e., a spatially constant relationship exists between the dependent and independent variables that can be interpreted by average (global) parameter estimates across an entire study area (Kim & Nicholls, 2016a; 2018). Spatial data include a variety of site and situation attributes that are based on the hotel location and may exhibit spatial effects, such as spatial dependence (i.e., spatial autocorrelation) and spatial heterogeneity (i.e., spatial non-stationarity).

Spatial dependence is defined as the spatial relationship of variable attributes or locations (Longley, Goodchild, Maguire, & Rhind, 2005). Spatial dependence is based on the premise that the value similarity is a result of locational proximity according to Tobler's First Law of Geography as follows: "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p. 236). Spatial heterogeneity is a special case of spatial dependence, representing spatial non-stationarity (Yang & Fik, 2014). As noted by Mennis and Jordan (2005), spatial heterogeneity is the tendency for "the relationships among the independent and dependent variables [to] vary over space" (p. 249). In other words, spatial heterogeneity is a spatially varying relationship between variables in which a global model cannot account for the relationships between some sets of variables (Gilbert & Charkraborty, 2011). Spatial heterogeneity occurs when a lack of spatial homogeneity is caused by the effects of spatial dependence between variables (Kim & Nicholls, 2016a). These spatial effects result in inaccurate regression results, including large residuals, misleading significance tests, and biased regression coefficients when employing non-spatial regression methods, such as OLS regression (Anselin, 1988). Thus, prior hotel pricing studies based on OLS-based HPMs did not consider these spatial effects by detecting the violations of the assumptions of OLS, such as homoscedasticity, linearity, and the independence and normality of residuals.

Although several studies have addressed spatial dependence using spatial econometric models to model hotel room prices (e.g., Lee and Jang, 2011; Santana-Jiménez et al., 2015; Zhang et al., 2011a), only a few studies (e.g., Zhang et al., 2011a; Latinopoulos, 2018; Soler & Germar, 2018) have simultaneously examined both spatial dependence and spatial heterogeneity in HPMs. Furthermore, these studies mainly focused on identifying local variations between room prices and hotel attributes without providing substantial location-based room pricing strategies. Location-based effective pricing is likely to be essential for service industries in general and the hotel industry in particular (Yang, Wong, & Wang, 2012) because this information may affect the choice of location for initial development and the business plan with regard to hotel design (Latinopoulos, 2018). As such, this study extends the prior literature on the utility of GWR-based s-HPMs by not only identifying local variations between room prices and hotel attributes but also providing location-based hotel room pricing strategies.

2.3. s-HPM with GWR

Because OLS-based HPMs cannot explore important local variations among variables, the assumption of spatial stationary in the HPM has been strongly questioned (Yoo, 2012). Therefore, considerable attention has been devoted to developing an s-HPM that can overcome the methodological limitations of the OLS-based linear HPM. Recently, GWR has become an effective spatial hedonic price analysis for addressing spatial effects, such as spatial dependence and spatial heterogeneity in spatial data. As a spatial statistical technique proposed by Fotheringham, Brunsdon, and Charlton (2003), GWR assumes that relationships between variables may differ from location to location. Thus, GWR can explore spatial heterogeneity in multivariate regression by generating regression coefficients for each observation point (Zhang et al., 2011a).

The OLS-based HPM can be expressed as follows:

$$\mathrm{PRICE}_i = \beta_0 + \sum_{j=1}^{k} \beta_j \chi_j + e_i$$

where PRICE_i is the hotel room price at the i^{th} point; i denotes the number of hotels (i = 1, 2, …, n); j is the number of site and situation variables (j = 1, 2, …, k); χ_j is the j^{th} variable explaining room prices, including the site and situation characteristics of a hotel; β_j is the associated parameter; and e_i is a random error term (Zhang et al., 2011a). The GWR-based s-HPM can extend the OLS-based HPM by allowing the local parameters to be estimated as follows:

$$PRICE_i = \beta_0(u_i, v_i) + \sum_{j=1}^{k} \beta_j (u_i, v_i)\, \chi_j + e_i$$

where (u_i, v_i) denotes the coordination of the i^{th} point in space and $\beta_j (u_i, v_i)$ is a realization of the continuous function at point i (Fotheringham et al., 2003). Thus, in contrast to a linear OLS-based HPM, the GWR-based s-HPM can explore important local variations in the relationships among the variables in space.

When estimating local parameters at each point in GWR, all observations are weighted by their spatial proximity to the regression point; observations closer to the regression point are weighted more than those located farther away (Kim & Nicholls, 2016a; 2018). Based on Tobler's (1970) First Law of Geography, two kernel functions, such as the Gaussian function and the bi-square function, are commonly employed to determine the spatial dependent weights (Zhang et al., 2011a). The Gaussian kernel function is defined as a kernel with a fixed bandwidth, whereas the bi-square kernel function is defined as a kernel with adaptive bandwidth (Fotheringham et al., 2003). The bi-square function has typically been employed in the hedonic price literature due to the spatial clustering of observations (residential properties) in space (Yoo, 2012). The spatial weight of the bi-square kernel function can be estimated as follows:

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

where d_{ij} is the Euclidean distance between regression point i and data point j, and b is the bandwidth. At regression point i, the weight of the observation is unity and falls to zero if the distance between i and j equals the bandwidth. If the distance between i and j is greater than the bandwidth, the weight of the observation is zero. The bandwidth may be defined by a fixed number of nearest neighbors from the location of the observation (Zhang et al., 2011a). The optimal number of nearest neighbors is typically determined by selecting a bandwidth that minimizes the Akaike Information Criterion (AIC) value, which is calculated as follows:

$$\mathrm{AIC} = 2n\log_e(\hat{\sigma}) + n\log_e(2\pi) + n\left(\frac{n+tr(S)}{n-2-tr(S)}\right)$$

where n is the number of observations in the dataset, $\hat{\sigma}$ is the estimate of the standard deviation of the residuals, and tr(S) is the trace of the hat matrix. According to Bozdogan (1987), the AIC value can be used when comparing the global model with a local GWR model.

Compared with OLS regression models, the corresponding GWR models provide significant benefits by mapping parameter estimates with better model performance (Fotheringham et al., 2003). Therefore, the GWR-based s-HPM has been widely utilized in housing market research (Bitter, Mulligan, & Dall'erba, 2007; Kestens, Theriault, & Des Rosiers, 2006). However, to date, only three studies (Zhang et al., 2011a; Latinopoulos, 2018; Soler & Gemar, 2018) have used GWR to study s-HPMs for hotel room pricing, and the present study further extends the literature on s-HPMs in two ways. First, this study identified and mapped spatial variations in modeling hotel room prices by employing a GWR-based s-HPM. Second, this study explored spatial clustering of hotel price-attribute relationships depending on each market segment using the estimated GWR coefficients.

