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Does Hotel Location Tell a True Story? Evidence from Geographically Weighted Regression Analysis of Hotels in Hong Kong

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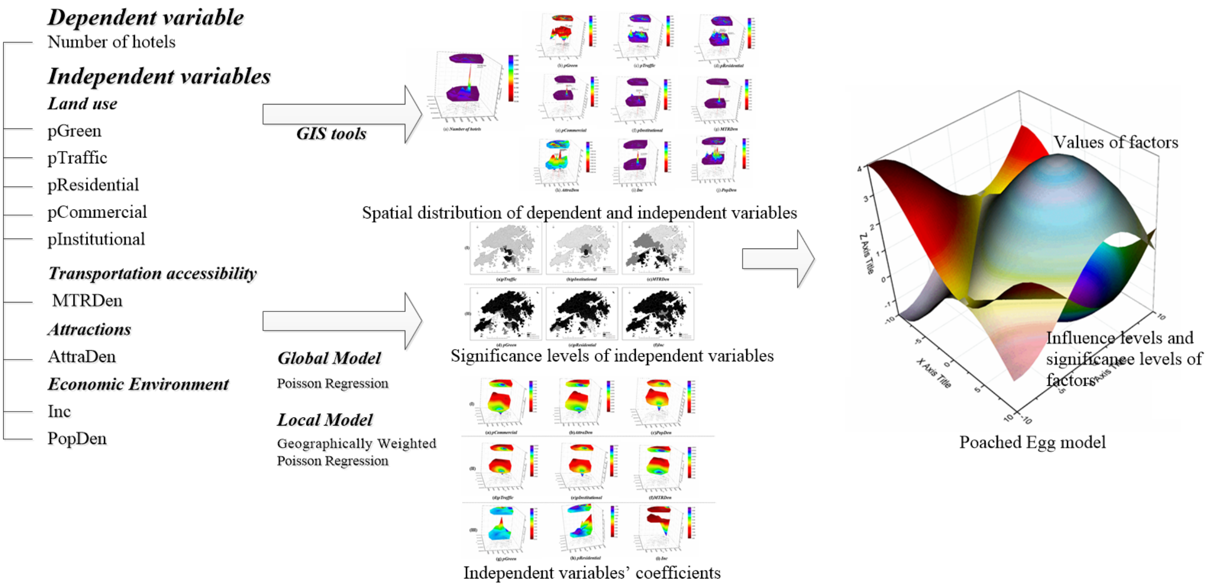
Highlights

- A geographically weighted Poisson regression model is developed to examine factors contributing to hotel distribution.
- Results suggest that factors influencing hotel location choice vary across regions.
- Traffic-related factors do not always influence hotel location choice in cities.
- The effects of independent variables in peripheral regions are stronger than in the city center.
- Clustering of hotels in city center is associated with agglomeration effects.

Graphical Abstract



Does Hotel Location Tell a True Story? Evidence from Geographically Weighted Regression Analysis of Hotels in Hong Kong

Abstract

This study is among the first attempts to understand hotel location choice by developing a local spatial model to investigate spatial determinants of hotel locations in an urban tourism destination, taking Hong Kong as the study context. The spatially diverse relationships between nine factors (i.e., land area, green land, traffic land, residential land, commercial land, institutional land, metro station density, attraction density, population density, and average income) and the number of hotels in Hong Kong are quantified by geographically weighted Poisson regression. Results indicate that (1) factors influencing hotel location choice vary across regions; (2) traffic factors do not always affect hotel location choice in urban destinations; and (3) the effects of independent variables in peripheral regions are strong and decrease gradually in the urban center, revealing a 'poached egg' pattern, where hotel clustering is associated with agglomeration effects.

Keywords: hotel location; spatial variation; geographically weighted Poisson regression; urban tourism destination

1. Introduction

Choosing a location wisely is crucial for a new hotel (Yang, Wong, & Wang, 2012), as it is almost impossible to relocate a hotel after it has opened. Compared to the manufacturing industry, the hotel industry—as a typical service industry—relies heavily on effective location choice strategies to attract tourists/customers and promote success amidst intense competition (Yang et al., 2012). Many studies have shown that hotel location can significantly influence a tourist's decision and choice of a hotel (Chu & Choi, 2000; Lewis & Chambers, 1989; Tsaur & Tzeng, 1996). Moreover, Yang, Luo, and Law (2014) and Luo and Yang (2016) pointed out that a good hotel location is closely related to a higher occupancy rate, revenue per available room, and profitability. Sim, Mak, and Jones (2006) also found that customers staying in an ideal hotel were more satisfied than those staying in a suboptimal location. Therefore, hotel location choice and associated determinants warrant in-depth analysis (Yang et al., 2012).

Several empirical studies have examined the drivers behind hotel location choice; pertinent factors include the convenience of transportation and parking (Li, Fang, Huang, & Goh, 2015; Tsaur & Tzeng, 1996), accessibility to tourist attractions (Yang et al., 2012), the surrounding public service infrastructure and economic environment (Yang et al., 2014), hotel characteristics (Yang et al., 2014), and agglomeration effects (Freedman & Kosová, 2014; Luo & Yang, 2016; Marco-Lajara, Zaragoza-Sáez, Claver-Cortés, Úbeda-García, & García-Lillo, 2017; Yang et al., 2012). However, two major gaps remain in the literature. First, hotel location choice is closely correlated with local development, especially in urban areas. Although land use type is the most direct representation of urban development, this indicator has been largely neglected in research on hotel location choice.

Second, although linear regression is pervasive in hotel location choice and prediction models (Yang et al., 2014), the method possesses several drawbacks including poor prediction accuracy, failure to consider nonlinearity, and inability to incorporate spatial heterogeneity and dependency (Yang, Tang, Luo, & Law, 2015). Furthermore, studies relying on statistical regression models have employed global models to investigate potential factors; however, a global model may not be appropriate because location, price, services, and other features may have closer spatial associations that cannot be ignored when data are aggregated at certain levels. Yang et al. (2014) thus advocated for more sophisticated hotel location models in hotel location choice analysis. Similarly, Yang et al. (2014) and Yang et al. (2015) suggested that more attention should be paid to spatial dependency and spatial heterogeneity in hotel location analysis.

Given the spatial essence of hotel-related data, the objective of this study is to examine spatial variations in the relationships between hotel location choice and land use types, transportation and tourist attraction accessibility, and surrounding economic environment factors in an urban destination. We use geographically weighted Poisson regression (GWPR), a type of geographically weighted regression (GWR), to contribute to the literature on hotel location choice in several ways. First, previous studies only focused on the influences of potential factors from a global perspective under the implicit assumption that relationships between hotel location and influencing factors do not vary across regions. The present study is among the first to consider influencing factors of hotel location by considering spatial dependency and spatial heterogeneity. Second, this study is one of the few to analyze the relationship between urban land use patterns and hotel location. Practically, the findings from this work should provide implications for the government to formulate better strategies to attract new hotels and for hotels to implement sound location choice strategies.

2. Literature review

Hotels in urban areas are not randomly distributed. Barros (2005) found that one incentive for choosing to establish a hotel near other hotels is to gain substantial benefits in hotel efficiency, indicating that hotels can acquire positive spillover effects from their neighbors. This phenomenon is even more obvious in Chinese cities because agglomeration economies may be especially important due to the vast size of the city (Egan, Chen, & Zhang, 2006). Taking hotels in Spain as the study object, Marco-Lajara, Claver-Cortés, Úbeda-García, and Zaragoza-Sáez (2016b) claimed that the degree of agglomeration has a substantial influence on hotel profit, suggesting a U-shaped relationship between the two variables. Cost, rather than income, has been identified as a major source of hotel profit due to the agglomeration effect (Marco-Lajara, Claver-Cortés, Úbeda-García, & Zaragoza-Sáez, 2016a). In fact, an inverted U-shaped relationship exists between agglomeration and hotel cost, but no relationship has been identified between agglomeration and hotel income (Marco-Lajara et al., 2016a). Moreover, Marco-Lajara et al. (2017) reported that the agglomeration of Spanish tourism firms appeared to exert a positive influence on the number of international brand hotels. Canina, Enz, and Harrison (2005) explored reasons for agglomeration from production and demand perspectives. On the production side, agglomeration allows individuals in the cluster to access resources that are not readily available to those not in the cluster; agglomeration also offers greater access to leading suppliers, special services, or special relationships. On the demand side, agglomeration reduces consumers' search costs. Even so, not all hotels benefit from agglomeration. In an investigation of the Texas lodging industry, Chung and Kalnins (2001) found that hotels benefit heterogeneously from agglomeration effects. Among hotels of a similar level, those that do not diffuse positive externality receive more revenue than hotels that do. Additionally, Canina et al. (2005) argued that the receiver and diffuser of positive spillover effects in agglomeration may differ.

A review of relevant research implies that hotels' spatial distribution pattern presents a core–periphery structure. Friedmann (1966) formally proposed core–periphery theory in his seminal work. In 1969, he further summarized the concept of core–periphery as an applicable principle used to explain uneven development between regions or between urban and rural areas. Although the driving forces of the core–periphery pattern may not be suited to explaining the spatial pattern of hotels, the 'core' and 'periphery' structure can help delineate hotels' spatial distribution. In this paper, we highlight innovative findings related to core–periphery structure in the context of hotel location.

2.1 Land Use Type

Hotel location choice in urban areas is highly associated with urban structure and urban development (Bégin, 2000; Oppermann, Din, & Amri, 1996; Shoval & Cohen-Hattab, 2001; Yang et al., 2012). For example, Bégin (2000) found that hotel location choice and preference shifted in Xiamen alongside changes in urban structure: hotels were mainly distributed in the Old Town before 1985; the downtown and new urban area began to attract hotels after 1990; and establishment of the Special Economic Zone exerted a significant influence on hotels' location choices thereafter.

Land use type is the most direct representation of urban structure and can influence hotel location choice in different ways. One example is the substitution/competition effect. In this case, the hotel industry competes with residents for many spaces and services, and it competes with other industries for resources such as labour and land. Thus, land use type can be considered the result of negotiation between a hotel and other industries and residential land use. Conversely, a complementary effect may also exist; if a region is devoted primarily to shopping and other businesses, hotels will likely be in these areas to be proximate to their potential markets, namely shopping and business tourists (Li et al., 2015). Therefore, different types of land use could serve as potential predictors of hotel location choice.

