International Journal of Geospatial and Environmental Research

Volume 8 | Number 3 Article 5

December 2021

Exploring Micro-scale Spatiotemporal Dynamics of Restaurant Entrepreneurship with Public Open Data

Chanwoo Jin
San Diego State University, cjin@sdsu.edu

Alan T. Murray
University of California, Santa Barbara, amurray@ucsb.edu

Exploring Micro-scale Spatiotemporal Dynamics of Restaurant Entrepreneurship with Public Open Data

Abstract

Commercial activities within a city have competed to attract people, and the interactions between these activities have affected urban dynamics. Among many services, the restaurant business accounts for a significant portion of the urban economy, with spatiotemporal variations in survivability reflecting crucial signs of changes in urban structure. This study aims to identify the patterns of spatiotemporal changes in restaurants locations to deepen our understanding of urban dynamics. Studies have utilized a variety of data sources, including social media and consumer review services, but they cover relatively short periods and focus on currently operating businesses. Public open data, however, offers potential to reveal continuous changes in urban space at micro scales since it covers an entire population with individual historic records, making it complete rather than a sample. In this study, we explore newly released public open data on licenses of restaurants in Seoul, South Korea to identify spatiotemporal dynamics of commercial activities in the city using three exploratory analytics, including hot spot analysis, trends analysis of spatial clusters, and space-time scan statistics. The results show continuous temporal changes in spatial clusters of restaurants. Hot spots remain in three traditional cores of Seoul, although each cluster has shrunk over time. Moreover, suburbs have become more risky, with significant declines and more closures than expected as well as relatively shorter lifespans. This implies a concentration of restaurants in central areas, which can further economic disparities within a city. By portraying spatiotemporal changes in restaurant entrepreneurship with public open data, this study provides essential knowledge about urban dynamics informing individual and public decision making processes, particularly associated with locating new businesses.

Keywords

spatiotemporal exploratory analysis, public data, urban dynamics, restaurants.

Acknowledgements

This research is based on a preliminary paper included in the 'Seoul Research Competition 2019', awarded as outstanding paper.

1 INTRODUCTION

Competition in commercial activities has a significant impact not just on the success of individual businesses, but also on urban structure and economy (Vandell and Carter 1994; Jung and Jang 2019). Within the tertiary industry, restaurants are one of the most common services, with an interesting tendency to open and close more frequently than other types of businesses. The diverse locations and popularity of restaurants aid in understanding changes in urban space since they regenerate or revitalize neighborhoods by attracting consumers and investment (Hyde, 2014; Zhai et al. 2015; Zukin et al. 2017). Although many socioeconomic factors can contribute to the success and failure of restaurants, the precise location of the restaurant usually plays a crucial role in entrepreneurship (Dock et al. 2015; Ghosh and Craig 1986). Some locations can be more accessible and profitable than other locations (Church and Murray 2009). Moreover, they compete and seek to gain strategic advantages, consequently generating agglomerations when successful (Hotelling 1929; Li and Liu 2012). However, locational advantages are not necessarily permanent (Prayag et al. 2011). Over time, once popular districts may become dilapidated, have outdated designs, and fail to reflect current trends or preferences of consumers. Therefore, identifying spatial patterns and temporal fluctuations is key to deepening our understanding of urban dynamics, providing insights on drivers of economic growth and development.

Big data analysis has been recently important in better understanding human and environmental complexities (Singleton and Arribas-bel 2021) and capable of discovering new knowledge about urban dynamics (Miller and Goodchild 2015). The advancement of information and communication technologies, computation technologies, and location-aware technologies enables the generation of large and diverse data in real-time, making them accessible for broad usage (Shaw et al. 2016). For example, location-based social networks and consumer review services provide information on people, revealing where they are and their impressions through check-in, messages and ratings. New types of data help to fill research gaps on micro-scale urban dynamics, including shop preference and restaurant popularity (Steiger et al. 2015; Tsou, 2015; García-palomares et al., 2018). However, it remains a challenge to utilize these data in urban studies when temporal changes are significant due to limited history and a lack of detailed information, such when the businesses opened, closed, etc.

On the other hand, public open data, or government administrative data, is routinely collected by authorities for public purposes, including welfare, taxation and licensing (Lansley et al. 2018). As a governmental tool, it generally covers an entire population and is regularly updated. Although public data has a long history and is considered "officially approved", its use has been limited in geographic studies at the individual level because of spatiotemporal aggregation. However, as interest in open data has increased, governments have made some raw individual data available to the public (Arribas-bel, 2014). As an example, the U.S. and U.K. recently launched websites to share the governmental data with other countries, including Japan and South Korea. It is expected that such data can help improve the effectiveness of public policies involving socioeconomic issues.

To understand dynamic patterns given increasing amounts of data, the importance and necessity of exploratory data analysis has become apparent. Exploratory approaches are generally grounded in statistics, supporting the identification of unique patterns in data before assuming hypotheses based on theories (Tukey 1962). Such an approach enables detection of underlying spatiotemporal trends in complex urban dynamics as the amount of fine scale data grows (Miller 2010; Mazur and Manley, 2016). Many studies have recently utilized Big Data, including call records and social media, to understand diverse patterns of human activities in urban spaces, effectively overcoming limitations associated with data reported via traditional aggregated geographic units (Tu et al. 2017). For example, using the check-in information from a consumer reviewing service, Zhai et al. (2015) and Zhang et al. (2021) discerned popular places in a city through exploratory analyses involving kernel density estimation and cluster detection. With public open data in Seoul, Korea, Lee et al. (2020) and Kim (2021) explored spatiotemporal patterns of restaurants by analyzing the annual number of openings and closings of restaurants. However, exploring spatial patterns of restaurants as temporal snap shots provides only a partial understanding of spatiotemporal dynamics because business lifespans are continuously changing.

In this paper we explore spatiotemporal dynamics in the entrepreneurship of restaurants through the application of three exploratory approaches using public open data. While several studies have analyzed social media and consumer review services data with points of interest to identify the popularity of places (Li et al. 2013; Zukin et al. 2017; Widaningrum et al. 2020; Zhang et al. 2021), they have not focused on the survivability of businesses. Because government agencies manage licensing of businesses, it is possible to explore the spatiotemporal changes in not only openings and closings of restaurants but also their lifespans. Among many businesses in a city, we focus on restaurants because of constant change and the significant impacts they have on local structure (see Zukin et al. 2009). We also advance replicability efforts in research by analyzing freely accessible public datasets, doing so using methods available through open software (Newman, 2010; Murray et al. 2013; Kedron et al. 2021). This study will investigate continuously changing spatiotemporal patterns of restaurant clusters in Seoul, Korea with public open data at micro scales to enhance our understanding of urban dynamics, providing a foundation for diverse planning and decision-making in cities.

2 LOCATION OF RESTAURANT BUSINESS

2.1 Location Theories for Restaurants in Cities

Restaurants have played a major role in economic growth of cities by providing jobs, tourism, and regenerating and revitalizing neighborhoods by attracting more consumers and investment (Zukin 2009; Hyde 2014; Self et al. 2015). Therefore, understanding their location patterns is a key issue for not only individual businesses but also for public policy and decision-makers. Seminal theories have been developed, often supported by empirical studies associated with retail location success in urban environments (Hurst 1972). Central place theory highlights that there is a maximum distance that people are willing to travel in consuming a good or service as well as requirements for a minimum level of demand to support a business. These two essential concepts explain why service providers prefer certain locations in central business districts with a larger customer base (Mulligan 1984; Austin et al. 2005; Church and Murray 2009). However, restaurant patronage is more complex, relying on intra-urban patterns of travel (Smith 1985). While the gravity law explains some aspects of trade area behavior (Huff 1964), particularly retail and restaurant locations (Li and Liu 2012), it cannot fully explain clustering effects.

Competition between vendors based on Hotelling (1929) offers some insights for the restaurant industry. Co-location in accessible areas results in profit maximization, provided total demand is sufficient. That is, agglomeration of businesses generates positive externalities, so restaurants gain an advantage by clustering together as long as the market is not saturated (Jung and Jang 2019). Since restaurant clusters provide favorable environments for enhanced food options and reduced costs of shared facilities, the spatiotemporal patterns of clusters are important (Prayag et al. 2012). Sun and Paule (2017), for example, detected restaurant clusters from Yelp reviews. As another example, Minner and Shi (2017) argued that spatial clusters of locally owned restaurants in commercial strips are signs of redevelopment. Recently, POI data enabled Zhang et al. (2021) to distinguish areal characteristics based on differences in clusters of local and non-local restaurants and Widaningrum et al. (2020) found spatial clusters of fast-food restaurants. Although these studies highlight the importance of restaurant clusters, rarely illustrated is their temporal change such information is lacking in social media and consumer review services data.

2.2 Restaurants in Seoul, South Korea

The South Korean restaurant sector represents a relatively large percentage of industry compared to other developed countries. According to the 2017 economic census in South Korea, 12.36% (496,915) of all establishments were restaurants while in the USA they represent 6.05% (598,656) of all establishments. However, the portion of employees in this sector was only slightly larger in South Korea (7.29%) than the USA (6.68%). Thus, the average number of employees per business is only 3.17 in Korea whereas in the USA it is 16.80. Furthermore, 95.81% of restaurants in Korea were operated by sole proprietors and 96.81% were single stores, having no headquarters or other locations. Low entry barriers encourage starting new businesses, but causes a saturated market, with economic fluctuations posing a risk to marginal operations. As small businesses comprise a large portion of the national economy in South Korea, a significant number of failures can lead to not only individual but also nationwide socioeconomic issues, such as a high unemployment (Kim and Lee 2019).