3. Method

3.1. Study area

The Chicago area, specifically Cook County located in the US state of Illinois and including 30 townships, was selected as the study area. As of the 2015 census, Cook County was the second most populous county in the US, with a population of 5,246,456 and an area of 1,635 square miles (4,234.6 km^2) (U.S. Bureau of the Census, 2010). The county seat of Cook County is Chicago, a popular tourist destination in the US. According to U.S. News Travel (2015), Chicago was selected as one of the top 18 best places to visit in the US, with 50.2 million visitors (almost 50% of the visitors to Illinois). Furthermore, Cook County includes a high number and density of hotels. The Smith Travel Research (STR) Global (2015) stated that 387 (26.9%) of the 1,435 hotels in Illinois are concentrated in Cook County. This area also includes five tracts (submarkets) in the STR Chicago market: Chicago CBD, Chicago airport, Chicago north, Chicago northwest, and Chicago south.

Identifying the unit of analysis is a prerequisite for any spatial analysis. In this study, hotel location was utilized as the unit of analysis. Figure 1 illustrates the locations of the 387 hotels and other urban facilities, such as highway exits, airports and popular tourist attractions, within the study area.

[Insert Figure 1 about here]

3.2. Variable definition and data collection

Because standard room rates are often advertised as the hotel room price (Latinopoulos, 2018; Santana-Jimenez et al., 2015; Zhang et al., 2011b), the average standard room rate for one hotel night was defined as the dependent variable in this study. Several site attributes, such as the hotel size (Danziger, Israeli, & Bekerman, 2006; De La Pena et al., 2016; Espinet, Saez, Coenders, & Fluyia, 2003; Hung et al., 2010, Lee & Zhang, 2012; Soler & Gemar, 2018; Zhang et al., 2011a; Zhang et al., 2011b), hotel age (Bull, 1994; Hung et al., 2010), hotel class (Israeli, 2002; Zhang et al., 2011b) and service quality (Hartman, 1989; Thrane, 2007; Zhang et al., 2011b), were used as independent variables based on previous studies. Specifically, the hotel class was categorized as (1) economy, (2) midscale (midscale and upper midscale), and (3) upscale (upscale, upper upscale, and luxury) based on six STR hotel classes. The traveler rating reviews (five-point range) from TripAdvisor were used as a proxy for customers' perceived service quality (Zhang et al., 2011b).

Concerning a hotel's situation attributes, the hotel's geographic location is considered an important component influencing the hotel room price. Location can be represented as the distance from the focal hotel to airports (Lee & Jang, 2011; Soler & Gemar, 2018), highways (Bull, 1994; Wu, 1999; White & Mulligan, 2002) and local attractions (Carvell & Herrin, 1990; Monty & Skidmore, 2003; Zhang et al., 2011a). Thus, the A-Distance (i.e., the shortest road network distance from each hotel to the nearest airport), H-Distance (i.e., the shortest road network distance from each hotel to the nearest highway exit), and T-Distance (i.e., the average distance from each hotel to the seven most popular tourist attractions) were adopted as situation attribute variables in this study[1]. The seven most popular Chicago tourist attractions selected by USA Today (2015) included Architecture Tour, Millennium Park, Lincoln Park Zoo, The Second City, John Hancock Center, Shedd Aquarium, and Adler Planetarium. Geographic Information Systems (GIS)-based network distance was utilized to represent the actual landscape in this study. All dependent and independent variables and their operational definitions are summarized in Table 2.

[Insert Table 2 about here]

Location data for the airports and highway exits in the study area were downloaded from the Environmental Systems Research Institute (2016). Geographic data such as county boundaries and the street network were acquired from the University of Illinois at Springfield.

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[1] As noted by Kim and Nicholls (2016b), "Seven plus or minus two is the upper limit of the human brain's capacity to process information simultaneously" when considering multiple destination choices (p. 121).

Information regarding the hotel locations and site attributes (e.g., number of rooms, hotel age, and hotel class) was collected from STR Global. Data related to hotel service quality were extracted from the hotel ratings in TripAdvisor.

3.3. Data analysis

Various software programs, including ArcGIS (version 10.3.1), the ArcGIS Network Analyst extension, SPSS (version 20.0), R (version 3.4.4) and GWR (version 4.0), were employed for the data analysis. First, the shortest road network distances for the A-Distance, H-Distance and T-Distance variables were calculated by performing a GIS-based network analysis. Second, a descriptive analysis was conducted in terms of numeric description (e.g., mean, standard deviation, and correlation coefficient) and visualization of the distribution patterns of all variables using GIS. Third, a multiple regression analysis was performed using OLS to investigate the relationship between the hotel room price and the hotel attributes. Fourth, the same dependent variable and set of independent variables from the OLS regression were utilized using GWR to explore important local variations between the independent and dependent variables. While employing GWR, a bi-square kernel function (a kernel with adaptive bandwidth), which identifies a certain number of neighbors that maximizes model fit, was employed due to the varying density of hotels in the study area (Fotheringham et al., 2003). The significance of the spatial variability in the local coefficient estimates was tested using the rho values generated by the Monte Carlo significance test (Deller, 2010). To determine the optimal kernel size, an iterative statistical optimization was utilized to minimize the AIC. To explore spatially varying relationships among variables, local coefficients and R^2 from GWR were mapped. Fifth, statistical diagnostics, such as R^2 and AIC from the OLS and GWR, were compared to assess whether the GWR-based s-HPM effectively addressed the spatial effects in the data, therefore outperforming the OLS-based HPM. Finally, spatial clustering patterns of local coefficients were explored by performing an exploratory spatial data analysis using the global Moran's I statistic and local indicator of spatial association (LISA). The global Moran's I measures the existence of spatial dependence among the values of two objects (e.g., two local coefficients of a particular variable) (Li, Calder, & Cressie, 2007). Furthermore, LISA cluster maps were classified into 5 types of spatial cluster: (1) HH (high-high): hot spots; (2) HL (high-low): spatial outliers; (3) LH (low-high): spatial outliers; (4) LL (low-low): cold spots; and (5) NS (not significant) (Jang & Kim, 2018; Jang, Kim, & von Zedtwitz, 2017).

4. Results

4.1. Descriptive statistics

Table 3 presents the descriptive statistics and correlation matrix for the variables. The average hotel room rate in this sample was $127.56, ranging from $20.50 to $530.00. In terms of site attributes, hotel size (i.e., number of rooms) ranged from 15 to 2,019, with a mean of 162.19, and hotel age (i.e., years) ranged from 1.0 to 155.0, with a mean of 30.95. The average hotel class was 1.94 out of 3, and the average service quality was 3.70 out of 5. Concerning situation attributes, the average A-Distance was 10.75 miles, ranging from 0.72 to 24.42 miles, and H-Distance ranged from 0.16 to 8.40 miles, with a mean of 2.06 miles. In addition, T-Distance ranged from 0.33 to 37.16 miles, with a mean of 14.93 miles. Figure 2 displays the visualized information about the spatial distribution of each variable. A dark-colored data point represents the hotel with a high value of the corresponding variable.

[Insert Figure 2 about here]

Regarding the correlation matrix among independent variables, the coefficients were relatively low. As hotel class and service quality had a relatively strong correlation (0.56), we detected the potential presence of multicollinearity by calculating the variance inflation factor (VIF). The VIF ranged from 1.14 to 1.84, indicating that multicollinearity was not a serious problem in the model (Myers, 1986).