Land use types are varied and include green land, traffic land, residential land, commercial land, and institutional land. Institutional land use is most often associated with land used by public buildings of educational institutions, hospitals, government offices, museums, art galleries, and religious or charitable organizations, collectively representing public safety and public infrastructure availability (Yang et al., 2012). Therefore, institutional land use is thought to influence the demand and supply sides of the hotel industry (Rigall-I-Torrent & Fluvià, 2007).

The second land use type is green land, a category of non-use involving an area as an ecological or wilderness reserve. This kind of land use precludes natural resource exploitation as well as industries requiring extensive facilities and buildings. Due to resource constraints (e.g., 70% forest coverage), a region with more green land may not have more hotels; green land use and hotels are thus in a competitive relationship.

The third land use type, residential, is commonly associated with apartment buildings. For example, competition between the housing and hotel industries has become more intense with the sustained growth in housing prices in Hong Kong since 2005. Traffic land represents transportation accessibility. Research has found that the traffic land type may be associated with hotel distribution, presumably because tourists are inclined to choose hotels near traffic facilities (Ashworth & Tunbridge, 1990; Wall, Dudycha, & Hutchinson, 1985; Weaver, 1993). Commercial land is mostly affiliated with land used by retail buildings and facilities as well as offices; this land use type may have a positive influence on hotel location, especially for a tourism destination targeting shopping tourists.

2.2 Transportation and Tourist Attraction Accessibility

Many empirical studies have been conducted to examine the importance of transportation and tourist attraction accessibility in determining hotel location choice (Arbel & Pizam, 1977; Lee & Jang, 2011; Li et al., 2015; Shoval, 2006). Arbel and Pizam (1977) and

Shoval (2006) stated that the number of tourist attractions around hotels is positively related to hotel location choice, as the function of a hotel is to provide accommodations for leisure and sightseeing tourists (Yang et al., 2012). Furthermore, Lee and Jang (2011) noted that location premiums for hotels are influenced by distance to the airport and to the central business district. Based on an ordered logit model, Yang et al. (2012) examined factors influencing hotel location choice in Beijing, identifying road accessibility, metro accessibility, and accessibility to tourist sites as important determinants. Moreover, the authors reported that compared with lower-grade hotels, upper-grade hotels place greater emphasis on accessibility. By contrast, using a geographic information system (GIS) and logistic regressions, Li et al. (2015) found that transportation facilities around hotels, as measured by the number of urban rail transit stations and extent of traffic land area, were not significant factors in hotel location choice (i.e., upper- or lower-grade hotels) in Hong Kong. Given inconsistent findings in the literature, the influence of transportation and tourist attraction accessibility on hotel location choice should be investigated further.

2.3 Surrounding Economic Environment

Economic factors may also affect the spatial distribution of hotels. An analysis from Urtasun and Gutiérrez (2006) suggested that the spatial distribution of hotels in Madrid depends on a range of socioeconomic and planning factors operating in a historical context. For example, hotels may be closed and replaced by a new residential community during an economic recession (Urtasun & Gutiérrez, 2006). Furthermore, highly developed regions usually boast well-developed public infrastructure and services. Scholars have argued that public attributes including environmental quality, public safety, and public infrastructure availability are believed to influence tourists' utility functions on the demand side and tourism agents' production functions on the supply side (Rigall-I-Torrent & Fluvià, 2007, 2011; Yang et al., 2012). Therefore, hotels are likely to choose locations that host a productive economic environment.

2.4 Analytical Methods

In relevant empirical studies, global regression has been used to explore factors influencing hotel location with different research aims. Joel and Mezias (1992) examined the effect of localized competition on failure rates in the Manhattan hotel industry from 1898 to 1990. In their exponential regression model, independent variables were size, geographic location (relative position of hotels), price, and population density and mass. Results revealed that hotels in densely populated regions with distributions of organizational size, geographic location, and price experienced substantially higher failure rates. Urtasun and Gutiérrez (2006) examined geographic location, price, size, and services to determine how the positioning of new hotels may be affected by the distribution of similar incumbent competitors. They identified the relative values of these four factors, combined data in four simultaneous equations, and compared the results using the ordinary least squares method. A recent study by Yang et al. (2012) investigated potential factors contributing to hotel location choice in Beijing by using the ordered logit model. They found that factors such as star rating, years since opening, service diversification, ownership, the agglomeration effect, public service infrastructure, road accessibility, metro accessibility, and accessibility to tourist sites were major location determinants.

However, most scholarly work has focused on either the agglomeration effects of hotels or the impacts of potentially influential factors; few authors have investigated both simultaneously. Questions such as “Is it the agglomeration of influential factors or the agglomeration of hotels that forms the core–periphery distribution of hotels?” or “Do both influence this spatial pattern?” remain untouched. Similarly, studies have indicated that the hotel industry has prominent drivers such as traffic accessibility and land use types but have scarcely investigated the spatial patterns of these factors. Do these influential factors also exhibit a core–periphery structure? If the spatial non-stationarity of hotels and their potential influential indicators are considered, is it possible to draw different conclusions? If the hotel distribution apparently has no relationship with conventional influential factors, can we confirm that the aggregation effect among hotels affects hotel location? As mentioned in the first section, most researchers have investigated the spatial pattern of hotels without using spatial analytical methods. However, inherent to spatial patterns is a problem of 'space', which is characterized by a set of geographic coordinates along with spatial interaction. It is challenging to fully reveal the rationale behind the spatial pattern of hotels by relying solely on global analytical methods and treating spatial patterns independently without assessing relationships between the spatial pattern of hotels and their potential factors.

3. Methodology

3.1 Study Site — Hong Kong

In an attempt to examine determinants of hotel location choice in an urban tourism destination, Hong Kong was selected for its mature hotel industry following decades of continuous tourism development. Hong Kong is on the eastern side of the Pearl River estuary in southern China (Fig. 1[a]). Hotel distribution during the first decade of the 21st century reveals two main characteristics: first, development is ongoing in the central business district; and second, hotels have expanded into surrounding suburban districts since 1990 due to urban development in Hong Kong. Traditionally, urban areas of Hong Kong refer to the northern part of Hong Kong Island and the Tsim Sha Tsui area. From 1973 to 1990, Hong Kong began to develop nine new towns to manage population growth. Resource constraints (e.g., 70% forest coverage) prevent the land use type from being modified for specific purposes (e.g., port back-up or areas of large development); hence, urban areas in Hong Kong grew slowly after 1990 and have developed a unique spatial pattern.

Based on data of hotels that opened in and before the end of 2010 in Hong Kong, hotel location information collected from each hotel's website was plotted onto maps using ArcGIS 10.2, as shown in Fig. 1(b). Fig. 1(b) also depicts the distribution of influencing factors including metro stations, tourist attractions, and the tertiary planning unit (TPU). Kowloon-Hong Kong Island was found to have an extremely high hotel count and density; several other areas, such as Tsuen Wan, south of Hong Kong Island, and Lantau Island, also hosted a relatively large number of hotels. As an example, Fig. 1(c) presents geographic location information for Kowloon-Hong Kong Island in terms of hotels, land use, attractions, and metro stations.

[Insert Fig 1 here]

The following analysis covers all areas of Hong Kong with hotels aggregated at the TPU level. There are 18 districts in Hong Kong, each of which generally consists of several TPUs. The TPU system was devised by the Planning Department of Hong Kong Special Administrative Region (HKSAR) for planning and population census purposes. There were 287 TPUs in total in 2010.

3.2 Variable Selection

Using GIS tools, the number of hotels, hotel density, and related location choice determinants were calculated for each TPU. Fig. 2(a) provides a 2D and 3D color map surface of hotel distribution in Hong Kong, in which the number of hotels in each TPU is denoted by a z value. TPUs with the highest numbers of hotels were Yau Tsim Mong and Wan Chai. Nine independent variables related to land use types, traffic and tourist attraction accessibility, and economic environment factors were identified for analysis. Land use data including green, traffic, residential, commercial, and institutional types (Fig. 2[b]–Fig. 2[f]) were derived from paper maps collected from the Planning Department of the HKSAR in 2010. ENVI software was used to digitize paper maps. The proportion of green land area was higher in the periphery than in the core (Fig. 2[b]), whereas proportions of traffic, residential, commercial, or institutional land were higher in the core (Fig. 2[c]–Fig. 2[f]). The number of Massive Transit Railway (the urban rail transit system in Hong Kong, hereafter referred to as MTR) stations nearby was used as a proxy for transportation accessibility (Fig. 2[g]) with data collected from Google Maps. Yau Tsim Mong and Central & Western District had the highest MTR density (Fig. 2[g]). Tourist attraction accessibility was measured by the number of attractions nearby, and data were mainly gathered from a list of tourist attractions provided by the Hong Kong Tourism Board (Fig. 2[h]). Despite the minimum values of attraction densities in Wan Chai

(Fig. 2[h]), the core area was higher than the periphery. Demographic and socioeconomic characteristics were measured based on residents' average monthly income (Fig. 2[i]) and population density (Fig. 2[j]). Data were obtained from the Hong Kong Population By-census 2010. Table 1 presents descriptive statistics for the independent variables; variance inflation factors ranged from 1.13 to 3.76, indicating small collinearity.

[Insert Table 1 here]

[Insert Fig 2 here]

3.3 Spatial Autocorrelation Analysis

Moran's *I* can be used to explore the spatial autocorrelation of area hotel data (Luo & Yang, 2013). This study employs Moran's *I* statistic to measure the spatial autocorrelation of dependent and independent variables in the model. The measure of Moran's *I* statistic is given as

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{1}$$

where z_i is the deviation in hotel data for TPU *i* from its mean; w_{ij} is the spatial weight between TPU *i* and *j*; *n* is equal to the number of TPUs; and S_0 is the aggregate of all spatial weights:

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \tag{2}$$

The null hypothesis of Moran's *I* is that the variable is randomly distributed in the study area; the alternative hypothesis states that the variable in the study area is not randomly distributed with spatial autocorrelation. The Moran's *I* value falls between -1.0 and +1.0. When nearby TPUs have highly similar values, the index is positive and close to 1. If nearby TPUs have diverse values, then the index is negative and close to -1.