Many studies have investigated spatiotemporal patterns of restaurants in Seoul, the capital and socioeconomic center of South Korea. Competition in Seoul is greater than most other cities. Shin and Shin (2009) found that restaurants tend to be concentrated in the central business district (*Jung-gu* and *Jongno-gu*) and the other centric regions, including *Gangnam* and *Seocho-gu* and *Mapo-gu*, relying on large demand from nearby office workers and young adults. Yu and Lee (2017) also investigated restaurant clusters in Seoul and categorize them by factors contributing to their level of agglomeration. While restaurants in the central business district depend on commuter demand, those in *Mapo-gu* are oriented to more diverse types of consumers such as tourists. Although these studies explain urban structure through the spatial configurations of restaurants, they are limited to recent changes, lacking sufficient temporal information about evolving spatial patterns.

The South Korean government made data on business licenses available, encompassing location and opening/closing information, making research possible for exploring spatiotemporal patterns of all businesses, no just samples. However, many studies have been limited in explaining citywide changes because they have focused solely on well-known commercial areas. Jeong and Yoon (2017) compared the survivability of restaurants along main streets and back streets in the *Itaewon* region, a prominent multicultural district in Seoul. Kim et al. (2018) illustrated expansions of commercial areas in *Hongdae* region, a well-known campus town with four prestigious universities. At a broader scale, Ryu and Park (2019) classified five popular commercial areas based on changes in types of businesses. Lee et al. (2020) attempted to follow temporal changes in restaurant clusters with yearly changes in density of operating restaurants. Kim et al. (2021) compared spatiotemporal differences in opening and closing restaurants before and after COVID19, but the temporal differences were not significant because the pandemic has persisted. Although these approaches are valuable spatiotemporal dynamic snapshots, they do not illustrate continuous changes at the city level.

3 METHODS

To better understand the spatiotemporal dynamics in restaurant entrepreneurship at the city level, we employ three exploratory methods in a space-time framework: 1) spatial hot spot analysis, 2) trend analysis of clusters, and 3) spatiotemporal scan statistics with exponential models. Collectively, these analytic approaches facilitate accessibility of public open data since they are available as open source software, making the analysis relatively easy to replicate.

3.1 Spatial Hot Spot Analysis

Methods to identify (dis)similarities in geographic events have been developed and widely applied in a variety of fields (Getis 2008). Global spatial autocorrelation measures the relationship of a variable across spatial units. Although global statistics are useful to evaluate the strength of spatial dependence between spatial units in a region, they are limited in identifying whether and where similarity or dissimilarity occurs. As an alternative, local statistics, such as the local indicator of spatial autocorrelation (LISA) (Anselin 1995) and G_i^* (Getis and Ord 1992), focus on interaction between neighboring units. Among many local autocorrelation indices, G_i^* is an effective measure/tool to identify statistically significant clusters. G_i^* calculates the local average in a neighborhood as follows:

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

where x_j refers the value in neighbor of target unit, *i,* $\bar{X}$ indicates the local mean of the value ($\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$), and $S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \bar{X}^2}$. As (1) facilitates the comparison of values in neighborhood *i*, it can detect either hot or cold spots by identifying areas with relatively high or low clustered values. Hot spots reflect a high number of clustered start-ups, and can be considered as booming or popular areas, whereas cold spots represent a declining area. In this study, we analyze the number of currently operating restaurants and the number of net start-ups by subtracting the number of closed restaurants from the number of opened restaurants at *dong*[i] level. The neighborhood is defined as the area sharing edges of the target unit.

3.2 Trend Analysis of Clusters

Trend analysis of clusters traces temporal changes via the local spatial autocorrelation index, G_i^*. Although the index is useful for exploring spatial distributions of geographic events, it is limited in its ability to identify temporal changes in spatial patterns. The Mann-Kendall statistic enables a test of temporal relationships between different time steps fora spatial unit (Mann 1945; Kendall 1948). As a rank correlation analysis, the test determines statistically significant temporal trends by comparing values in a time sequence as follows:

$$S = \sum_{t}^{n-1}\sum_{p=1}^{n} sgn\left(x_{i,t+p} - x_{i,t}\right) \quad (2)$$

where $x_{i,t} = \begin{cases} 1, & z_{it} > z_{i,t-1} \\ 0, & z_{it} = z_{i,t-1} \\ -1, & z_{it} < z_{i,t-1} \end{cases}$, ($t$ = 0, 1, … n).

If the current value of standardized G_i^*, $z_{i,t}$, is larger than the previous value, $z_{i,t-1}$, the result of the paired comparison is 1. On the other hand, a result of -1 occurs when $z_{i,t-1}$ is larger. The paired results are summed by units and compared to the null hypothesis that trends do not exist over time (S = 0). As a result, the analysis categorizes current clusters into one of eight types of hot and cold spots.

For this study, we aggregate restaurants into a space-time cube defined by *dong* and year, and calculate the number of net start-ups in each spatiotemporal bin by counting 1 when a shop opens and -1 when a shop closes. In other words, the value of each bin in the space-time cube represents the number of net start-ups in a year from January 1st to December 31st at the *dong* level. The spatial neighborhood is defined as the area sharing edges of the target unit and each bin is analyzed in comparison to the entire time period.

3.3 Spatiotemporal Scan Statistics

The spatial and space-time scan statistics suggested by Kulldorff (1997) have been widely used to detect clusters of geographic events such as disease outbreaks (Smith et al. 2015) and crimes (Nakaya and Yano 2010; Leitner and Helbich 2013). Initial statistics relied on the Bernoulli probability distribution of binary events, whether it happens or does not happen. It detects subareas in which events more (or less) frequently occur than they do in other areas by scanning the study region using a moving window. However, the Bernoulli assumption is restricted to spatiotemporal disparities of continuous variables, such as lifespan of diseases. Huang et al. (2007) propose using an exponential distribution for these scan statistics to find lower (or higher) survivability areas, and it has been widely used to identify geographic disparity of survivability in diverse diseases (Henry et al. 2009; Lin et al. 2015; Wan et al. 2012). Let θ_z represent the mean survival time for each individual inside a subarea, Z. The null hypothesis is that there is no difference in the mean survival time inside or outside the subarea (e.g., H_0: $\theta_Z = \theta_{Z'}$). The likelihood function for the exponential case is:

$$L(Z, \theta_Z, \theta_{Z'}) = \frac{1}{(\theta_Z)^r} e^{-\sum_i \frac{t_i}{\theta_z}} \frac{1}{(\theta_{Z'})^{r'}} e^{-\sum_j \frac{t_j}{\theta_{Z'}}} \tag{3}$$

where t is the survival time of an individual ($i \in Z, j \in Z'$) and r the number of non-censored individuals ($R = r + r'$; $G = Z + Z'$). Under the alternative hypothesis (H_α: $\theta_Z \neq \theta_{Z'}$), one is interested in the zone $\hat{Z}$ that maximizes likelihood function (3). This can then be derived as:

$$\lambda = \frac{max_{Z,\theta_Z \neq \theta_{Z'}} L(Z, \theta_Z, \theta_{Z'})}{max_{Z,\theta_Z = \theta_{Z'}} L(Z, \theta_Z, \theta_{Z'})} = \frac{L(\hat{Z})}{L_0} = \frac{max_Z (\frac{1}{\theta_Z})^r (\frac{1}{\theta_{Z'}})^{r'}}{(\frac{1}{\theta_G})^R} \tag{4}$$

The statistical significance of λ is assessed using a p-value generated through Monte Carlo simulation. Therefore, a detected cluster indicates that individuals in the subarea are significantly shorter (or longer) in survival than outside of the subarea if the null hypothesis is rejected.

The spatiotemporal scan statistic under exponential conditions is applied to survival data for restaurants in order to assess not only spatial clusters but also which restaurants survive shorter (or longer) durations. If a restaurant closed before the end of 2018, it is regarded as non-censored and its survival time is counted from its opening date to the closing date. On the other hand, for a restaurant still operating at the end of 2018, its survival time is counted from its opening date to 12/31/2018 by censoring data. The maximum size of each cluster is restricted to 50% of the total individuals, and the p-value of each cluster is derived from 999 random permutations.

4 DATA

Local governments in South Korea, *si-gun-gu*[ii], have the authority to approve new businesses. All businesses are required to report their closure to their local government. South Korea recently made this business data available, detailing business types, location, starting date and closing date. The data covers 191 types of business, such as markets, residential services, and restaurants, and updates in real time are available through an open application programming interface. It has been used in a wide range of fields, including academia, public, and private sectors, because it is regarded as a population versus a sample of businesses. With a focus on restaurants (general food services and drinking places), 1.7 million records were identified at the end of 2018. Seoul has 21% of total restaurants whereas the population and household represent 18.9% and 19.6% of the country, respectively. Due to uncertainty in old records, we only use currently operating restaurants and those that closed after 2000.