[Insert Table 3 about here]

4.2. Results of OLS-based HPM

Table 4 reports the estimation results of the OLS-based HPM (Model A). All independent variables, except H-Distance, were statistically significant at the 0.05 level. The hotel class (β = 44.07) was the most important determinant of the room price of hotels located in Cook County. The hotel size (β = 0.07), hotel class (β = 44.07), service quality (β = 14.25), A-Distance (β = 1.34), and H-Distance (β = 0.36) were positively associated with the hotel room price, whereas the hotel age (β = -0.40) and T-Distance (β = -3.23) were negatively related to the hotel room price. In other words, hotels with more rooms, higher levels of class and service quality and shorter average distance to popular tourist attractions exhibited higher room prices, but hotels with older age and shorter distance to the nearest airport exhibited lower room prices.

To examine any spatial heterogeneity in the OLS model, Model B (including dummy variables of 5 submarkets) was analyzed. While the results of the hotel attribute-room price relationship were similar to those of Model A, the variables of 5 submarkets were not statistically significant. Thus, this result implies that spatial heterogeneity of hotel room prices cannot be captured through the OLS model. The GWR analysis might capture spatial variations within each segment.

[Insert Table 4 about here]

4.3. Results of GWR-based s-HPM

The results of the GWR-based s-HPM (Model C) are also presented in Table 4. The local adjusted R^2 ranged from a minimum of 0.58 to a maximum of 0.69 with a mean of 0.65. The local condition index ranged from a minimum of 18.98 to a maximum of 29.97, representing the absence of local collinearity among the independent variables[2]. Based on the rho values, all independent variables revealed significant evidence of spatial variability in the parameter estimates at the 0.05 level. The local coefficients of the independent variables ranged from 0.05 to 0.19 with a mean of 0.08 (hotel size), -0.54 to -0.34 with a mean of -0.42 (hotel age), 21.48 to 49.73 with a mean of 43.84 (hotel class), 8.14 to 22.22 with a mean of 14.67 (service quality), 1.08 to 2.61 with a mean of 1.46 (A-Distance), -5.27 to 4.07 with a mean of 0.27 (H-Distance), and -3.95 to -2.62 with a mean of -3.24 (T-Distance). This variability in the local coefficients suggests spatial non-stationarity, representing spatially varying relationships among variables across the study area.

[Insert Figure 3 about here]

Figure 3 maps the spatial distribution of local coefficients for the independent variables and local R^2 in the GWR model. All local coefficients were divided into six categories based on the Natural Breaks (Jenks) algorithm (Jenks, 1967). Specifically, although the OLS coefficient for the hotel size was 0.07, its local coefficients ranged from 0.05 to 0.19, representing the lowest local variability. Hotels with strong positive local coefficients for the hotel size variable were

[2] According to Fotheringham et al. (2003), local collinearity is a problem if a condition number is less than 0 or greater than 30.

observed mainly in northwest areas, such as Arlington Heights, Elk Grove Village, Mount Prospect, and Schaumburg. Hotels with relatively lower positive coefficients were located mostly in south areas, such as the cities of Calumet Park, Lansing, and South Holland. Such spatially varying relationships between other hotel attributes (i.e., hotel age, hotel class, service quality, A-Distance, H-Distance, and T-Distance) were also found across the study area. Finally, different from the OLS model, the GWR model exhibited varying values of the adjusted R^2 ranging from 0.58 to 0.69. These findings indicate that the explanatory power of the local model was not stationary across the study area. Table 5 summarizes descriptive information of the estimated local coefficients, including the positive and negative values and sizes compared to the OLS coefficients, across the independent variables.

[Insert Table 5 about here]

To examine whether the GWR-based s-HPM exhibits better model performance than the OLS-based HPM, the values of R^2 and AIC were compared. As shown in Table 4, the adjusted R^2 value increased from 0.62 (OLS) to 0.65 (GWR), and the AIC decreased from 4,141.20 (OLS) to 4,131.77 (GWR). Thus, the GWR-based s-HPM could offer a slightly better goodness-of-fit than the OLS-based HPM in modeling hotel room prices across the study area.

4.4. Results of segmentation analysis using GWR coefficients

Based on the local coefficients obtained from the GWR analysis, a segmentation study was performed by investigating in which market segment numerous hotels clustered with relatively higher or lower local coefficients, depending on their characteristics of site and situation attributes. Specific segments were classified by STR in terms of hotel type (chain and non-chain), location segment (airport, interstate, suburban, and urban), and submarket segment (airport, CBD, north, northwest, and south). STR defines location segment as physical location and submarket as geographic area (in this study, a subset of the Chicago market). Table 6 and Figure 4 present numeric and visual information about the spatial clustering of local coefficients in terms of hot spots and cold spots in Cook County. A hot spot represents a high-high (HH) cluster of local coefficients, whereas a cold spot represents a low-low (LL) cluster of local coefficients.

[Insert Table 6 about here]

Hotel size. Most large-sized chain hotels (91.8%) clustered with higher room rates across the Chicago suburban (94.5%) – from the location perspective – or northwest (89.1%) – from the submarket perspective – areas (i.e., hot spots), whereas some large-sized non-chain hotels (47.2%), compared to hot spot hotels, set less higher room rates across urban (91.3%) or CBD (87.5%) areas (i.e., cold spots)[3]. As illustrated in Figure 4A, if a large-sized new hotel is built in northwest, it can set higher room rates (i.e., red-colored), but if it is built in CBD or south, it may need to set relatively less higher room rates (i.e., blue-colored).

Hotel age. While some old chain hotels (69.1%) co-located with much lower room rates across suburban (45.7%) or airport (43.3%) areas, some old non-chain hotels (58.1%) clustered with relatively less lower room rates across suburban (68.9%) and south (86.4%) areas. Although hotel age was negatively related to room rates overall, relatively higher-priced old hotels agglomerated in Chicago south, and much lower-priced old hotels clustered in airport areas. The results imply that new (young) hotels can set relatively higher prices in Chicago south, where room rates are less affected by hotel age (Figure 4B).

[3] As GWR coefficients for the hotel size variable ranged from 0.05 to 0.19, those located in the HH cluster (hot spot) had higher values close to 0.19, and those located in the LL cluster (cold spot) had lower, but still positive, values close to 0.05. Hence, we noted that, compared to large-sized hotels in the HH cluster, large-sized hotels in the LL cluster set “less higher” room rates.

Hotel class/Service quality. Some upper-class chain (51.8%) and non-chain (48.2%) hotels, possibly in Chicago urban or CBD areas, agglomerated with higher room rates, and most upper-class chain hotels (89.4%), possibly in suburban or northwest areas, agglomerated with relatively less higher room rates (Figure 4C). A possible explanation is the different demand in those segments. That is, upper-class hotels in urban/CBD areas, either chain or non-chain, tend to target business or high-income travelers, whereas upper-class hotels in suburban areas seem to target leisure or less high-income travelers. Similarly, some high-quality chain (56.6%) and non-chain (43.4%) hotels in urban or CBD areas clustered with higher room rates, and most high-quality chain hotels (86.5%) in suburban or northwest areas co-located with relatively less higher room rates (Figure 4D).