3.4 Global Model Specification — Poisson Regression

In this study, global Poisson regression is used to model the hotel count of the 287 TPUs in Hong Kong for comparison with the local model. The specification of the global Poisson regression is as follows:

$$\ln(\lambda) = \beta_0 + \beta_1 pGreen + \beta_2 pTraffic + \beta_3 pResidential + \beta_4 pCommercial + \beta_5 pInstitutional + \beta_6 MTRDen + \beta_7 AttraDen + \beta_8 Inc + \beta_9 PopDen \quad (3)$$

where λ is the expected number of hotels in each TPU; β_0 is the intercept term, and $\beta_1, \beta_2 \ldots \beta_9$ represent the parameters to be estimated; *pGreen is* the proportion of green land area in each TPU; *pTraffic* is the proportion of road and railway land area in each TPU; *pResidential* is the proportion of residential land area in each TPU; *pCommercial* is the proportion of commercial land area in each TPU; *pInstitutional* is the total area of institutional land area in each TPU; *MTRDen* is the number of MTR stations per km^2 in each TPU; *AttraDen* is the number of attractions per km^2 in each TPU; *Inc* is the average monthly employment income in each TPU; and *PopDen* is the extent of resident population per km^2 in each TPU. Finally, the set of parameters ($\beta_1, \beta_2 \ldots \beta_9$) can be approximated using maximum likelihood estimation.

3.5 Local Model Specification — Geographically Weighted Poisson Regression

Considering spatial non-stationarity, GWPR is used to model the hotel count of 287 TPUs in Hong Kong for comparison with the global regression results. The specification of GWPR is as follows:

$$\ln(\lambda_i) = \ln(\text{Area}) + (u_i, v_i)\beta_0 + \beta_1(u_i, v_i) pGreen_i + \beta_2(u_i, v_i) pTraffic_i$$

$$+ \beta_3(u_i,v_i)pResidential_i + \beta_4(u_i,v_i)pCommercial_i$$

$$+ \beta_5(u_i,v_i)pInstitutional_i + \beta_6(u_i,v_i)MTRDen_i + \beta_7(u_i,v_i)AttraDen_i$$

$$+ \beta_8(u_i,v_i)Inc_i + \beta_9(u_i,v_i)PopDen_i \quad (4)$$

where λ_i is the expected number of hotels in TPU *i*; β_0 is the intercept term, and $\beta_1, \beta_2 ... \beta_9$ represent parameters to be estimated; and (u_i, v_i) is the *x*–*y* coordinate of the centroid of the TPU *i*. The TPU area (the variable "Area") is introduced into the model as an offset variable.

GWPR is an extension of GWR (Fotheringham, Brunsdon, & Charlton, 2002; Hadayeghi, Shalaby, & Persaud, 2010), as the dependent variable in the model is a count variable (hotel number). Unlike the global Poisson regression model where the coefficient estimates are fixed over space, the GWPR model is more likely to capture local effects. GWPR allows parameter estimates to vary across regions. The model is calibrated based on the assumption that observations closer to TPU *i* have a greater influence on the estimation of *i*'s $\beta_k(u_i,v_i)$ parameter than data farther from TPU *i*. The estimation of parameters $\beta_k(u_i,v_i)$ is given by (Fotheringham et al., 2002):

$$\hat{\beta}(u_i,v_i) = [X^T W(u_i,v_i) X]^{-1} X^T W(u_i,v_i) Y \quad (5)$$

where W is an $n \times n$ matrix, with diagonal elements denoting the geographic weighting of observation data for TPU *i* and the off-diagonal elements equal to zero. The weight matrix is computed for each TPU and represents the different importance of each observation in the dataset (Yao, Loo, & Lam, 2015). The Gaussian and bi-square functions, which are commonly used in calculating weighting functions, are as follows:

Gaussian:

$$W_{ij} = \exp\left(-\left(\frac{d_{ij}}{h}\right)^2\right) \quad (6)$$

Bi-square:

$$W_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}}{h}\right)^2\right]^2, & \text{if} \quad d_{ij} < h_i \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where h is a non-negative parameter known as bandwidth, which produces a decay of influence with distance. Using TPU centroid point coordinates (x_i,y_i) and (x_j,y_j), the distance is usually defined as a Euclidean distance (Fotheringham, Charlton, & Brunsdon, 1997):

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{8}$$

The bandwidth is constant in the Gaussian fixed kernel function. A potential problem with a fixed kernel is that for sparsely distributed TPUs, local models might be calibrated on few observations, resulting in parameter estimates with large standard errors and unpredictable results. As TPUs are not homogenously distributed in Hong Kong, the adaptive bi-square kernel is employed in this research; adaptive kernels have larger bandwidths where data are sparse and other bandwidths where data are concentrated. The optimal bandwidth size is determined by comparing the corrected Akaike information criterion (AICc) with different bandwidth sizes. The model with the lowest AICc has the best performance (Fotheringham et al., 2002; Hadayeghi et al., 2010). GWPR models were established in GWR 4 software. All independent variables were standardized by z-transformation so each variable had zero mean and one standard deviation.

4. Results and Discussion

4.1 Spatial Autocorrelation

Following Equations 1 and 2, Table 2 presents the results of Moran's *I* statistics for both the dependent variable and each independent variable; Fig. 3 shows the local Moran's *I* statistics for the dependent variable. All variables demonstrated significant positive spatial autocorrelations. The Moran's *I* value for hotel count was 0.250 with a *p*-value less than 0.001, indicating a positive spatial autocorrelation among TPUs. Positive autocorrelations also existed in all independent variables; therefore, their underlying spatial process may influence corresponding effects on hotel distribution in different regions, which should be examined in detail.

If the autocorrelation is ignored, results may not present a complete picture of hotel distribution and its determinants. Results of the autocorrelation in this study suggest that the distribution of hotels and potential factors exhibited spatial aggregation effects in a city with a mature hotel industry. This clustering pattern of hotel distribution has also been confirmed by other studies using different methods (Joel & Haveman, 1997; Luo & Yang, 2013, 2016). As mentioned earlier, the nature of the spatial agglomeration effect is spatial interaction. Despite the proliferation of research on hotel clustering, no significant progress has been made in dealing with this critical issue. In fact, previous work (Barros, 2005; Urtasun & Gutiérrez, 2006) took hotels' unbalanced distribution as a result of agglomeration on aspects such as hotels' operating status, scale, framework, and brand; few studies focused on agglomeration in the context of space or location or treated the phenomenon of clustering *in space* as a primary factor. Accordingly, policy suggestions from applied geographers, touristologists, or other professionals regarding the agglomeration effects of hotels could be biased and premature.

[Insert Table 2 here]

[Insert Fig 3 here]

4.2 Global Model — Poisson Regression

Global statistical models, such as Poisson or linear regression, construct equations that describe data relationships in a study area. If these relationships are consistent across the study region, then the Poisson regression equation models the correlations well. Table 3 displays the result of using a global Poisson model to estimate coefficients of the variables in Table 1. The number of hotels was positively associated with population density (*PopDen*), tourist attraction accessibility (*AttraDen*), and traffic accessibility (*MTRDen*) along with traffic (*pTraffic*), commercial (*pCommercial*), and institutional (*pInstitutional*) land use types; however, the influences of green land use (*pGreen*), residential land use (*pResidential*), and income (*Inc*) were insignificant.

The global model estimated factors influencing hotel location choice under the assumption that the study area was homogeneous across different regions. Therefore, the global model has the limitation of ignoring heterogeneity across different regions in the study area. Specifically, it neglects 1) differences in independent variables and the dependent variable in different TPUs; and 2) the spatial relationships of independent variables and the dependent variable between neighbor TPUs. On this basis, the conclusions of global model estimation may not tell the whole story of hotel location choice.

[Insert Table 3 here]

4.3 Local Model — Geographically Weighted Poisson Regression

The global model only describes the global average of relationships. As noted previously, spatial attributes of the data may result in spatial non-stationarity. Using a global statistical model (i.e., Poisson regression in this study) to estimate hotel location choice may not reflect spatial heterogeneity. Therefore, a GWPR model was established using GWR 4 software to capture the varying effects of determinants on hotel location choice across regions in Hong Kong. Moreover, the local estimates provide a clear picture of the distribution of effects suggested by the global model (Li et al., 2015). Findings are summarized in Table 4, and the significance levels of independent variables are mapped in Fig. 4(a)–(f). Fig. 5(a)–(h) depict the local estimation results per independent variable using the Jenks natural breaks classification method (Jenks, 1967), and Fig. 6(a)–(i) illustrate the local estimation results using continuous 3D surfaces.

According to Table 4, small shares of TPUs were significant at the 95% level for *pGreen, pResidential*, and *Inc* (10.5%, 15.7%, and 7.7%, respectively). These results are consistent with the global model estimation displayed in Table 3, where the impacts of *pGreen, pResidential*, and *Inc* were insignificant. Fig. 4(d)–(f) indicate that these significant TPUs were in the center districts of Hong Kong, including Tsing Yi, Yau Tsim Mong, Wan Chai, South, Sha Tin, and the Central district (see light-colored areas in Fig. 4[d]–[f]). Green land use, residential land use, and residents' income were thus only significantly related to hotel location choice in the urban center. In addition, the estimated coefficients of these three independent variables were all negative in the urban center (see Fig. 5[g]–[h]), suggesting that green land use, residential land use, and residents' income were negatively related to hotel count in the urban center.

Most TPUs in Hong Kong were significant at the 95% level for *pTraffic, pInstitutional*, and *MTRDen* (72.5%, 85.4%, and 71.4%, respectively), aligning with the results of the global model where these independent variables were generally significantly related to hotel count. However, different from the global model, Fig. 4 shows that the effects of *pTraffic, pInstitutional*, and *MTRDen* were insignificant in some TPUs. Specifically, the effect of *pTraffic* was insignificant in the Western, Central, and Yau Tsim Mong districts (see dark-colored areas in Fig. 4[a]–[c]), implying that traffic land use was not an important factor for hotels in locations with convenient transportation. In other words, expanding traffic land use would not attract more hotels to these areas. Similarly, the effect of *MTRDen* was insignificant in the Yau Tsim Mong and Western and Central districts of Hong Kong, indicating that these areas with more metro stations do not necessarily host more hotels (see dark-colored areas in Fig. 4[c]). The coefficient of *pInstitutional* was not significant in TPUs in Yau Tsim Mong (see dark-colored areas in Fig. 4[b]) because the hotels in this district provide services geared toward shopping customers. Lastly, coincident with the global model estimation results in Table 3, all TPUs in Hong Kong were significant at the 95% level for *pCommercial*, *AttraDen*, and *PopDen* (Table 4).