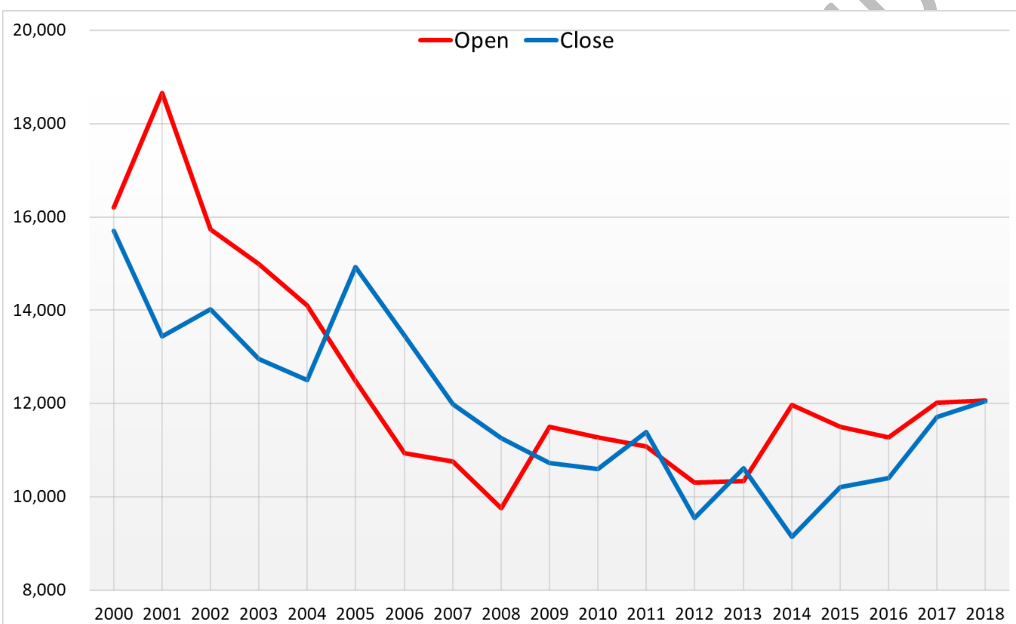


Figure 1. The number of opening and closing restaurants from 2000 to 2018.

Since 2000, 346,628 restaurants have opened and closed in Seoul. The number of start-ups peaked in 2001 with 18,659, but steadily declined until reaching a low in 2008. The number of closures outnumbered starts-up beginning in 2005 until 2008. The number decreased by 2014 but increased again, whereas the number of opening restaurants had been quite constant. As a consequence, the number of openings and closings in 2018 are almost even (Figure 1). Figure 2 suggests an exponential distribution with a long right tail associated with survival times of restaurants. The overall average of the life span is 8.24 years and the median is 5.73 years. However, closed restaurants have survived for 6.98 years on average and 31.4% of businesses have failed in 3 years.

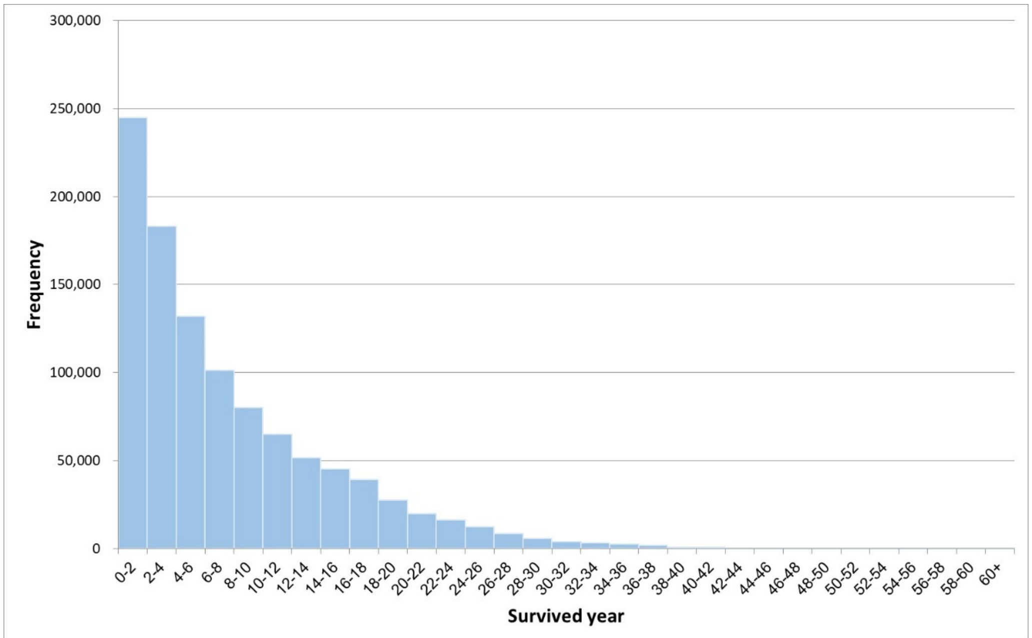
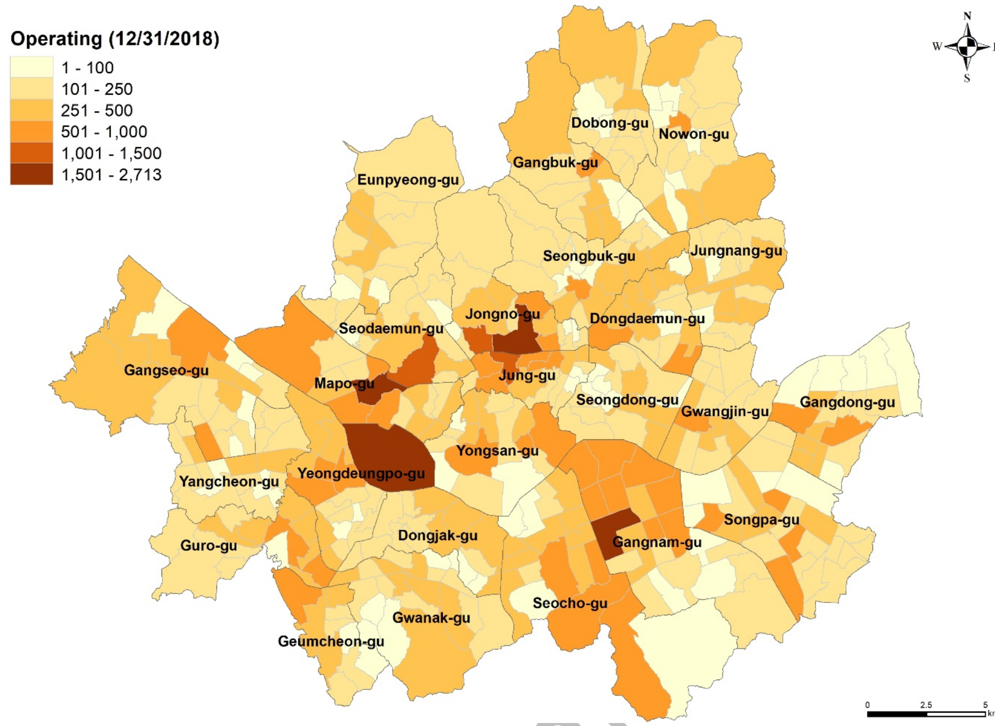
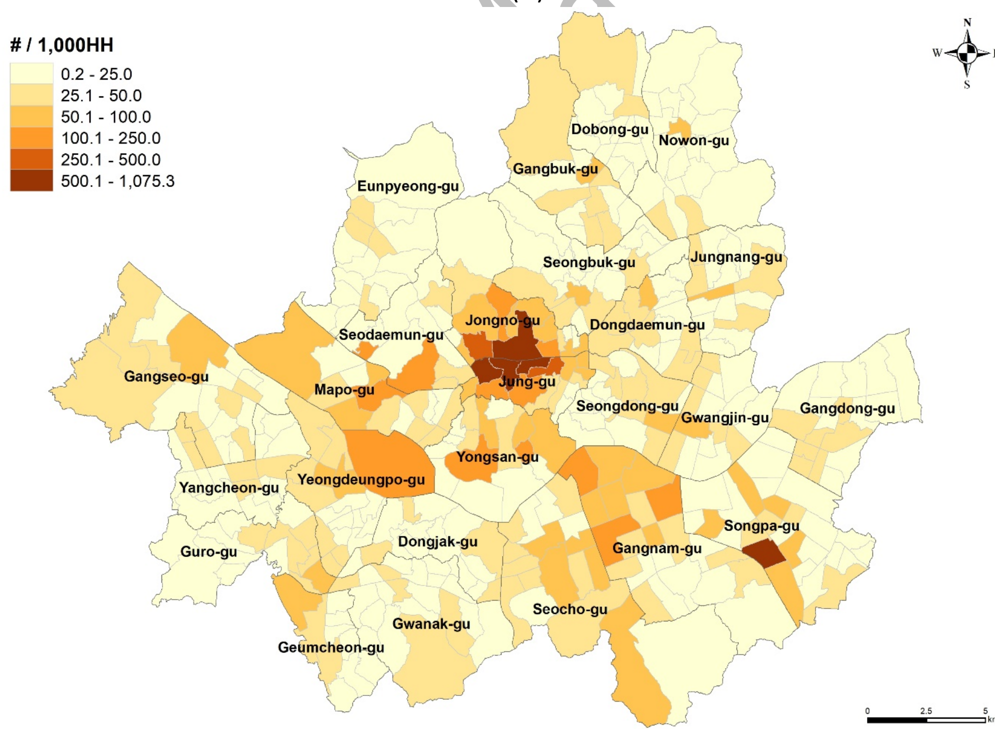


Figure 2. Distribution of survived years of restaurants.