A-Distance/H-Distance/T-Distance. As a hotel's distance from the nearest airport increased in the suburban segment, some hotels (54.5%) set higher rates, but others (47.1%) set less higher rates. Specifically, hotels (66.6%) located in the south submarket and far away from the airport set higher rates, but those located in the airport submarket set relatively lower rates (Figure 4E). As a hotel's distance from the nearest highway exit increased, hotels located in the urban (62.4%) or CBD (55%) segment set higher rates, but those in the suburban (83.4%) or northwest (58.2%) segment set less higher rates (Figure 4F). Finally, as a hotel's distance from seven top tourist attractions increased, hotels located in the suburban (87%) or northwest (73.1%) segment set much lower rates, but those in the urban (63.4%) or CBD (58.7%) segment set less lower or relatively higher rates (Figure 4G).

[Insert Figure 4 about here]

5. Discussion and conclusion

This study contributes to the understanding of the utility of the GWR-based s-HPM in modeling hotel room prices in terms of (1) whether the GWR-based s-HPM outperformed the traditional HPMs, (2) how the relationships between hotel room prices and site/situation attributes varied across hotel locations, and (3) how the GWR-generated local coefficients enabled hotels to build location-based hotel room pricing strategies. As empirically demonstrated, the GWR-based s-HPM improved the model performance compared to the corresponding OLS-based HPM, which is consistent with previous studies on the housing market (Bitter et al., 2007; Kestens et al., 2006) and hotel industry (Latinopoulos, 2018; Soler & Germar, 2018; Zhang et al., 2011a). Using the GWR-based s-HPM, this study examined the spatial variations in modeling hotel room prices in the Chicago area, further supporting the development of location-based hotel room pricing strategies when combined with visualized maps. It is important for hotel researchers and practitioners alike to utilize geospatial data and analytic techniques when deciding the location of a new hotel and designing hotel rooms with a consideration of optimal room prices.

Specifically, the empirical results identified spatially varying relationships between hotel room prices and site/situation attributes in the Chicago area. The overall findings are consistent with those of prior studies in Beijing, China (Zhang et al., 2011a), Halkidiki, Greece (Latinopoulos, 2018) and Malaga, Spain (Soler & Gemar, 2018). Despite considerable local variations in the relationships among variables, the mean values of the GWR coefficients indicated that hotel size, hotel class, service quality, A-Distance, and H-Distance have significant positive effects on hotel room price, whereas T-Distance and hotel age have significant negative effects, which is in line with prior research (e.g., Espinet et al., 2003; Hung et al., 2010; Israeli, 2002; Zhang et al., 2011a; Thrane, 2007).

Regarding the Chicago-specific findings, this study reinforces the finding by Lee and Jang (2012) that distance from the city center (i.e., Chicago downtown) has a negative effect on hotel room price because most tourist attractions (i.e., the T-Distance variable in this study) are located in the Chicago downtown area. However, some results are inconsistent with prior findings. For example, although hotels close to airports benefit from higher room rates in six cities (i.e., Cincinnati, Kansas City, Minneapolis–St. Paul, Oklahoma City, Providence, and Tucson (Lee & Jang, 2011), hotels in the Chicago area do not benefit from airport proximity. In addition, hotel room prices are negatively influenced by the hotel size in Beijing (Zhang et al., 2011a), but this study found a positive relationship between room price and hotel size in Chicago. Such incongruent results can be explained by spatial variations in local people's tastes or attitudes or by social or contextual issues that generate different responses to the same stimulus (e.g., hotel size) (Fotheringham et al., 1998; Hasse & Milne, 2005).

The findings from the use of GWR-based s-HPMs also facilitate meaningful implications for hotel practitioners, who may rely on traditional pricing methods, such as OLS-based HPM. For example, regarding the effect of the distance from the nearest highway exit (H-Distance) on room price, the OLS-estimated parameters (Model A: 0.36, Model B: 0.51) suggest that the farther is the hotel from the nearest highway exit, the higher is the room price. This pattern is applicable for the majority of hotels, but there is nonconformity for hotels located in the airport, north, and northwest areas of the Chicago market, indicating a negative relationship between hotel room price and H-Distance. Thus, for H-Distance, the results of the OLS-based HPM can be misleading for certain hotels. Although access to a main road, such as a highway, has been regarded as one of the key determinants of guests' perceptions of hotel location (Lee, Kim, Kim, & Lee, 2010), no empirical study has measured the effect of highway accessibility on hotel room price. This study provides strong empirical evidence via a case study of Cook County that the effect of highway accessibility on hotel room price can be influenced by hotel location.

Furthermore, the results of the segmentation study demonstrated how the use of GWR-based s-HPM can provide hotel practitioners a substantial method to build location-based effective room pricing strategies while considering a focal hotel's attributes and characteristics of market segment. Specifically, this study incorporated three dimensions of market segment: type (chain, non-chain), location (airport, interstate, suburban, urban), and Chicago submarket (airport, CBD, north, northwest, south). Depending on the geographic context of a certain hotel, the hotel can utilize the general tendency of room pricing in each segment when deciding the location for new hotel development and the price for a newly designed room (Latinopoulos, 2018). For instance, a newly entering large-sized chain hotel may set higher room rates in northwest suburban area of Chicago but will need to set relatively less higher room rates in the urban and CBD areas (Table 6). A possible explanation is that the urban and CBD areas have higher tourist demand – due to multifaceted tourist attractions, such as museums, art galleries and shopping centers (Wall, Dudycha, & Hutchinson, 1985) – than the suburban area, bringing higher price competition. However, upper-class hotels, higher service quality, longer distance from a highway exit, and/or shorter distance from tourist attractions could enter the Chicago CBD market with higher room rates but may have to avoid setting higher rates in the suburban market because other competing hotels set relatively lower rates. For existing hotels, hotel managers in the CBD area should devote greater efforts to improve quality of both tangible and intangible services, including a concierge, a gourmet restaurant, a bellman service, room design, and hotel renovation. Furthermore, hotel marketers could focus on promotional activities taking advantage of easy accessibility to tourist destinations.

The application of a GWR-based s-HPM facilitates the broadening of the scope of how to model hotel room prices. Unlike prior literature on OLS-based HPMs that identify the general relationship between room price and hotel attributes, this study focuses on what (site and situation attributes) affects hotel room price, where (location) and to what extent (spatial variation) and how effectively (segmentation), allowing the identification of location-based room pricing strategies for existing and new hotels. This study clearly indicates that the hotel industry relies heavily on the effective location strategy to compete against neighboring hotels to attract hotel guests (Yang et al., 2012). Because each local community has its own regional characteristics (Hasse & Milne, 2005), examining spatial variations in modeling hotel room prices is necessary. The findings of this study not only support the argument of Hasse and Milne (2005) but also emphasize the necessity of exploring regional variations within individual communities due to spatial heterogeneity at the local level.