[Insert Table 4 here]

The local estimation results tend to demonstrate a core–periphery structure, in which the effects of independent variables in the urban center were low and increased gradually in peripheral regions. Specifically, the coefficients of *pTraffic* and *MTRDen* grew larger further from the urban center; that is, hotels in the suburbs appeared more likely to choose locations with convenient transportation facilities. In TPUs of the Western and Central District, comprising another important area in the urban core, the coefficients of *pInstitutional, pCommerical*, and *AttraDen* had significantly positive relationships with hotel distribution. These results enrich core–periphery theory from the perspective of spatial non-stationarity. The pattern of hotels in the suburban area may be influenced by conventional indictors to a larger extent than hotels in the urban core area, whereas the hotel distribution in the urban core area may result from complex driving forces such as agglomeration effects, which can substantially weaken the influences of indicators traditionally perceived as critical. Combining the results in Fig. 2, Fig. 4, Fig. 5, and Fig. 6, the spatial patterns of hotels and distribution of influencing factors in a developed city can be generalized as a 'poached egg' model, which is an extension of core–periphery theory (Fig. 7). The effects of independent variables demonstrated spatial heterogeneity such that they were low in the urban center and increased gradually in the peripheral regions. However, the number of hotels was high in the urban center but low in peripheral regions. Furthermore, Fig. 2 indicates that hotels in the urban center exerted significant positive spatial autocorrelations. The poached egg model suggests that hotels aggregate in the urban center not because of influencing factors but to capitalize on agglomeration effects between each other.

[Insert Fig 4 here]

[Insert Fig 5 here]

[Insert Fig 6 here]

[Insert Fig 7 here]

5 Conclusion and Implications

5.1 Conclusion

To better understand influencing factors on hotel location choice, this study proposes an empirical local model based on GWPR to investigate the spatial determinants of hotel locations in Hong Kong. The following conclusions were reached. First, the impacts of different land use types vary with regard to hotel location choice. Commercial land use was found to exert a significantly positive influence on hotel location choice across different regions of Hong Kong.

Hotels were closer to commercial and business areas, suggesting that business facilities and shopping play important roles in determining hotel locations in Hong Kong. Compared to many urban destinations in Europe or mainland China, Hong Kong suffers from a lack of major historical and heritage sites and landmarks. The tourism industry in Hong Kong therefore relies heavily on business travellers, tourists visiting friends and relatives, and tourists who come to take advantage of the shopping facilities (Heung & Cheng, 2000; Zhang Qiu & Lam, 1999). The positive effects of institutional land and traffic land use on hotel location choice were significant in most regions in Hong Kong, especially in the peripheral areas, but remained comparatively weak in areas close to the city center. This pattern implies that hotel investors can consider other factors when selecting locations without focusing strongly on traffic accessibility and public facilities in the city center areas. This finding is inconsistent with most previous studies (e.g., Ashworth & Tunbridge 1990; Yang et al. 2012) in which tourists were more likely to choose hotels near traffic facilities. However, the influences of green land use and residential land use were insignificant in most regions of Hong Kong except for districts close to the urban center (i.e., the Tsuen Wan, Eastern, and Southern districts). These negative influences indicate that hotels become denser in the urban center as green space and residential areas diminish, presumably due to land policy and land use competition. Newly built hotels may occupy green space and residential land in the urban center.

Second, tourist attraction accessibility and population density were found to exert significantly positive influences on hotel location choice in all regions of Hong Kong. The positive coefficients of attraction accessibility and population density suggest that the number of hotels has positive relationships with places with high attraction density and population density. This result is consistent with that of Arbel and Pizam (1977) and Shoval (2006); indeed, the function of a hotel is to provide services for tourists and residents. The effect of transportation accessibility was strong in the peripheral areas of Hong Kong but insignificant in areas near the urban center, likely because all hotels in a region with highly convenient transport facilities appeal to potential tourism markets. Traffic factors do not necessarily determine hotel locations in highly convenient areas; that is, in available areas for building hotels, owners can consider other factors over traffic accessibility when choosing locations. Moreover, findings of this study indicate that residents' average monthly income had a negative influence on the hotel count in the center area of Hong Kong, such that the lower the income, the more hotels the area contained. This result contradicts that of Kalnins and Chung (2004), who claimed that hotels tend to be built in upmarket communities. Possibly, compared with high-income districts, hotel investors may acquire land to build a hotel more easily in low-income districts.

Third, our findings suggest that the aggregation of hotels in the urban center is grounded in leveraging agglomeration effects among hotels. Barros (2005) indicated that one incentive for choosing to establish a hotel close to other hotels is to gain a significant positive influence in hotel efficiency, in which hotels can take advantage of positive spillover effects from their neighbors. Similarly, the degree of agglomeration apparently exerts significant influences on increased hotel profits (Marco-Lajara et al., 2016b), lower hotel costs (Marco-Lajara et al., 2016a), and hotel internationalization (Marco-Lajara et al., 2017).

5.2 Theoretical Implications

The contributions of this study are threefold. First, our analysis is theoretically important, as it enriches the methodologies used to evaluate relationships between hotels and urban structure. Second, extensive literature has examined the typical relationship between hotel location and the surrounding environment, but a paucity of studies have assessed diverse relationships across regions. Conventional (nonspatial) statistical methods tend to assume that observations are spatially independent; however, the effect of spatial autocorrelation, particularly spatial agglomeration (Canina et al., 2005; Chung & Kalnins, 2001; Urtasun &

Gutiérrez, 2006), has been identified among hotels. Independent variables also demonstrate spatial autocorrelation, resulting in complex situations. Failure to account for spatial effects may contribute to misleading results; therefore, it is important to consider spatial non-stationarity when conducting spatial analytical studies of hotels. To solve this problem, a common approach has involved dividing the study area into several parts. For example, Yang et al. (2012) divided Beijing into ring-shaped zones and estimated the determinants of hotel location choice in respective zones. However, a major limitation of this method is that it relies heavily on division rules. To overcome these limitations, a local model was created, and the GWPR method was used for the first time in this study to explore varying effects of independent variables on hotel location choice across different regions. Our findings provide additional insight into hotel location patterns. Third, we highlight innovative findings related to the core–periphery structure in the context of hotel location. As the relationship between hotel distribution and surrounding environmental indicators assumes a core–periphery structure, our results extend the core–periphery theory regarding hotel location. Core–periphery structures identified in this study belong to specific spatial patterns in the hotel industry, offering the revelation that hotel aggregation in the urban center is not related to influence factors but exclusively to benefits from mutual agglomeration effects.

These findings can help scholars and practitioners better understand variations in the driving forces of the hotel industry in different areas of a city. Results can also inform decision making when choosing appropriate locations for new hotels. Accordingly, when hotel investors face an array of location options, they should select the most desirable location to maximize associated utility subject to certain constraints (Yang et al., 2014). The non-significance of influencing factors in the urban core area indicates that the establishment and operation of hotels do not depend on conventional indictors but rather the agglomeration effect (most probably). If a hotel is planned to be built in the suburbs, then conventional factors such as traffic should be seriously considered.

5.3 Limitations and Future Research

Finally, several limitations of this study deserve attention. First, when analyzing the effect of traffic accessibility on hotel location, we treated traffic land type and the number of MTR stations as proxies. If more comprehensive data such as bus stops and routes were available, we would be able to compute the travel cost (e.g., in terms of time) from each hotel to various attractions, which could provide further information about the influence of traffic accessibility. Second, a limitation of the GWPR model is that it cannot analyze time-series data; traditional regression is based on one dimension, and GWPR extends the weighted regression from one dimension to two by introducing a spatial dimension. However, it cannot analyze factors with spatial-temporal characteristics simultaneously. GWPR must therefore be extended to include the time dimension to validate the results over time. Future research should be dedicated to the development of a temporal GWPR model and its application to the spatiotemporal analysis of hotel location. Third, our study did not consider the potential influence of tourist flow distribution. In fact, given the rapid development of travel-related technology and mobile apps, tourist flow information and its distribution could be obtained easily. Therefore, future studies can use tourist flows as a factor in predicting hotel location choice by collecting big data on these flows. Fourth, due to limitations of the dataset in our study (from 2010), we could not evaluate the influences of the build-ups of Hong Kong–Zhuhai–Macao Bridge and Hong Kong–Guangzhou High-speed Railway on hotel location choice and its spatial distribution. The establishment of the bridge and high-speed railway will greatly reduce travel time for people who travel between Hong Kong and the Pearl River Delta region and may affect city spatial structure and land use types, which will influence hotel location choice. Future studies can collect updated data to test how these two developments may shape hotel distribution in the Hong Kong and Pearl River Delta regions.

Endnotes:

For ease of description of TPU locations, the discussion focuses on districts. For instance, 'Wan Chai' refers to most TPUs in the Wan Chai district.

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Table 1. Descriptive statistics of dependent and independent variables.

Variable	Description	*N*	Minimum	Maximum	Mean	S.D.
Dependent variable						
(a) Number of hotels	---	287	0	13	.50	1.493
Hotel density	Number of hotels per km^2	287	0	33	1.31	4.21
Land use characteristics						
LnArea	Natural log of total land area (km^2)	287	-2.829	3.349	0.562	1.311
(b) pGreen	Proportion of green land area	287	0.000	1.000	0.514	0.299
(c) pTraffic	Proportion of traffic land area	287	0.000	0.674	0.172	0.133
(d) pResidential	Proportion of residential land area	287	0.000	0.609	0.149	0.144
(e) pCommercial	Proportion of commercial land area	287	0.000	0.208	0.005	0.020
(f) pInstitutional	Proportion of institutional land area	287	0.000	0.302	0.010	0.069
Transportation accessibility						
(g) MTRDen	Number of MTR stations per km^2	287	0.000	16.943	0.392	1.378
Attractions						
(h) AttraDen	Number of attractions per km^2	287	0.000	36.665	1.690	4.594
Economic Environment						
(i) Inc	Average employment monthly income (HK$)	287	6,000	25,000	11267.1	3431.5
(j) PopDen	Number of residents per km^2	287	0.000	16.667	2.302	3.309

Table 2. Moran's *I* statistics for independent variables.