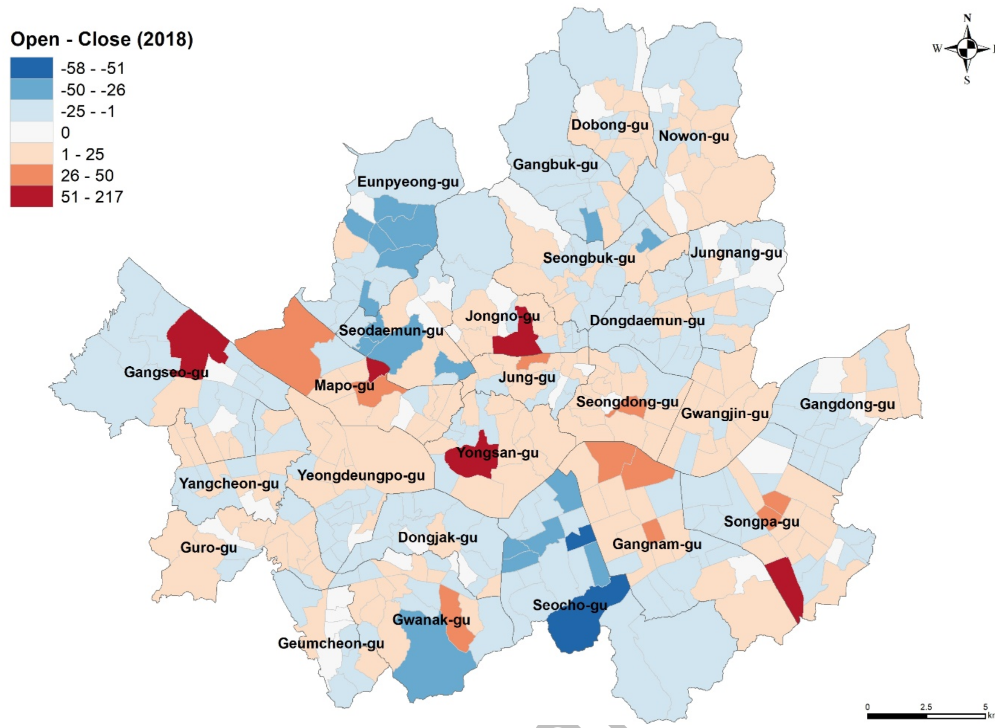
The number of currently operating restaurants at the end of 2018 was 120,011. That equates to 198.3 shops per km^2 and 28.28 shops per 1,000 households. Figure 3a illustrates the spatial distribution at the dong scale. 283.04 restaurants were operating in a unit on average, but four dongs, *Jongno-gu*, *Mapo-gu*, *Yeongdeungpo-gu*, and *Gangnam-gu,* showed significantly high numbers. With the exception of *Seogyo-dong* in *Mapo-gu*, which is a popular college campus town, the other areas are major business districts in Seoul. When the number is normalized by households, *Jongno-gu* and *Jung-gu* are stand out (Figure 3b). While those major commercial areas contained more start-ups than closures in 2018, most areas experienced more closures. Notably, decreases in *Seocho-gu*, which is considered a thriving area, were considerable (Figure 3c). Based on Figure 3d presenting the average survival years for closed businesses, restaurants in the campus town of *Mapo-gu* survived less than the other major districts.


Operating (12/31/2018)
1 - 100
101 - 250
251 - 500
501 - 1,000
1,001 - 1,500
1,501 - 2,713
N
W
E
S
Dobong-gu
Nowon-gu
Gangbuk-gu
Eunpyeong-gu
Seongbuk-gu
Jungnang-gu
Jongno-gu
Dongdaemun-gu
Seodaemun-gu
Gangseo-gu
Mapo-gu
Jung-gu
Seongdong-gu
Gwangjin-gu
Gangdong-gu
Yongsan-gu
Yangcheon-gu
Yeongdeungpo-gu
Songpa-gu
Guro-gu
Dongjak-gu
Gangnam-gu
Seocho-gu
Gwanak-gu
Geumcheon-gu
0
2.5
5
km

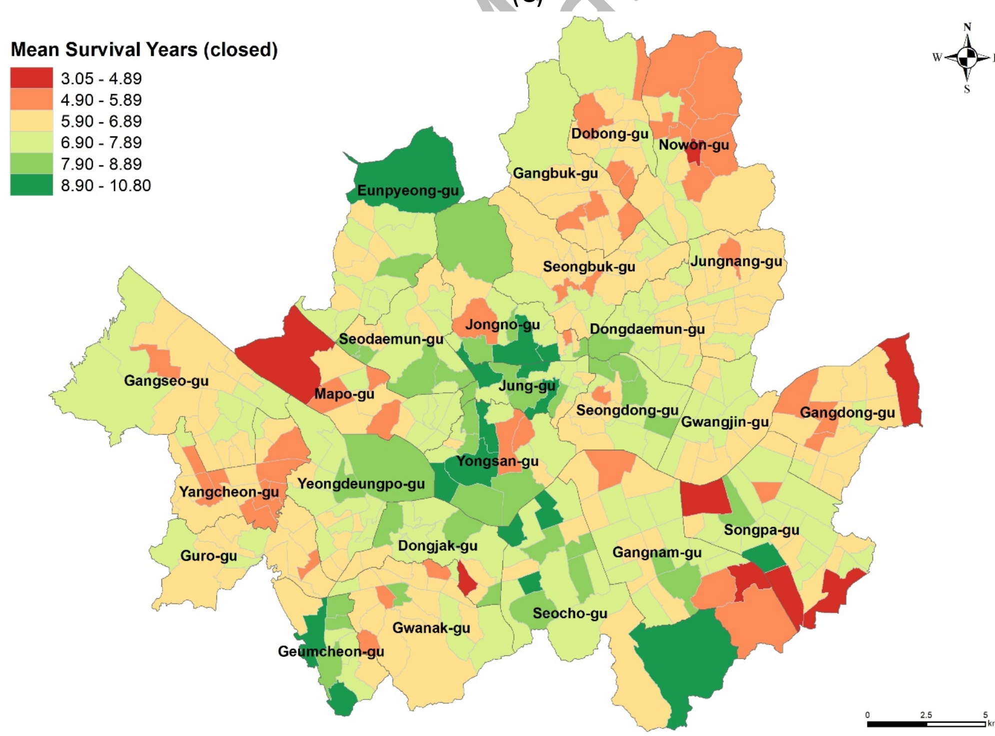
(A)


/ 1,000HH
0.2 - 25.0
25.1 - 50.0
50.1 - 100.0
100.1 - 250.0
250.1 - 500.0
500.1 - 1,075.3
N
W
E
S
Dobong-gu
Nowon-gu
Gangbuk-gu
Eunpyeong-gu
Seongbuk-gu
Jungnang-gu
Jongno-gu
Dongdaemun-gu
Seodaemun-gu
Gangseo-gu
Mapo-gu
Jung-gu
Seongdong-gu
Gwangjin-gu
Gangdong-gu
Yongsan-gu
Yangcheon-gu
Yeongdeungpo-gu
Songpa-gu
Guro-gu
Dongjak-gu
Gangnam-gu
Seocho-gu
Gwanak-gu
Geumcheon-gu
0
2.5
5
km

(B)



(C)



(D)

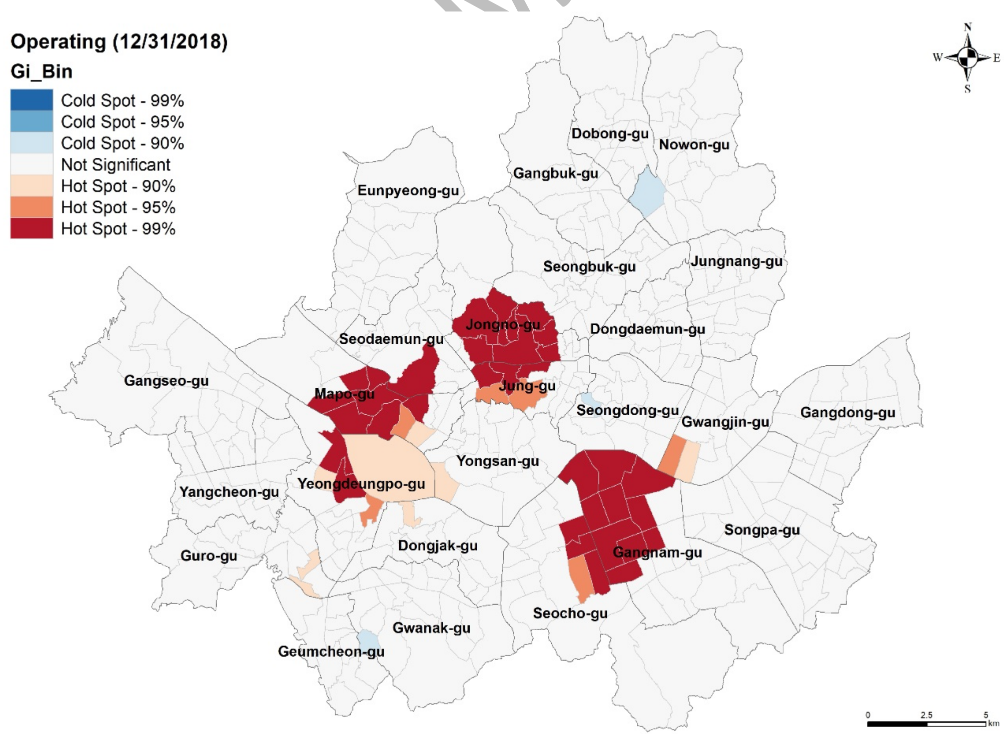
Figure 3. Spatial distribution of restaurant businesses. (A) the number of operating restaurants at the end of 2018; (B) the number of restaurants per 1,000 households; (C) the number of net openings in 2018; (D) the mean survival years of closed restaurants.