Despite the significant methodological and practical implications of this study, several limitations should be acknowledged. First, the findings of this study are limited by the use of limited site and situation attributes to model hotel room price. Previous literature has indicated that hotel facilities, number of housekeeping staff per room, quality of room service, breakfast (yes/no), and distance to downtown are also important site and situation determinants that influence hotel room price. Future studies should incorporate these attributes into their analyses to provide a more comprehensive understanding of hotel room price modeling. Second, the findings of this study are limited to a single geographic area (Cook County). Each area has its own unique local color and regional characteristics. Therefore, additional studies should be conducted in other geographical regions to demonstrate the utility of the s-HPM by considering the heterogeneous nature of the regional characteristics. Third, although the overall rating from the travel advice website (i.e., TripAdvisor) was used as a proxy for hotel service quality (Zhang et al., 2011b), this rating may not provide the entire picture of customers' satisfaction due to non-responders, who cannot be quantified. Future studies should employ additional data collection at the individual level via a visitor's survey to accurately measure customers' perceived hotel service quality.

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Table 1. Empirical evidence of hedonic pricing models.

Model type	Study	Study area	Dependent variable	Independent variables	
				Site attributes	Situation attributes
Linear HPM	Carvell and Herrin (1990)	San Francisco, US	Room rate	Amenities	Distance from the hotel to Fisherman's Whart
	Israeli (2002)	Israel	Room rate	Star rate, hotel brand	*Not included*
	Monty and Skidmore (2003)	Southeast Wisconsin, US	Willingness to pay	Hot tub, private bath, larger room, fireplace, themes, room service, scenic view	*Not included*
	White and Mulligan (2002)	Four Corners region, Southwestern US states	Room rate	Pool, spa, complimentary breakfast	Temperature, interstate location, specialization of the local economy
	Wu (1999)	Arkansas and Kansas, US	Room rate	AAA rate, restaurant pool, movies, chain	State, interstate
	Zhang et al. (2011b)	New York City, US	Room rate	Hotel class, average travelers' rating of rooms, cleanliness, service	*Not included*
Log-linear HPM	Bull (1994)	Ballina, Australia	Room rate	Rating, age, restaurant, scenic view	Distance to town center
	Thrane (2007)	Oslo, Norway	Room rate	Chain, mini-bar, parking, restaurant, hairdryer, room service, beds	Distance to Oslo central station
s-HPM	Lee and Jang (2011)	Cincinnati, Kansas City, Minneapolis–St. Paul, Oklahoma City, Providence, and Tucson, US	Room rate	Hotel amenities (breakfast, parking, internet suite room)	Distances to airport & central business district
	Zhang et al. (2011a)	Beijing, China	Room rate	Number of rooms, star rating, age	Distances to the nearest scenic spot & transport hub
	Lee and Jang (2012)	Downtown Chicago, US	Room rate	Number of rooms, number of restaurants, pool, lounge, business center, spa, fitness center, minibar, flatscreen TV, room service, chain, valet parking, valet laundry	Distance from city center
	Santana-Jimenez et al. (2015)	La Palma, Spain and PengHu, Taiwan	Room rate	Number of beds, barbecue, satellite TV, pool, jacuzzi, fireplace, pets allowed, sea view	Urban/rural, landscape diversity, times to airport, port, diving place, beach, observation point & health center, isolation
	Latinopoulos (2018)	Halkidiki, Greece	Room rate	Sea view, star rating, type, hotel amenities (spa, outdoor/sport activity, room service, breakfast, refund, all-inclusive service, pool, parking, Wi-Fi), service quality	Distances to the nearest beach with a blue flag, nearest beach, nearest forest area; average distance from the 5 nearest neighbors (hotels); urban
	Soler and Gemar (2018)	Malaga, Spain	Room rate	Number of rooms, star rating, booking day, the difference in days between the search day and the booking day	Driving/walking distance to the city center, train station, and airport

Note: HPM refers to hedonic pricing model.

Table 2. Operationalization of dependent and independent variables.

Variable	Operationalized definition	Literature	Source (year)
Room rate	Average room rate for double or equivalent room	Bull (1994); Carvell and Herrin (1990); Israeli (2002); Latinopoulos (2018); Lee and Jang (2011; 2012); Santana-Jiménez et al. (2015); Thrane (2007); White and Mulligan (2002); Wu (1999); Zhang et al. (2011a; 2011b)	STR (2015)
Site attributes			
Hotel size	Number of rooms	Coenders et al. (2003); Hung et al. (2010); Lee and Zhang (2012); Zhang et al. (2011a)	STR (2015)
Hotel age	Hotel age (years)	Bull (1994); Zhang et al. (2011b)	STR (2015)
Hotel class	STR hotel class (economy, midscale and upscale)	Zhang et al. (2011b)	STR (2015)
Service quality	Average traveler 5-point rating review from Tripadvisor.com	Zhang et al. (2011b)	Tripadvisor (2016)
Situation attributes			
A-Distance	Shortest road network distance from each hotel to the nearest airport (in miles)	Lee and Zhang (2011); Santana-Jiménez et al. (2015); Soler and Germar (2018)	ESRI (2016)
H-Distance	Shortest road network distance from each hotel to the nearest highway exit (in miles)	Bull (1994); White and Mulligan (2002); Wu (1999)	ESRI (2016)
T-Distance[a]	Average road network distance from each hotel to the top seven tourist attractions selected by USA Today in 2015 (in miles)	Carvell and Herrin (1990); Santana-Jiménez et al. (2015); Zhanag et al. (2011a)	USA Today (2015)

Notes: STR: Smith Travel Research; ESRI: Environmental Systems Research Institute; [a] While three sources considered one nearest tourist attraction for T-Distance, this study included seven tourist attractions (Kim & Nicholls, 2016b).

Table 3. Descriptive statistics and correlation coefficients.

Variable	Mean	Min	Max	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Room rate	127.56	20.50	530.00	81.58	1.00							
(2) Hotel size	162.19	15.00	2,019.00	199.40	0.49**	1.00						
(3) Hotel age	30.95	1.00	155.00	21.69	-0.12**	0.09**	1.00					
(4) Hotel class	1.94	1.00	3.00	0.85	0.70**	0.47**	-0.16**	1.00				
(5) Service quality	3.70	1.50	5.00	0.72	0.48**	0.22**	-0.17**	0.56**	1.00			
(6) A-Distance	10.75	0.72	24.42	5.11	-0.12	-0.12**	-0.05*	-0.04	0.00	1.00		
(7) H-Distance	2.06	0.16	8.40	1.33	-0.19**	-0.23**	0.01	-0.15**	-0.07	-0.14*	1.00	
(8) T-Distance	14.94	0.33	37.16	8.93	-0.44**	-0.24**	-0.20*	-0.20**	-0.13*	0.48**	0.19**	1.00

Notes: N = 387.
** Significant at the 0.01 level (2-tailed).
* Significant at the 0.05 level (2-tailed).

Table 4. Results of OLS- and GWR-based spatial hedonic pricing models.