Variable	Moran's *I*	*z*-score	*p*-value
Hotel count	0.250	30.314	<0.001
pGreen	0.327	39.417	<0.001
pTraffic	0.425	49.879	<0.001
pResidential	0.254	29.995	<0.001
pCommercial	0.246	30.879	<0.001
pInstitutional	0.217	25.658	<0.001
MTRDen	0.100	11.683	<0.001
AttraDen	0.279	34.048	<0.001
Inc	0.103	12.245	<0.001
PopDen	0.313	36.871	<0.001

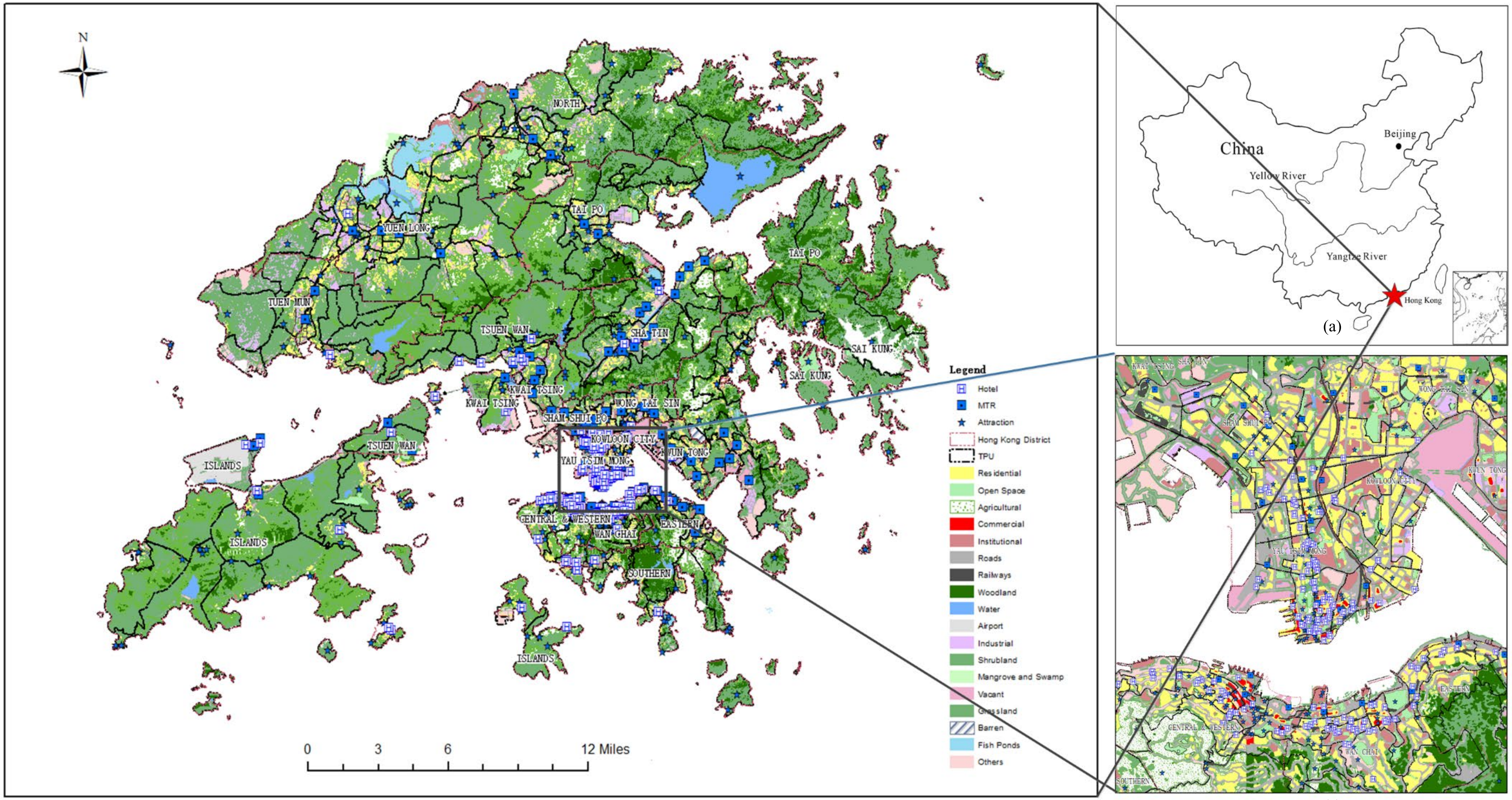
Table 3. Estimation results of global Poisson model.

Variable	Coef.	Std. Err.	Z	*p*-value
pGreen	-0.11	0.28	-0.40	0.689
pTraffic	0.40	0.15	2.62	0.009*
pResidential	0.15	0.17	0.94	0.348
pCommercial	0.15	0.06	2.43	0.015*
pInstitutional	0.21	0.08	2.75	0.006*
MTRDen	0.11	0.06	2.03	0.042*
AttraDen	0.26	0.06	0.06	<0.001**
Inc	-0.09	0.10	0.10	0.335
PopDen	0.27	0.13	2.06	0.040*
(Constant)	-1.44	0.14	-10.07	<0.001**
AIC: 539.166; AICc: 539.963; Percent deviance explained: 0.423				

* Significant at 0.05 level; ** Significant at 0.001 level

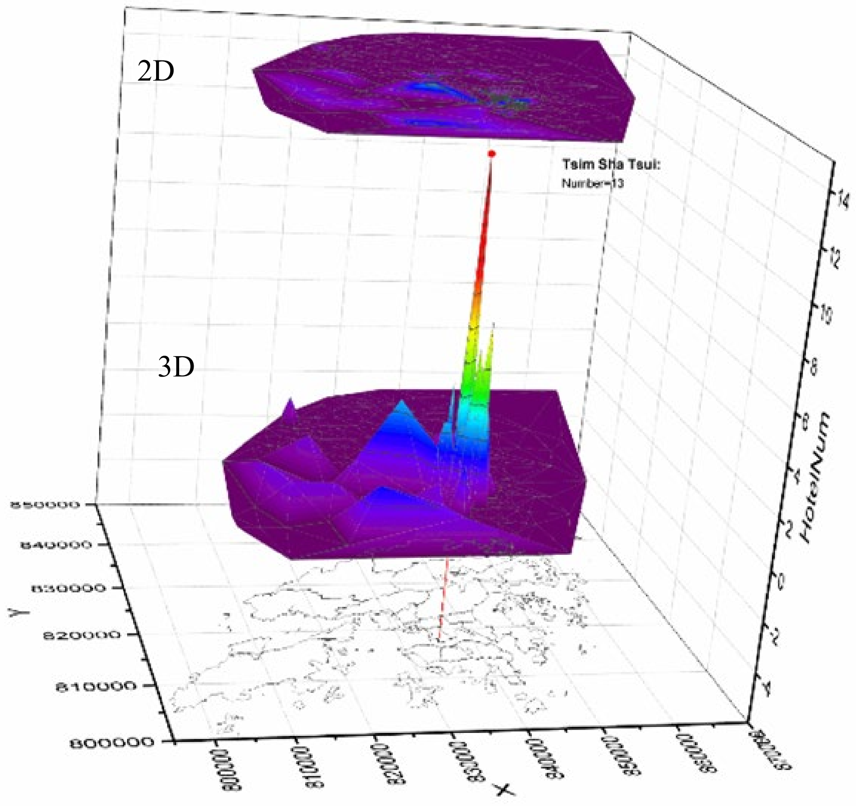
Table 4. Descriptive statistics of coefficients of GWPR.

	Minimum	Lower quartile	Median	Upper quartile	Maximum	Proportion of TPUs significant at 95% significance level (%)*
pGreen	-6.974	-0.449	-0.037	0.399	20.178	10.5
pTraffic	0.053	0.193	0.307	0.394	0.461	72.5
pResidential	-1.542	-0.312	0.252	0.669	6.748	15.7
pCommercial	0.111	0.143	0.163	0.181	0.197	100.0
pInstitutional	0.098	0.152	0.193	0.222	0.262	85.4
MTRDen	0.066	0.099	0.121	0.148	0.169	71.4
AttraDen	0.054	0.055	0.057	0.057	0.062	100.0
Inc	-11.165	-0.237	-0.154	-0.017	1.000	7.7
PopDen	0.260	0.359	0.419	0.479	0.574	100.0
(Constant)	-1.938	-1.597	-1.260	-0.825	-0.302	10.5
AIC: 275.683; AICc: 288.669; Percent deviance explained: 0.679						

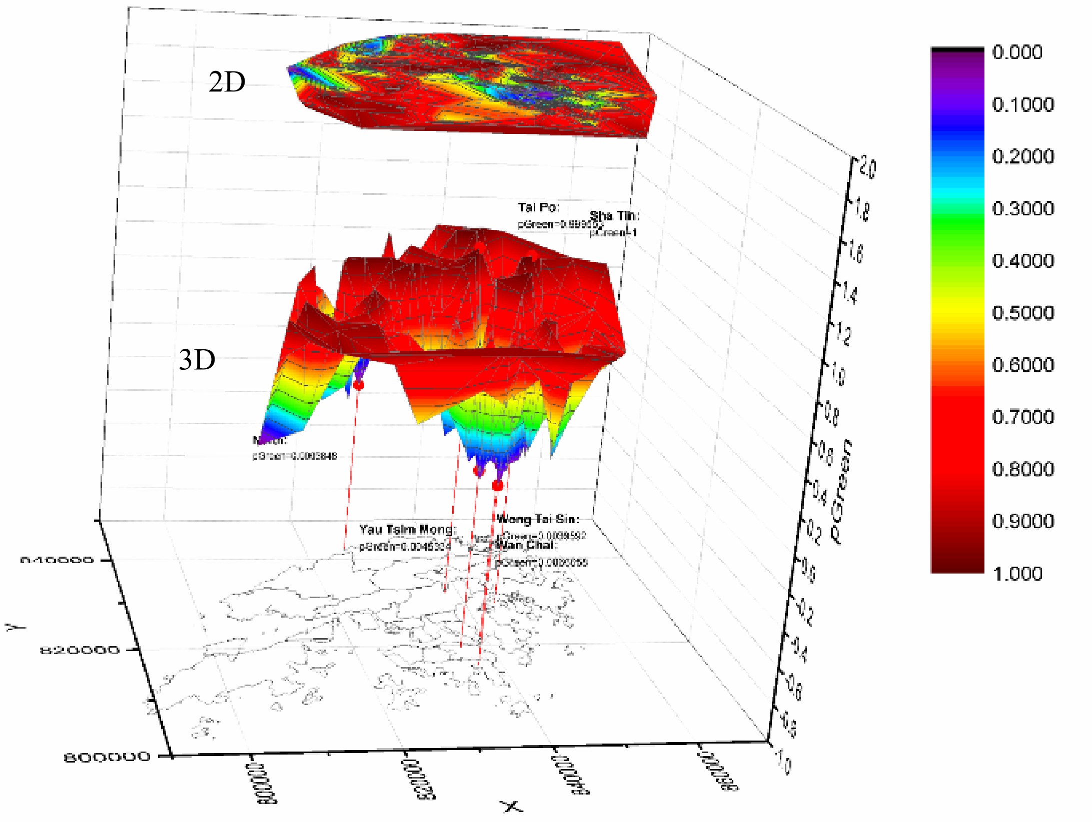


(b) (c)