5 RESULTS

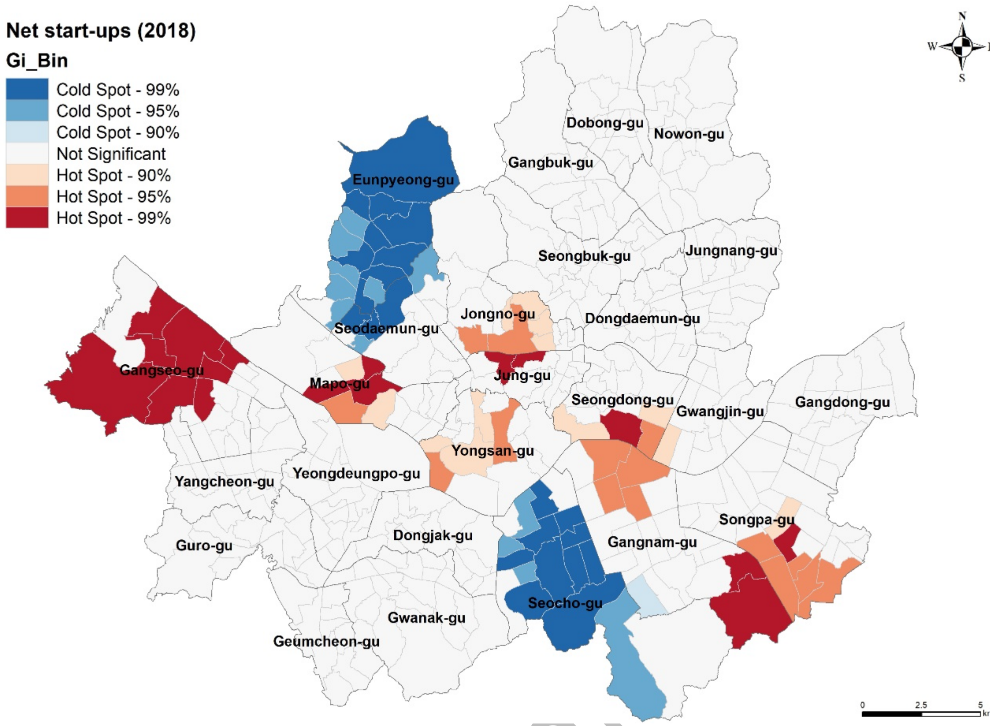
Moving beyond the descriptive details offered in the previous section regarding restaurant openings and closings, exploratory analysis is not offered based on the application of the previously reviewed methods.

5.1 Spatial Clusters of Restaurants

To assess spatial patterns observed in Figure 3, G_i^* local spatial autocorrelation statistics were derived. Figure 4 displays detected hot and cold spots of current businesses and net start-ups in 2018. The first map shows three large hot spots with a significantly higher number of operating businesses than their neighbors (Figure 4a). These areas include three major cores in Seoul: *Jongno-Jung-gu* (central business district: CBD), *Yeongdeunpo-Mapo-Seodaemun-gu* (Yeouido business district: YBD), and Gangnam-Seocho-gu (Gangnam business district: GBD) (Seoul, 2014; Shin and Shin 2009). In *Jongno-Jung-gu*, as the traditional central business district, there are many restaurants for both tourists and office workers. *Gangnam-Seocho-gu* is also a well-known district and a socioeconomic center of Seoul which supports many popular shopping districts. On the other hand, *Mapo-gu* has mixed characteristics. The area has a business-oriented section, but it is well-known as a campus town with four prestigious universities. The general location patterns of restaurants have not much changed since 2000.



(A)



(B)

Figure 4. Spatial hot and cold spots of restaurant businesses. (A) operating restaurants at the end of 2018; (B) the number of net openings in 2018.

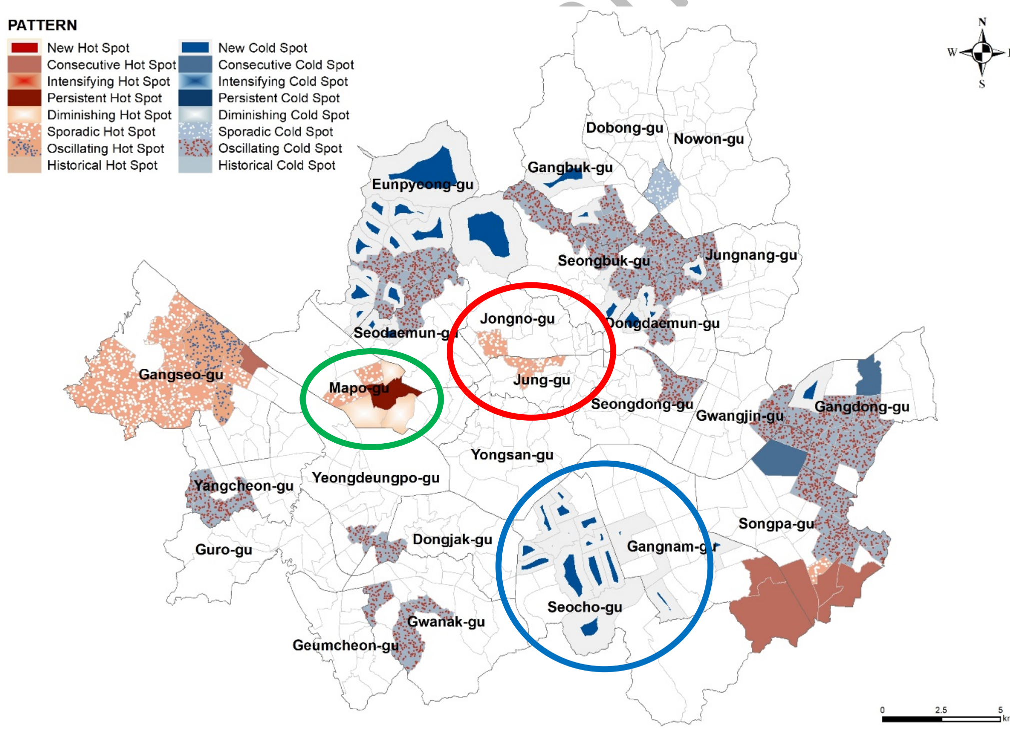
These clusters are still viable for starting new establishments (Figure 4b). The central business district area shows hot spots for the number of net start-ups in 2018, which indicates the new business outnumbered closed shops. Although the year is considered as an economic downturn period, significantly large numbers of businesses started in the three core areas. However, the area of hot spots is much smaller than the area of currently operating restaurants' hot spots (See Figure 4a). In the region, the most significant hot spots shrink from 11 to 2 dongs. Similarly, the hot spots in *Yeouido Business District* diminished to three dongs. *Seocho-gu* resulted in significant cold spots indicating that more restaurants closed than opened. Moreover, *Seongdong-gu*, rather than *Gangnam-gu*, is detected as a new hot spot for new restaurants. Additionally, the southern part of *Gangnam-gu*, which does not contain hot spots of current businesses (See Figure 4a), became a hot spot because new towns had been developed (similarly for *Gangseo-gu*).

5.2 Temporal Dynamics of Spatial Clusters

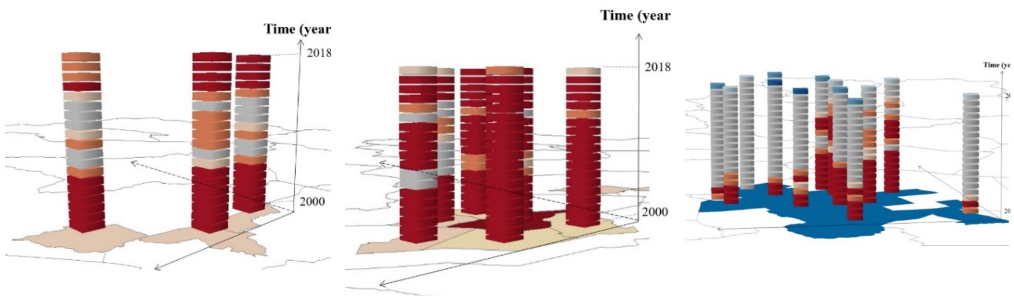
Based on a space-time cube with bins representing net openings in a dong by year, the results of emerging hot spot illustrate temporally categorized current clusters. Compared to Figure 4b, Figure 5 shows a large area of cold spots. The north-eastern area, including *Gangbuk, Seongbuk, Jungnang, Dongdaemun-gu*, have oscillating cold spots. This indicates areas that have a history of statistically significant hot spots for less than 90% of the total time period, but become a cold spot at the final time step,

2018. Another notable pattern is the large area of new cold spots in *Eunpyeong-gu* and *Seocho-gu*. New cold spots represent areas which have never been a cold spot except in the final time step, 2018. Although these areas have different socioeconomic composition, current environments in both areas are not favorable for restaurants starting new businesses.

On the other hand, centric areas appear as hot spots, except Gangnam district. The central business district contains sporadic hot spots, which have never been cold spots. During most of the time period, the area has shown statistically significant hot spots especially from 2000 to 2006 and 2015 to 2018 (Figure 5b). Although the net opening restaurants from 2005 to 2006 were negative at the entire city level (see Figure 1), more restaurants opened than closed in the region. Also, *Yeouido* district has significant hot spots with persistent, diminishing and sporadic areas. A persistent hot spot denotes that the areas have maintained the status of a hot spot for 90% of the time period. Diminishing hot spots are like persistent hot spots, but the intensity of clusters decreases. In the *Mapo-gu* area (Figure 5c), the two diminishing hot spots are detected in 2018 compared to the persistent hot spots even though they have more significant clusters over time. Unlike the two centers, *Gangnam* district (Figure 5d) presents new cold spots referring the areas were favorable for restaurants to start at least by 2015 but it recently turned to be cold spots.



(A)



(B) (C) (D)

Figure 5. Temporal changes in spatial clusters of restaurant businesses. (A) the number of net openings from 2000 to 2018; (B) yearly bins of spatial cluster in Jongno and Jung-gu (area encircled in red in A); (C) yearly bins of spatial cluster in Mapo-gu (area encircled in green in A); (D) yearly bins of spatial cluster in Gangnam and Seocho-gu (area encircled in blue in A).