Variable	OLS coefficient (Model A)	OLS coefficient (Model B)	GWR coefficient (Model C)				
			Min	Mean	Max	Range	Rho
Intercept	23.03	20.78	-13.74	19.67	61.88		0.12
Hotel size	0.07**	0.07**	0.05	0.08	0.19	0.14	< 0.05
Hotel age	-0.40**	-0.40**	-0.54	-0.42	-0.34	0.20	< 0.05
Hotel class	44.07**	43.21**	21.48	43.84	49.73	28.25	< 0.05
Service quality	14.25**	14.43**	8.14	14.67	22.22	14.08	< 0.05
A-Distance	1.34*	1.85*	1.08	1.46	2.61	1.53	< 0.05
H-Distance	0.36	0.51	-5.27	0.27	4.07	9.34	< 0.05
T-Distance	-3.23**	-4.01**	-3.95	-3.24	-2.62	1.33	< 0.05
Airport (dummy)		13.72					
North (dummy)		15.04					
Northwest (dummy)		17.54					
South (dummy)		9.05					
Adjusted R^2	0.62	0.62	0.58	0.65	0.69	0.11	
Condition index			18.98	22.68	29.97		
AIC	4141.20	4,147.70			4,131.77		

Notes: N = 387. In the OLS (B) model, dummy variables of 5 Chicago segments were included to analyze the effect of the hotel's geographical segment on room price, and the variable of Central Business District was used as the reference variable. The rho value is equivalent to a p-value with regard to spatial variability and was drawn from a Monte Carlo analysis attributed to Hope (1968).

** Significant at the 0.01 level.

* Significant at the 0.05 level.

Table 5. Classification of hotels by values of local coefficient and local R^2.

Variable	GWR coefficient > 0	GWR coefficient < 0	GWR coefficient > OLS coefficient	GWR coefficient > OLS coefficient
Hotel size	387 (100.0%)	0 (0.0%)	166 (42.8%)	221 (57.2%)
Hotel age	0 (0.0%)	387 (100.0%)	247 (63.8%)	140 (36.2%)
Hotel class	387 (100.0%)	0 (0.0%)	271 (70.0%)	107 (30.0%)
Service quality	387 (100.0%)	0 (0.0%)	160 (41.3%)	227 (58.7%)
A-Distance	387 (100.0%)	0 (0.0%)	260 (67.1%)	127 (32.9%)
H-Distance	229 (59.1%)	158 (40.9%)	218 (56.3%)	169 (43.7%)
T-Distance	0 (0.0%)	387 (100.0%)	103 (26.6%)	284 (73.4%)
Adjusted R^2			149 (38.5%)	238 (61.5%)

N = 387.

Table 6. Results of segmentation analysis based on spatial clustering of local coefficients (HH cluster vs. LL cluster).

Market segment	Hotel size (β: 0.05 – 0.19)		Hotel age (β: -0.54 – -0.34)		Hotel class (β: 21.48 – 49.73)		Service quality (β: 8.14 – 22.22)		A-Distance (β: 1.08 – 2.16)		H-Distance (β: -5.27 – 4.07)		T-Distance (β: -3.95 – -2.62)	
	HH	LL	HH	LL	HH	LL	HH	LL	HH	LL	HH	LL	HH	LL
Hotel type (%)														
Chain	**91.8**	**52.8**	**69.1**	**58.1**	**51.8**	**89.4**	**56.6**	**86.5**	**65.1**	**60.3**	**54.3**	**90.4**	**92.4**	**57.9**
Non-chain	8.2	47.2	30.9	41.9	48.2	10.6	43.4	13.5	34.9	39.7	45.6	9.6	7.6	42.1
Location segment (%)														
Airport	1.3	0.0	32.7	0.0	0.0	1.1	0.0	2.0	0.0	33.9	0.0	13.9	9.6	0.0
Interstate	4.0	3.8	0.0	28.3	0.7	3.5	0.0	3.0	31.8	0.0	12.0	2.6	3.2	14.2
Suburban	**94.5**	3.8	**45.7**	**68.9**	20.3	**95.2**	5.6	**94.8**	**54.5**	**47.1**	24.8	**83.4**	**87.0**	21.4
Urban	0.0	**91.3**	22.4	1.3	**77.4**	0.0	**94.3**	0.0	12.1	18.8	**62.4**	0.0	0.0	**63.4**
Submarket segment (%)														
Airport	2.7	0.0	**43.3**	0.0	0.0	2.3	0.0	6.1	0.0	**50.0**	0.0	15.6	11.8	0.0
CBD	0.0	**87.5**	21.5	0.0	**63.9**	0.0	**93.3**	0.0	3.0	24.5	**55.0**	0.0	0.0	**58.7**
North	4.0	0.0	28.9	0.0	0.0	10.5	5.6	1.0	0.0	19.8	0.0	18.2	7.5	0.0
Northwest	**89.1**	0.0	5.6	13.5	0.0	**87.0**	0.0	**68.0**	28.7	0.0	0.0	**66.0**	**80.6**	0.0
South	0.0	12.5	0.0	**86.4**	36.0	0.0	0.9	24.7	**66.6**	5.6	44.9	0.0	0.0	41.2
Segment descrition														
Number of hotels	74	104	107	74	133	85	106	97	66	106	149	115	93	126
Room price per night ($)	103.8	188.3	123.4	82.8	165.7	105.0	191.6	102.2	79.3	117.6	153.6	114.6	108.0	162.9
Number of rooms	145.0	243.9	166.5	86.4	207.8	143.7	245.7	135.8	87.2	156.7	196.4	163.2	153.9	217.2
Hotel age (years)	24.4	35.4	33.9	26.8	33.6	24.6	36.3	24.1	26.7	34.0	32.2	25.2	24.4	31.1

Notes: CBD refers to central business distrct. HH denotes high-high cluster of local coefficients, and LL denotes low-low cluster of local coefficients. Specific market segments are classified by Smith Travel Research (STR). Bold values represent the highest percentage among corresponding segments. The total percentage of location or submarket segments per hotel attribute can be below 100% (e.g., 99.80%) because some hotels located between two segments were excluded.