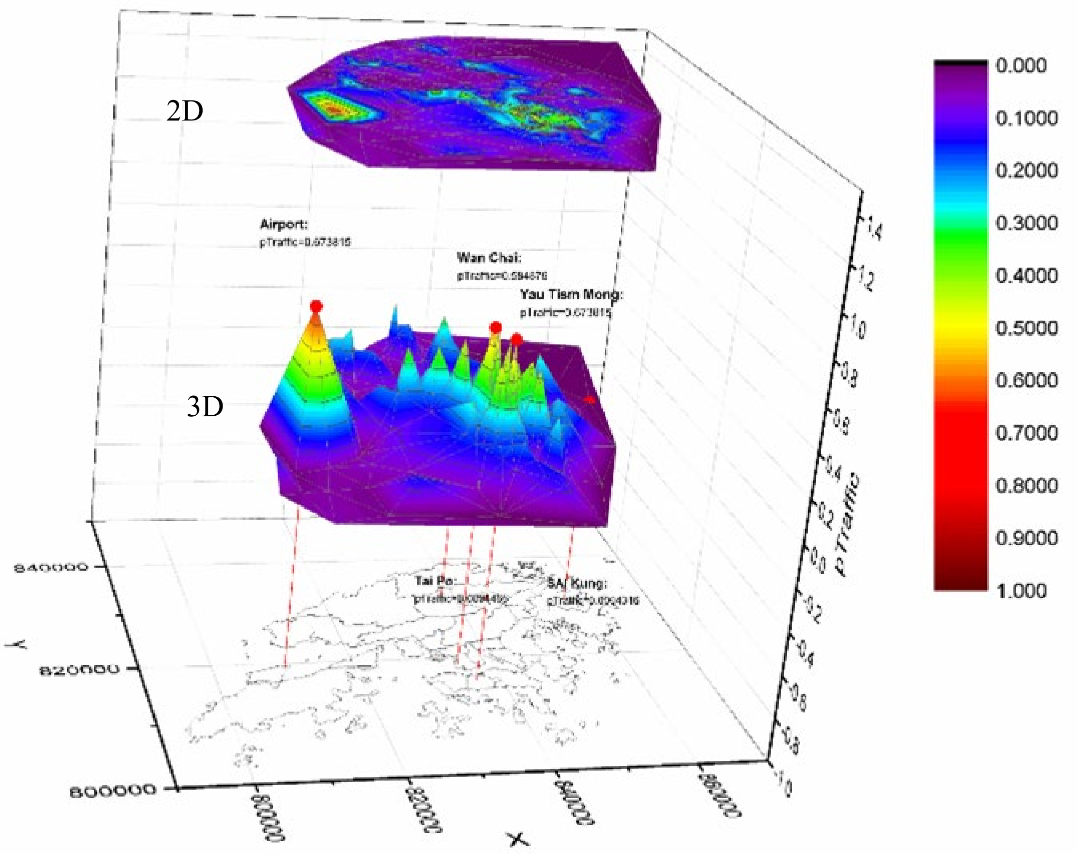
Fig. 1. Overview of study area and data.