These temporal fluctuations in clusters implies that the preferable locations for new restaurants have changed even for cores of the city. While *Yeouido* district is still attractive for business investments and the central business district recovers its reputation, *Gangnam* district is experiencing a decline in popularity of its restaurants. Also, recent economic decreases are observed through many cold spots in local (or town) centers where it has never occurred before. Although some edge areas are booming in 2018 with development of new towns, the restaurant business generally has faced a downturn and thus, its concentration into city centers has intensified.

5.3 Spatiotemporal Variations in Survivability of Restaurants

To identify spatiotemporal disparities in survivability of restaurants, we analyze survival time of restaurants with a spatiotemporal scan statistic (exponential model). We count only statistically significant clusters with greater than 0.05 p-values derived from 999 random permutations. Moreover, we define a risky cluster of restaurants when it has a significantly large number of observed closures than expected. On the other hand, a safe cluster is when the number of observed closures is significantly lower than expected. The number of expected closures is calculated under the hypothesis that survival times of all restaurants in the city follow an exponential distribution with the homogeneous mean over space and time. As a result, 34 clusters in Seoul over19 years are identified, with 23 clusters deemed risky. The detected clusters are ordered by λ denoting higher likelihood of being a statistically significant.

First, restaurants in the major districts survived longer than those in other areas (Figure 6). Based on relative survival time (RST), restaurants in cluster 1 in *Jongno-gu* last 73.8% longer than those outside of the area (RST: 1.738). In cluster 7 in *Gangnam* district and 9 in *Yeouido* district, restaurants had shorter lifespans than ones in cluster 1 in the central business district; they show 26.0% and 23.3% longer survived time, respectively. In contrast, restaurants in cluster 8 ran their businesses for an average 47.3% shorter length of time than those outside of the area.

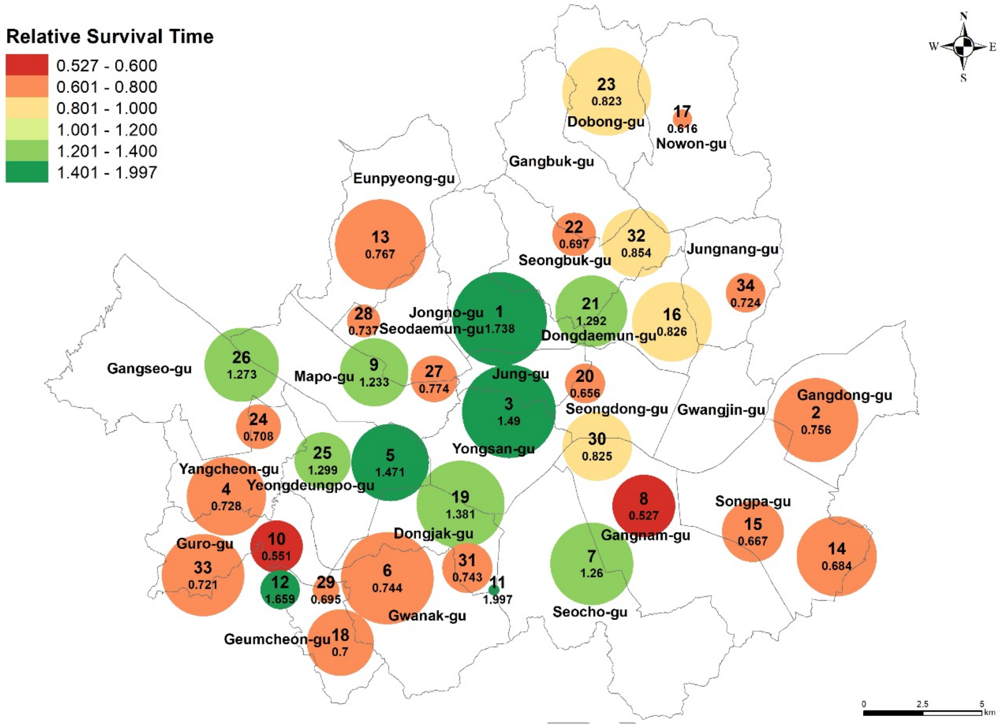
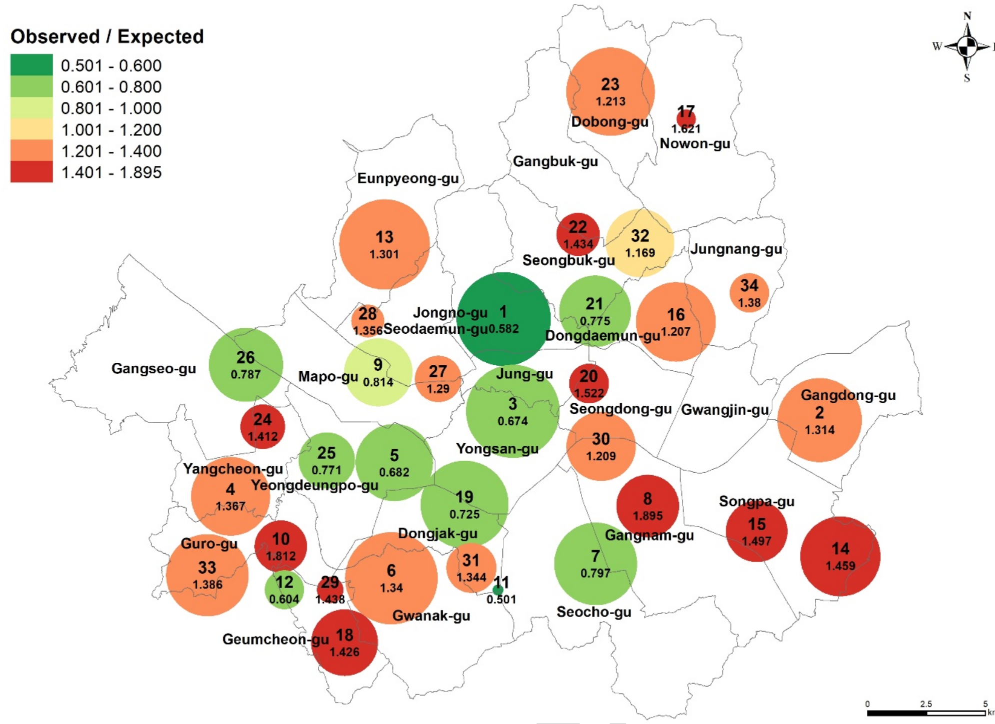
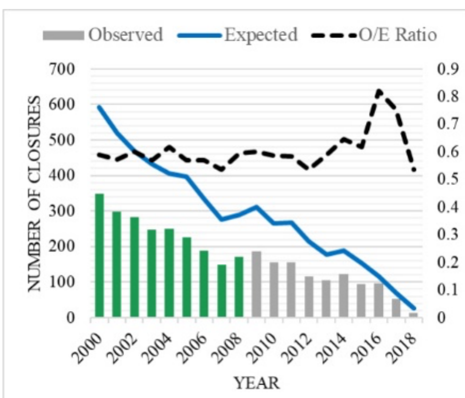


Figure 6. Spatial distribution of relative survival time.

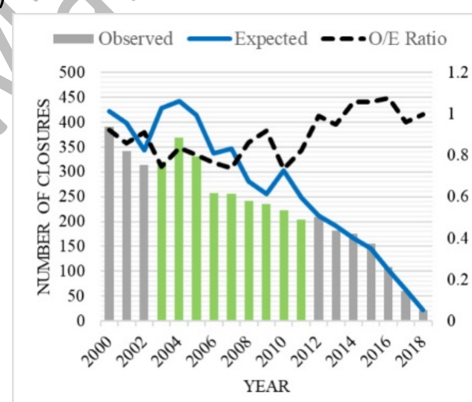
Figure 7a shows the ratio of observed closures compared to expectations. Generally, the three cores have higher survivability clusters than suburban areas. Most of the risky clusters are located in the north-eastern and south-western areas while the safest cluster with the lowest observation to expectation ratio (OE ratio: 0.582) is detected in the central business district (Figure 7b). This means that in that particular cluster, 41.8% more restaurants had survived than the expected number whereas the riskiest cluster (Figure 7d) located in the *Gangnam* district indicates 89.5% more restaurants failed in the cluster area. Another cluster across *Gangnam-gu* and *Seocho-gu* (Figure 7c) is identified as a safe cluster with relatively low OE ratio (0.797). Compared to *Gangnam*, a cluster in *Yeouido* district (Figure 7e) shows a high survivability with 0.814. Both indices, OE ratio and relative survival time, demonstrate that the cluster in *Gangnam* district (#8) is the riskiest area for restaurant businesses in this study area and time period.