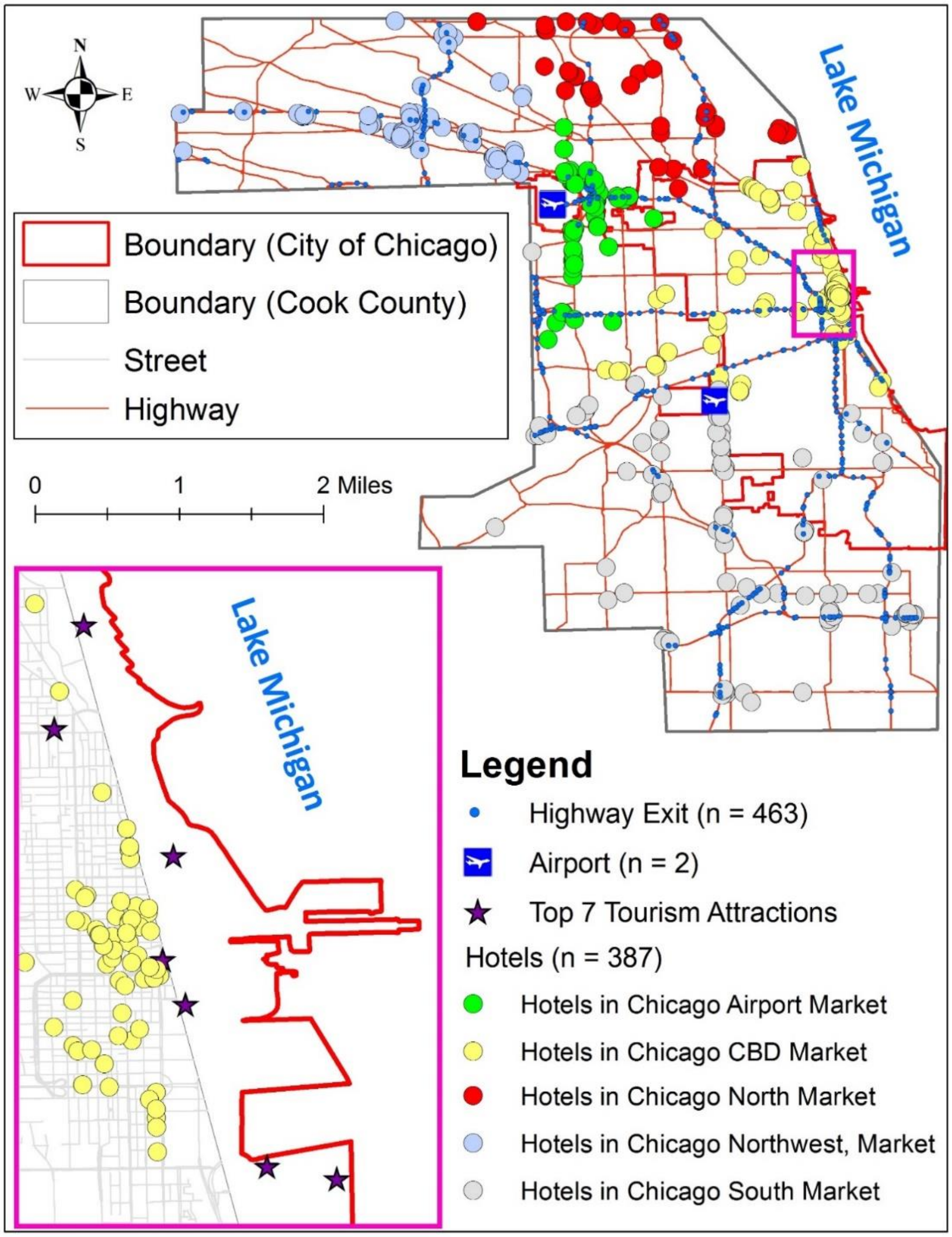

Figure 1. Study area

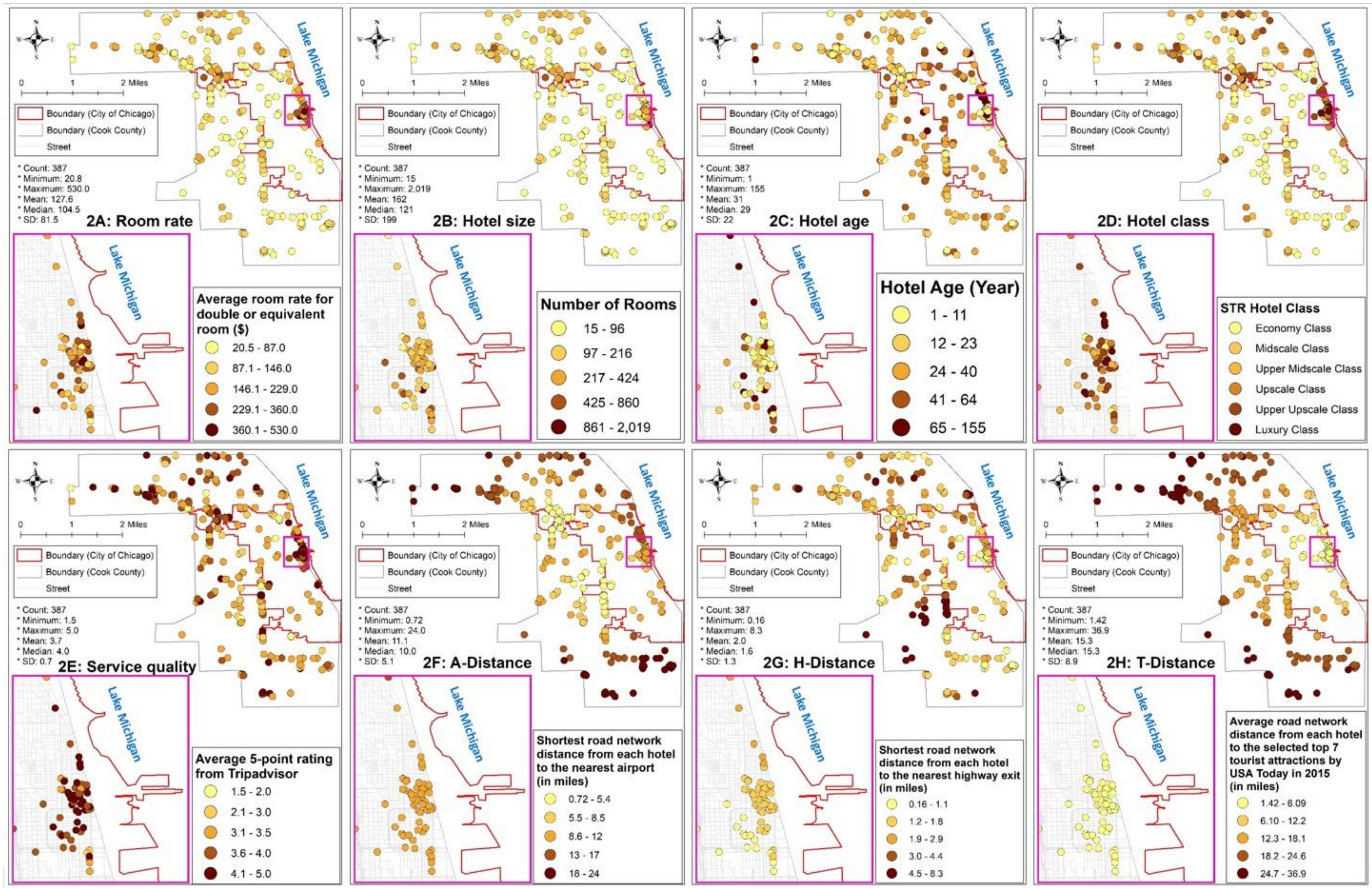

Figure 2. Spatial distribution of dependent and independent variables

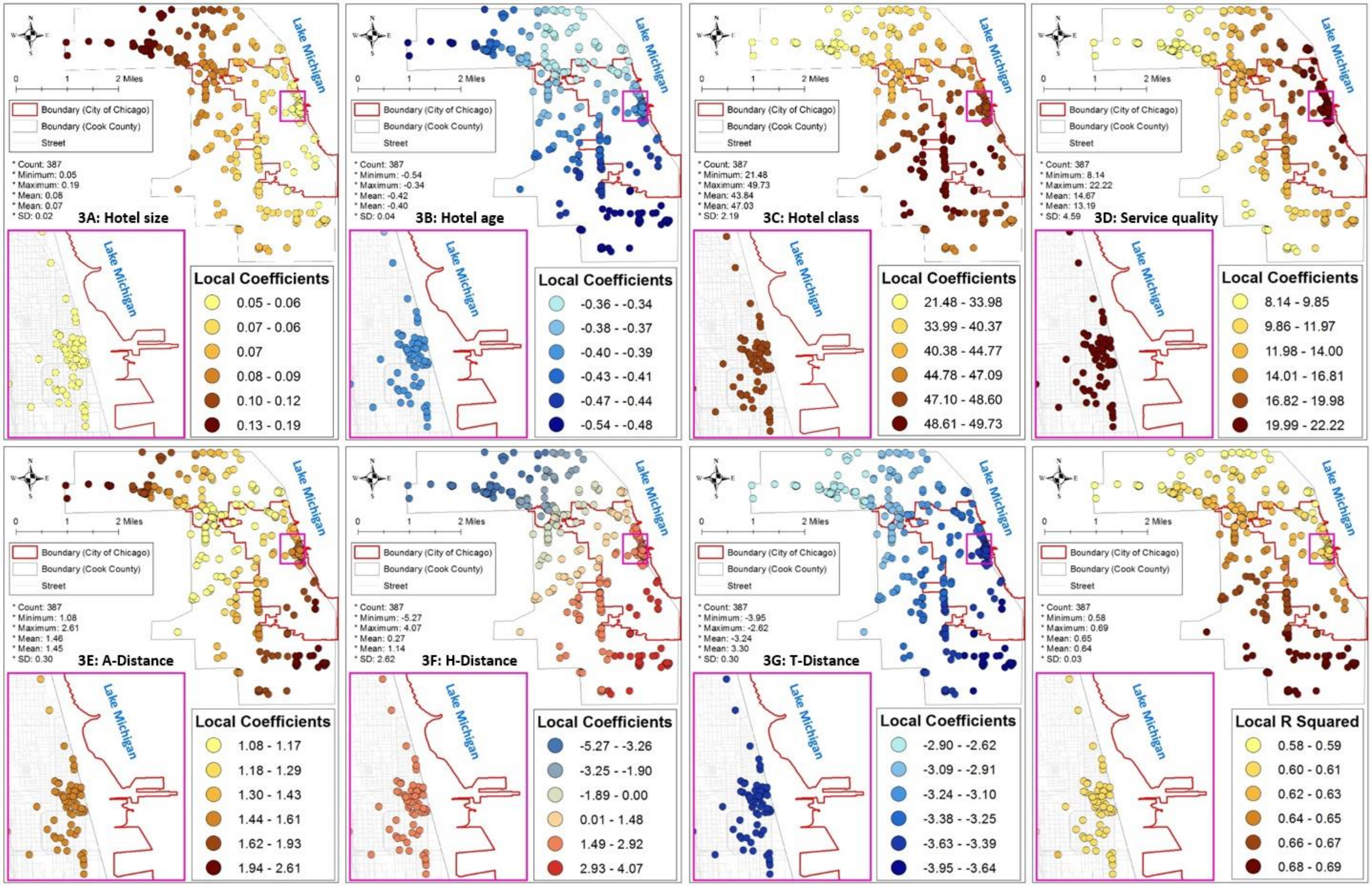