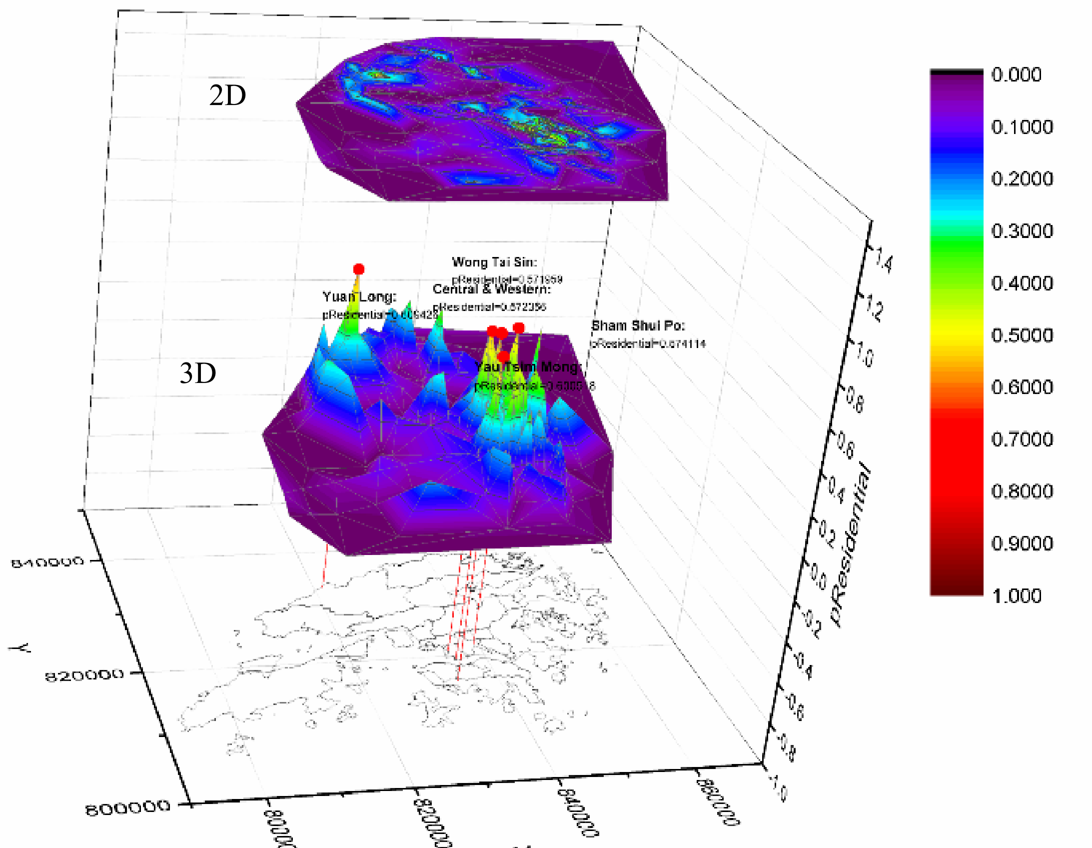
(a) ***Number of hotels***



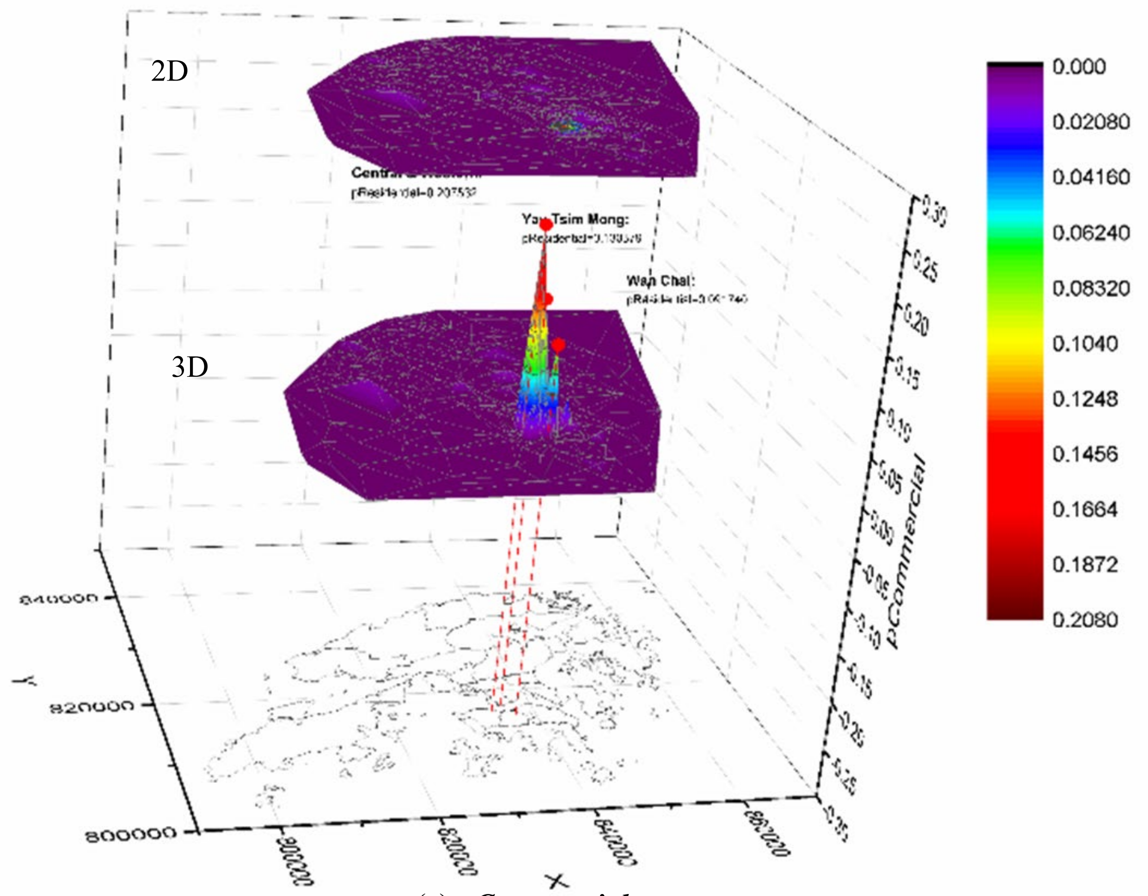
(b) ***pGreen***



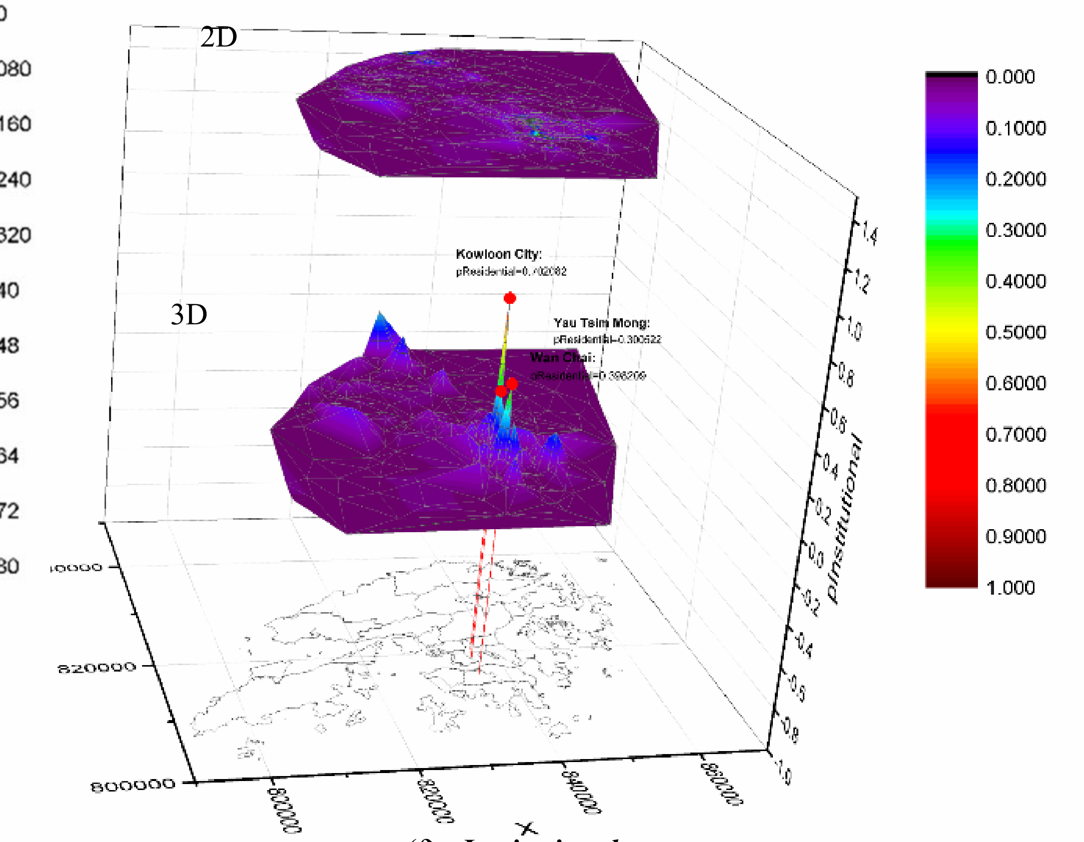
(c) ***pTraffic***



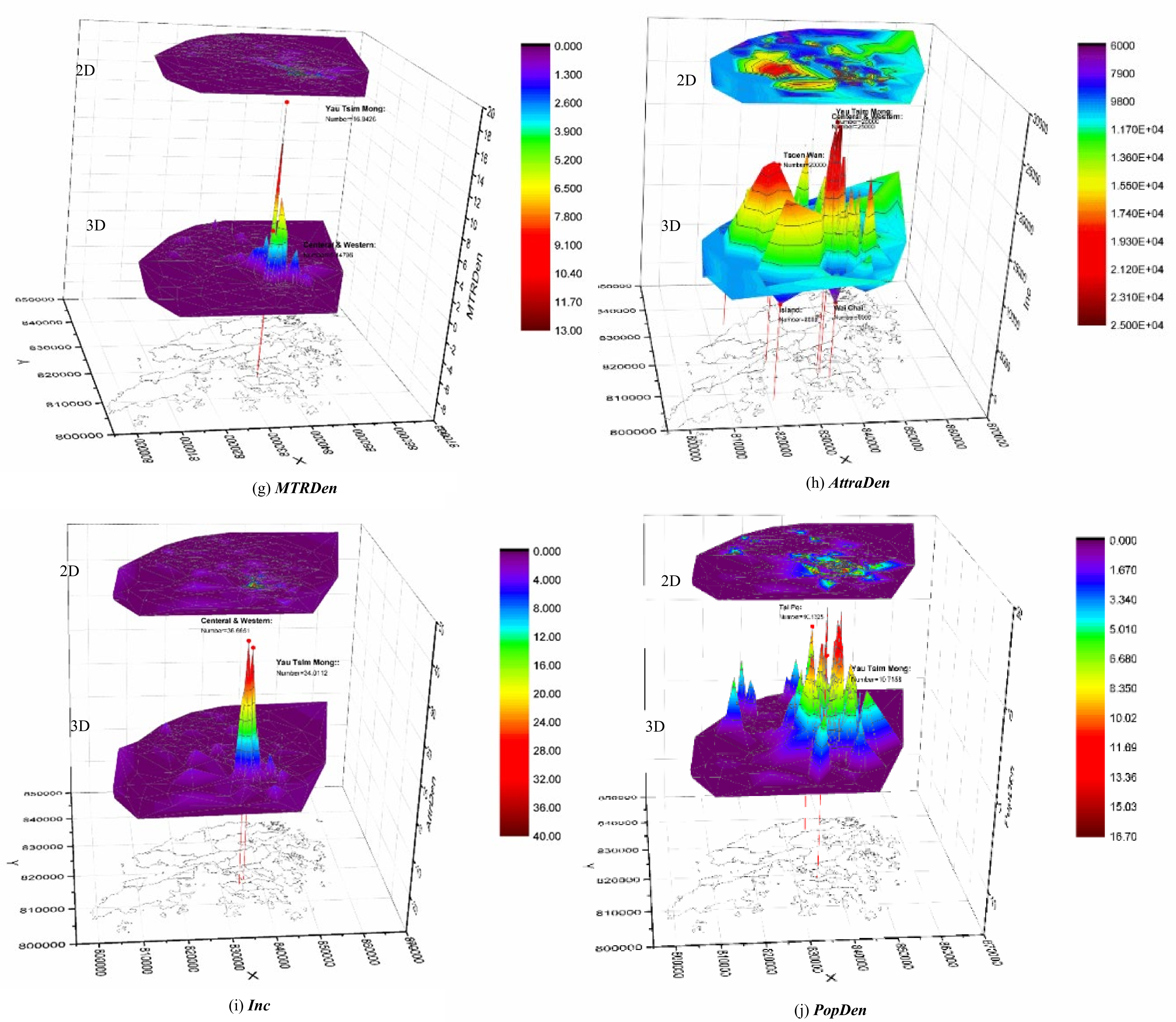
(d) ***pResidential***



(e) ***pCommercial***



(f) ***pInstitutional***



(g) ***MTRDen***

(h) ***AttraDen***

(i) ***Inc***

(j) ***PopDen***

Fig. 2. 2D and 3D colormap surface of distribution of dependent and independent variables.