Observed / Expected
0.501 - 0.600
0.601 - 0.800
0.801 - 1.000
1.001 - 1.200
1.201 - 1.400
1.401 - 1.895
N
W
E
S
23 1.213 Dobong-gu
17 1.621 Nowon-gu
Gangbuk-gu
Eunpyeong-gu
13 1.301
22 1.434
32 1.169
Seongbuk-gu
Jungnang-gu
34 1.38
1 0.582 Jongno-gu
28 1.356 Seodaemun-gu
21 0.775 Dongdaemun-gu
16 1.207
26 0.787 Gangseo-gu
9 0.814 Mapo-gu
27 1.29
Jung-gu
20 1.522
3 0.674
Seongdong-gu
Gwangjin-gu
Gangdong-gu 2 1.314
24 1.412
25 0.771
5 0.682
Yongsan-gu
30 1.209
Yangcheon-gu
4 1.367
Yeongdeungpo-gu
19 0.725
8 1.895
Songpa-gu
15 1.497
14 1.459
Guro-gu
10 1.812
Dongjak-gu
Gangnam-gu
33 1.386
12 0.604
29 1.438
6 1.34
31 1.344
11 0.501
7 0.797
Seocho-gu
Gwanak-gu
Geumcheon-gu 18 1.426
0 2.5 5 km

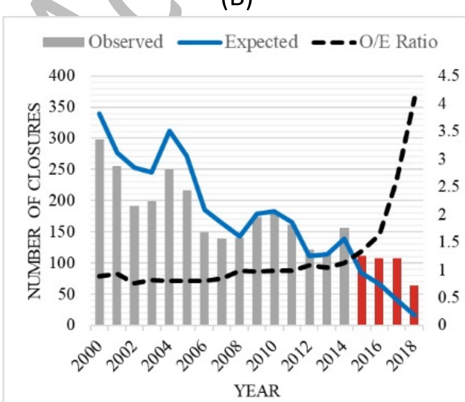
(A)


Observed
Expected
O/E Ratio
NUMBER OF CLOSURES
YEAR

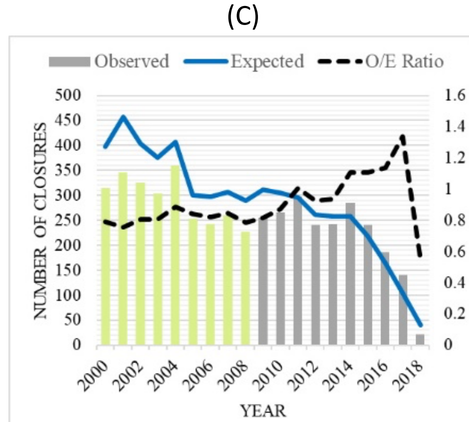
(B)


Observed
Expected
O/E Ratio
NUMBER OF CLOSURES
YEAR

(C)


Observed
Expected
O/E Ratio
NUMBER OF CLOSURES
YEAR

(D)


Observed
Expected
O/E Ratio
NUMBER OF CLOSURES
YEAR

(E)

Figure 7. Spatiotemporal distribution of observation to expectation ratio. (A) spatial distribution of risky clusters; (B) the number of observed and expected closures in cluster #1; (C) the number of observed and expected closures in cluster #7; (E) the number of observed and expected closures in cluster #8; (E) the number of observed and expected closures in cluster #9.

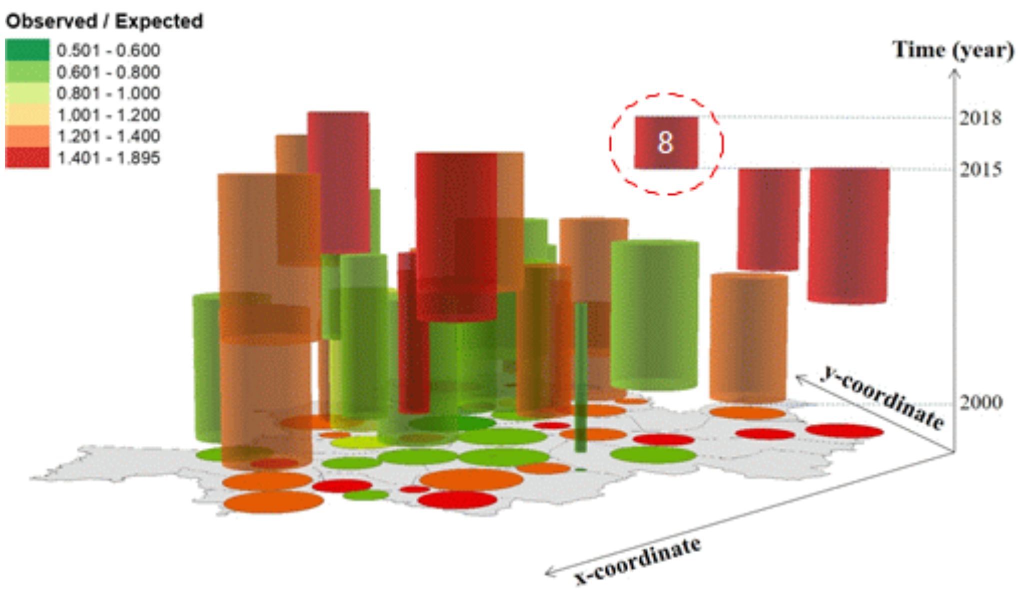


Figure 8. Spatiotemporal distribution of observation to expectation ratio in 3D view.

From a 3D perspective, Figure 8 illustrates the temporal gaps between clusters. Red cylinders represent risky clusters with high OE ratio and occur in relatively recent years compared to safe clusters. For example, the most likely and safest cluster (#1) was from 2000 to 2008. This result corresponds to the patterns of net opening clusters in Figure 4b. Although these two clusters do not share the same time period and spatial extent, the results demonstrate that the central business district was a favorable environment for restaurants in the early 2000s. During the period, restaurants in the area could survive longer than they could in other areas and more restaurants opened rather than closed. Likewise, *Yeouido* district also experienced a longer survivability of restaurants in the early 2000s. The area still has more openings than closures (see Figure 5c), but the restaurant's lifespans shortened from 2014 to 2017 compared to its history. Another safe cluster across *Gangnam-gu* and *Seocho-gu* (#7) appeared from 2003 to 2011 while the riskiest cluster (#8) started in 2015. Since 2015, both areas experienced a higher number of closures than expected even though the ratio in cluster #7 was not statistically significant. In 2018, the OE ratio in cluster 8 soared to about 4.0, indicating that the number of closed restaurants is four times higher than the expected failures. Similar to the result of spatiotemporal cluster analysis on net openings, the results strongly support the posture that *Gangnam* district has recently undergone a decline in restaurant businesses.

6 DISCUSSION

Within three core areas in Seoul, including the central business district, *Yeouido* and *Gangnam*, they have been the most favorable for restaurants since 2000. These patterns are based on advantages of agglomeration. These business districts are the most profitable areas with the highest number of lucrative companies, including headquarters of global conglomerates. A large number of workers in these areas has generated a great amount of demand for restaurants. Not just commuters, but also travelers, contribute to the growth of restaurant businesses in the areas because of their unique vibes and media impacts. International travelers, in particular, have been major consumers in the central business district. However, these advantages are not fully observed in all areas through time. Reflective of this is the downturn in *Gangnam* compared to central business district and *Yeouido*, which have been revitalized and remain favorable environments. There are two potential reasons for the observed declines. Firstly, the overall regional economy has slowed due to a recent nationwide downturn. Although *Gangnam* is the most affluent area, it can be impacted by national scale economic changes. Another possible reason is that the environment for restaurant businesses in the district is no longer favorable. As a huge commercial center in Seoul, rents have been increasing in the area, but restaurants are less likely to be able to afford rising rents compared to other services, such as shopping or other leisure services.

Failures in smaller markets can be more critical than those in the core areas. In the context of Korean economic and labor structure, a considerable number of small restaurants are launched by the early-retired, who have low capital and little experience in the restaurant industry. They have few choices except opening a new restaurant in a small market with limited capital. This likely causes saturation of the local market, leading to massive failure during economic downturns. As small businesses in a local market consume labor, including the early-retired as well as low-skilled workers, their failures have a great impact on the local and national economy. This aggravates an economic downturn. Evaluating the level of saturation based on risky cluster detection suggested in this research is helpful to manage stability of local markets by alerting government agencies to potential risk in opening new businesses in certain areas. Based on the knowledge of risky clusters for new businesses, individuals can re-consider start-ups and county-level local governments can require stricter standards to open new businesses in the risky areas.

Although this exploratory approach is noteworthy, it has a few limitations. For instance, it is challenging to explain reasons underlying spatiotemporal patterns of clusters. Although two potential causes of declines in *Gangnam* were highlighted, more formal modeling with additional covariates, including relationships with hotels, shopping centers, etc., would be important as a secondary assessment. Secondly, details about different types of restaurants could present diverse patterns of urban dynamics. More information about ownership and food types would be particularly valuable. As many studies have pointed out, type of food and/or ownership can determine a phase of development in a region (Zukin et al. 2009; Hyde, 2014; Minner and Shi 2017; Ryu and Park 2019; Widaningrum et al. 2020). This would facilitate the evaluation of risky local markets. Finally, impacts of failures on local markets should be closely investigated to determine whether governmental interventions are helpful.

Further research extension along these lines to address such issues would be of great interest.

7 CONCLUSION

This paper explored the spatiotemporal dynamics of restaurant entrepreneurship in Seoul, South Korea based on the availability of public open data using three exploratory methods within a space-time framework. Spatial hot spot analysis identified core areas in Seoul that remain favorable for restaurants. The individual records of restaurants facilitated delineating a more precise extent of restaurant hot spots, generally not corresponding to traditional administrative units. Moreover, the individual records on opening and closing date allowed us to examine temporal changes in restaurant businesses. Trend analysis revealed intensifying or diminishing cluster patterns, finding that *Gangnam* district and many other areas had recently become less favorable for restaurants in contrast to other core areas. Spatiotemporal scan statistics examined risky areas, revealing that lifespans of restaurants were significantly shorter than other areas.

Based on the findings, we conclude that the general downturn in restaurant businesses in Seoul started after 2010, but Gangnam district experienced significant decreases in restaurant businesses beginning in 2015. The applied spatiotemporal exploratory approaches illustrate dynamic changes in restaurant businesses, with the results highlighting that the concentration of restaurants in popular areas has intensified in Seoul. Despite limitations of exploratory approaches, this study suggests a methodological framework for investigating spatiotemporal changes at micro scales within a city featuring a series of analyses verifying the changes from multiple perspectives. This research provides fundamental knowledge of urban dynamics by demonstrating that locational advantages are not permanent, but rather change continuously, and even dramatically, over time. This knowledge enables the private and public sectors to make better decisions such as avoiding high-risk areas to open new businesses and imposing stricter requirements for new start-ups within riskier areas.