Figure 3. Spatial distribution of local coefficients for independent variables and local R^2

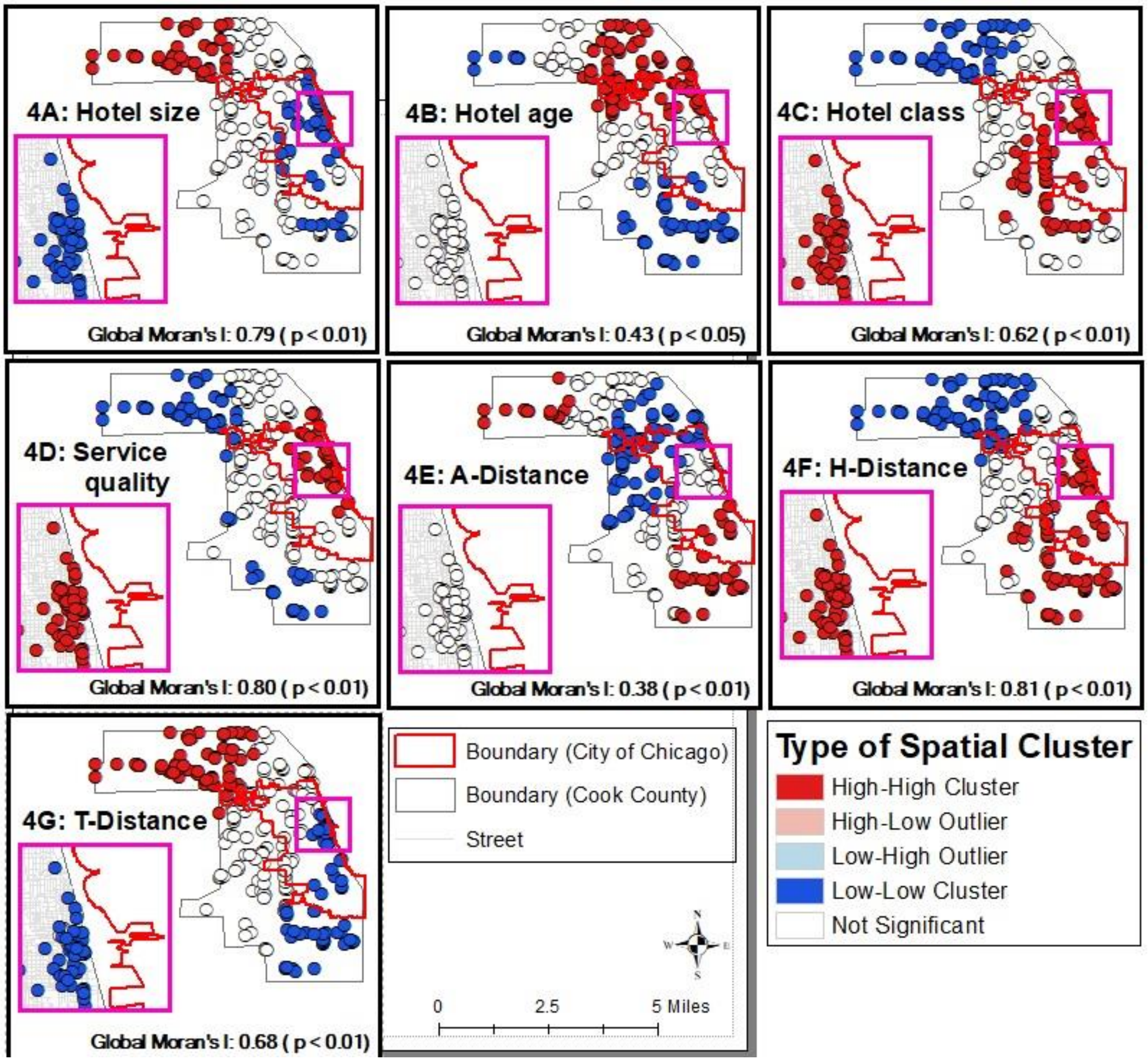

Figure 4. Spatial clustering of GWR-based local coefficients for independent variables