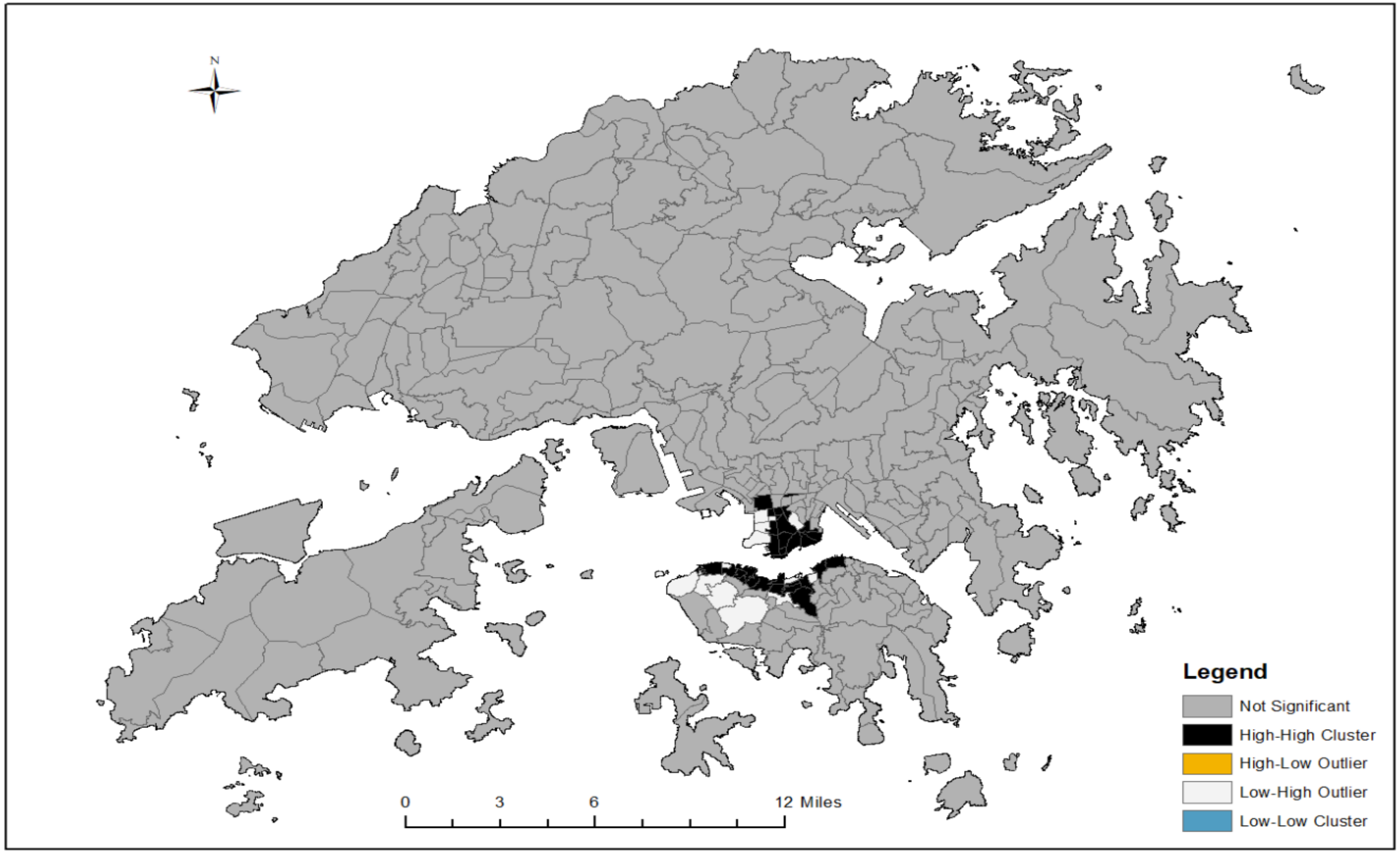
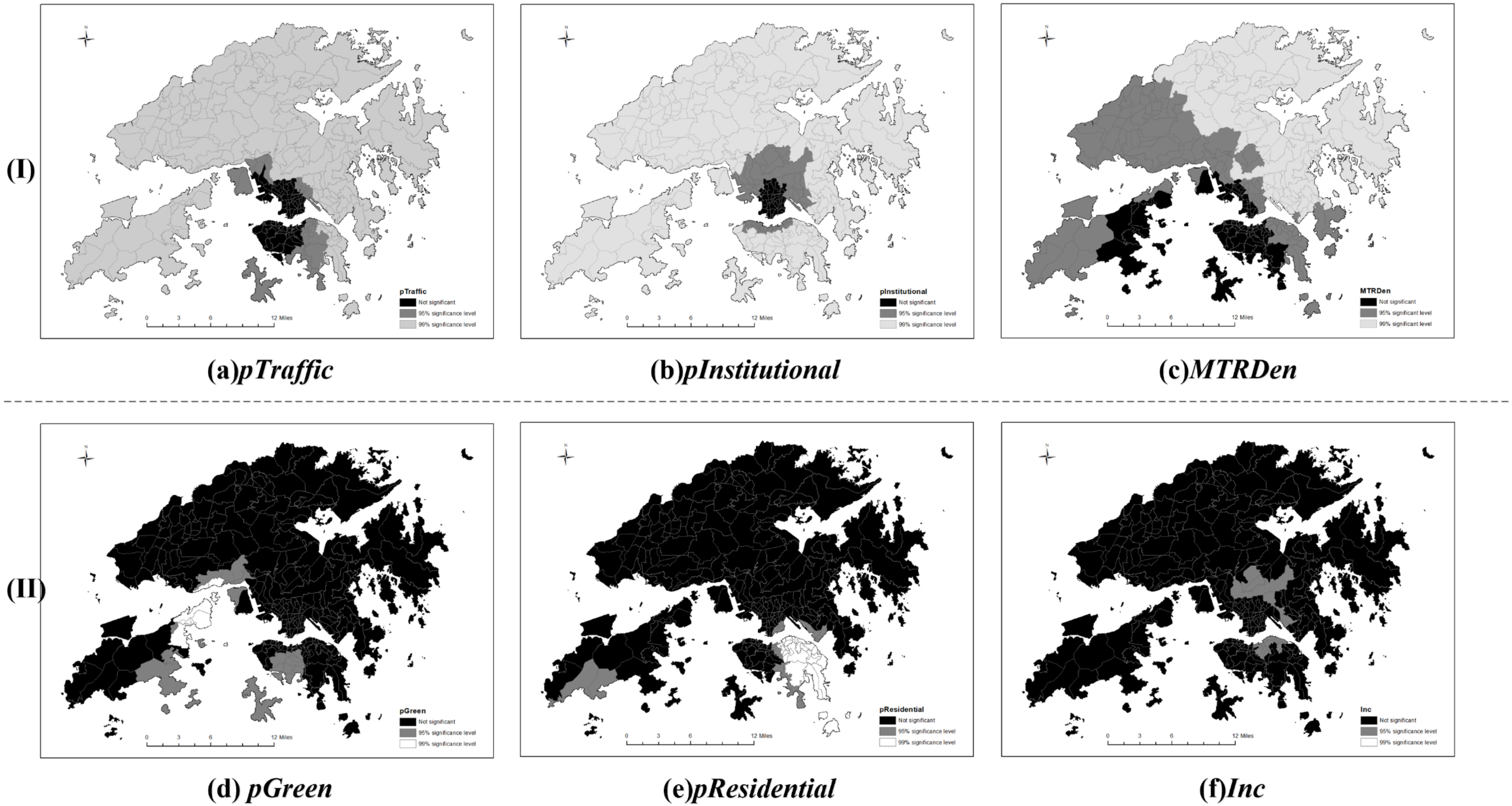
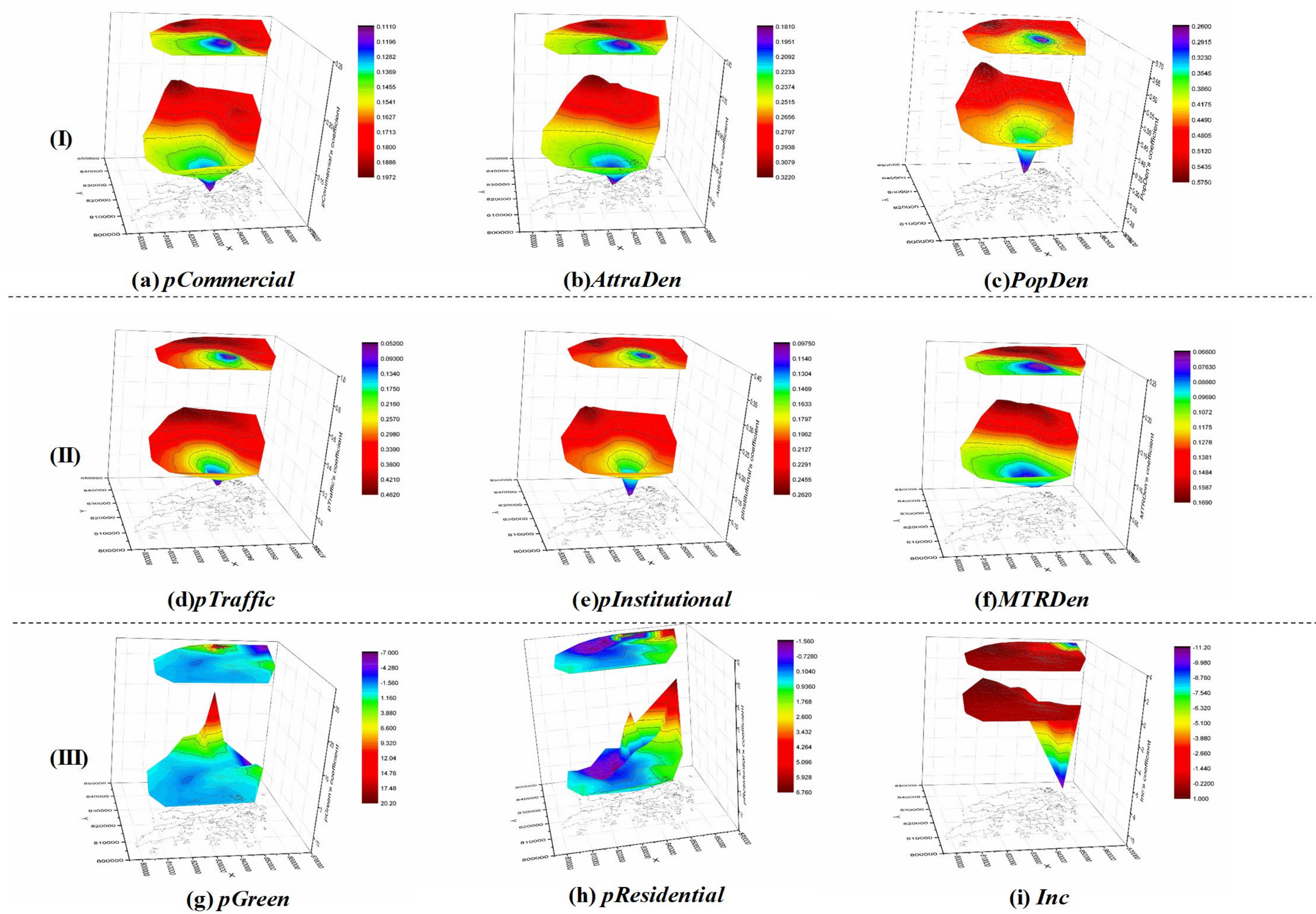


Fig. 3. Local Moran's *I* statistics for hotel count.



I: Overall significant independent variables; II: Overall insignificant independent variables

Fig. 4. Significance levels of independent variables.



I & II: Overall significant independent variables; III: Overall insignificant independent variables

Fig. 6. 3D of distribution of estimations of independent variables' coefficients.

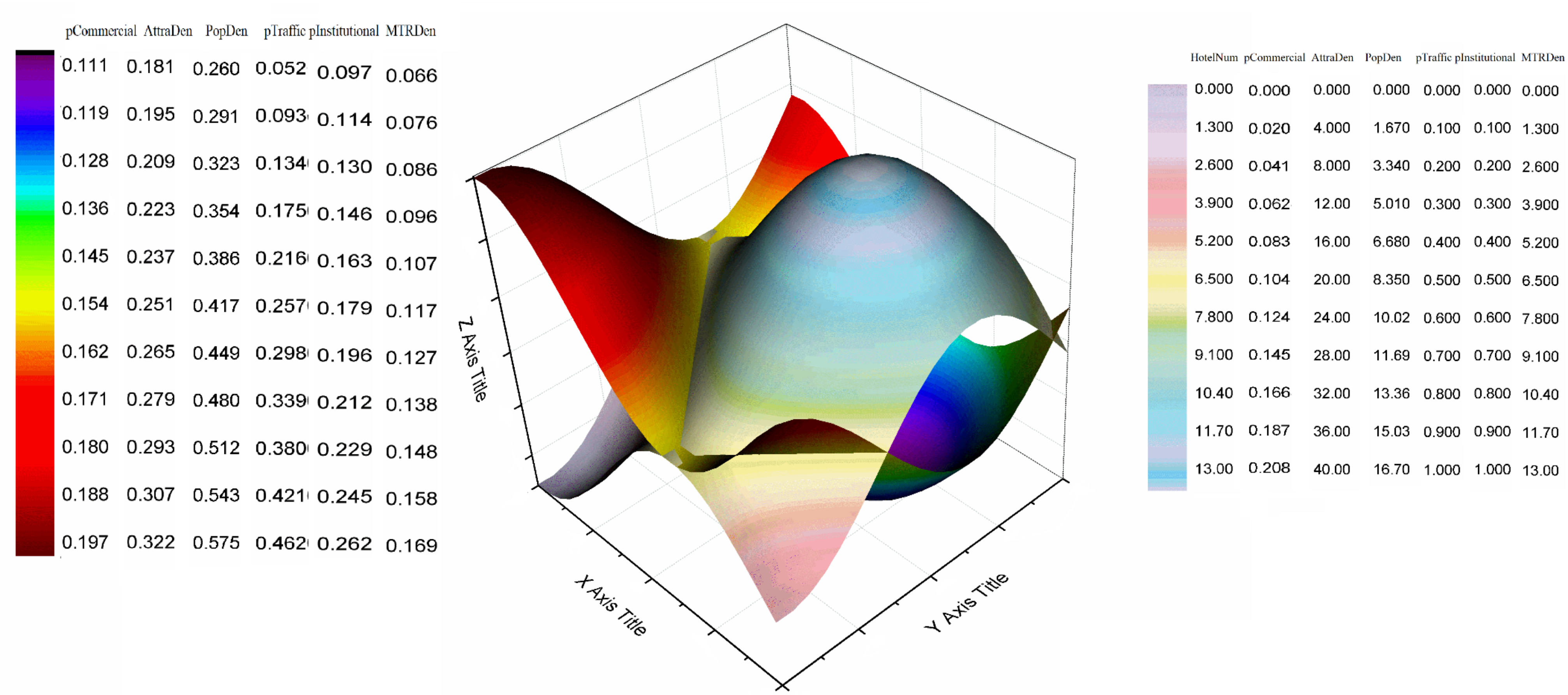


Fig. 7. Poached egg model.