---

[i] *Dong* is the smallest administrative unit in Korea and Seoul has 424 *dong*s. The average population in 2015 was 24,343.12 and the average area was 1.43km^2.

[ii] *Si-gun-gu* is a lower level local autonomy unit, or municipality, in Korea. Seoul has 25 *gu*s instead of *si*s and *gun*s and each *gu* has an average of 17 *dong*s. The average population in 2015 was 411,885.52 and the average area was 24.21 km^2.

REFERENCES

Anselin, L. (1995) Local indicators of spatial association - LISA. *Geographical Analysis*, 27(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Arribas-bel, D. (2014) Accidental, open and everywhere: Emerging data sources for the understanding of cities. *Applied Geography*, 49, 45–53. https://doi.org/10.1016/j.apgeog.2013.09.012

Austin, S.B., Melly, S. J., Sanchez, B. N., Patel, A., Buka, S. and Gortmaker, S. L. (2005) Clustering of Fast-Food Restaurants Around Schools: A Novel Application of Spatial Statistics to the Study of Food Environments. *American Journal of Public Health*, 95(9), 1575–1581. https://doi.org/10.2105/AJPH.2004.056341

Church, R. L. and Murray, A. T. (2009) *Business Site Selection, Location Analysis, and GIS*. Hoboken, New Jersey: John Wiley & Sons.

García-palomares, J. C., Salas-olmedo, M. H., Moya-gómez, B., Condeço-melhorado, A. and Gutiérrez, J. (2018). City dynamics through Twitter: Relationships between land use and spatiotemporal demographics. *Cities*, 72, 310–319. https://doi.org/10.1016/j.cities.2017.09.007

Getis, A. (2008) A History of the Concept of Spatial Autocorrelation: A Geographer's Perspective. *Geographical Analysis*, 40(3), 297–309. https://doi.org/10.1111/j.1538-4632.2008.00727.x

Getis, A. and Ord, J. K. (1992) The Analysis of Spatial Association by Distance Statistics. *Geographical Analysis*, 27(4), 286–306.

Henry, K. A., Niu, X. and Boscoe, F. P. (2009) Geographic disparities in colorectal cancer survival. *International Journal of Health Geographics*, 8(1), 48. https://doi.org/10.1186/1476-072X-8-48

Hotelling, H. (1929) Stability in competition. *Economic Journal*, 39(153), 41–57.

Huang, L., Kulldorff, M. and Gregorio, D. (2007) A Spatial Scan Statistic for Survival Data. *Biometrics*, 63(1), 109–118. https://doi.org/10.1111/j.1541-0420.2006.00661.x

Huff, D. L. (1964) Defining and estimating a tread area. *Journal of Marketing*, 28(3), 34–38.

Hurst, M. E. (1972) *A Geography of Economic Behavior*. North Scituate, Massachusetts: Duxbury Press.

Hyde, Z. (2014) Omnivorous Gentrification: Restaurant Reviews and Neighborhood Change in the Downtown Eastside of Vancouver. *City and Community*, 13(4), 341–359. https://doi.org/10.1111/cico.12088

Jeong, D.-G. and Yoon, H.-Y. (2017). Survival Analysis of Food Business Establishments in a Major Retail District and Its Extended Area. *Journal of The Architectural Institute of Korea Planning & Design*, 33(3), 57–68. https://doi.org/10.5659/JAIK_PD.2017.33.3.57

Jung, S. and Jang, S. (2019). To cluster or not to cluster?: Understanding geographic clustering by restaurant segment. *International Journal of Hospitality Management*, 77, 448–457. https://doi.org/10.1016/j.ijhm.2018.08.008

Kedron, P., Frazier, A. E., Trgovac, A. B. and Fotheringham, A. S. (2021) Reproducibility and Replicability in Geographical Analysis. *Geographical Analysis*, 53(1), 135-147. https://doi.org/10.1111/gean.12221

Kim, H. and Lee, S. (2019) A Study on the Factors Affecting the Revenue in Seoul's Side Street Trade Areas. *Seoul Studies*, 20(1), 117–134.

Kim, W., Yim, J. and Song, A. (2018) Spatio-temporal Changes of the Agglomerated Marketplace by Use of the Pedestrian Flow Data. *Journal of Korean Cartographic Association*, 18(1), 49–63. http://doi.org/10.16879/jkca.2018.18.1.049

Kulldorff, M. (1997) A Spatial Scan Statistic. *Communications in Statistics - Theory and Methods*, 26(6), 1481–1496. https://doi.org/10.1080/03610929708831995

Lansley, G., Smith, M. De, Goodchild, M. and Longley, P. (2018) Big Data and Geospatial Analysis. *Big Data and Research*, 547–570.

Leitner, M. and Helbich, M. (2013). The Impact of Hurricanes on Crime: A Spatio-Temporal Analysis in the City of Houston, Texas. *Cartography and Geographic Information Science*, 38(2), 213–221. https://doi.org/10.1559/15230406382213

Li, Yanhua, Steiner, M., Wang, L., Zhang, Z.-L., and Bao, J. (2013) Exploring venue popularity in Foursquare. *Proceedings IEEE INFOCOM* (pp. 3357–3362). IEEE. https://doi.org/10.1109/INFCOM.2013.6567164

Li, Yingru, and Liu, L. (2012) Assessing the impact of retail location on store performance : A comparison of Wal-Mart and Kmart stores in Cincinnati. *Applied Geography*, 32, 591–600. https://doi.org/10.1016/j.apgeog.2011.07.006

Lin, Y., Schootman, M., and Zhan, B. F. (2015) Racial/ethnic, area socioeconomic, and geographic disparities of cervical cancer survival in Texas. *Applied Geography*, 56, 21–28. https://doi.org/10.1016/j.apgeog.2014.10.004

Mazur, M. and Manley, E. (2016) Exploratory Models in a time of Big Data. *Interdisciplinary Science Reviews*, 41(4), 366–382. https://doi.org/10.1080/03080188.2016.1257196

Miller, H. J. (2010) The Data Avalanche is Here. Shouldn't We Be Digging. *Journal of Regional Science*, 50(1), 181–201. https://doi.org/10.1111/j.1467-9787.2009.00641.x

Miller, H. J. and Goodchild, M. F. (2015) Data-driven geography. *GeoJournal*, 80(4), 449–461. https://doi.org/10.1007/s10708-014-9602-6

Minner, J. S. and Shi, X. (2017) Churn and change along commercial strips : Spatial analysis of patterns in remodelling activity and landscapes of local business. *Urban Studies*, 54(16), 3655–3680. https://doi.org/10.1177/0042098016684274

Mulligan, G. F. (1984) Agglomeration and central place theory: A Review of the Literature. *International Regional Science Review*, *9*(1), 1–42. https://doi.org/10.1177/016001768400900101

Murray, A. T., Koschinsky, J., Liu, Y., Rey, S. J. and Brown, L. A. (2013) Are foreclosures contagious?an exploratory space-time analysis of franklin county, Ohio, 2001-2008. *International Journal of Applied Geospatial Research*, 4(4), 19–36. https://doi.org/10.4018/jagr.2013100102

Nakaya, T. and Yano, K. (2010). Visualising Crime Clusters in a Space-time Cube : An Exploratory Data-analysis Approach Using Space-time Kernel Density Estimation and scan statistics. *Transactions in GIS*, 14(3), 223–239. https://doi.org/10.1111/j.1467-9671.2010.01194.x

Newman, K. (2010) Go public! *Journal of the American Planning Association*, 76(2), 160–171. https://doi.org/10.1080/01944360903586738

Prayag, G., Landre, M. and Ryan, C. (2012) Restaurant location in Hamilton , New Zealand : clustering patterns from 1996 to 2008. *International Journal of Contemporary Hospitality Management*, 24(3), 430–450. https://doi.org/10.1108/09596111211217897/

Ryu, H.-Y. and Park, J. (2019) A Study on the Variation Process of Commercial Gentrification Phase in Residential Area in Seoul. *Journal of Korea Planning Association*, 54(1), 40–51. https://doi.org/10.17208/jkpa.2019.02.54.1.40

Shaw, S. L., Tsou, M. H. and Ye, X. (2016) Editorial: human dynamics in the mobile and big data era. *International Journal of Geographical Information Science*, *30*(9), 1687–1693. https://doi.org/10.1080/13658816.2016.1164317

Shin, W.-J. and Shin, W.-H. (2009) Spatial Patterns of Retail Stores in Seoul, Korea. *Korea Real Estate Review*, *19*(2), 279–296.

Singleton, A. and Arribas-bel, D. (2021) Geographic Data Science. *Geographical Analysis*, 53(1), 61-75. https://doi.org/10.1111/gean.12194

Smith, C., Comber, S. Le, Fry, H., Bull, M., Leach, S. and Hayward, A. (2015) Spatial methods for infectious disease outbreak investigations: systematic literature review. *Eurosurveillance*, 20(39), 1-21. https://doi.org/10.2807/1560-7917.ES.2015.20.39.30026

Smith, S. (1985) Location Patterns of Urban Restaurants. *Annals of Tourism Research*, *12*(4), 581–602. https://doi.org/10.1016/0160-7383(85)90079-9

Steiger, E., de Albuquerque, J. P. and Zipf, A. (2015). An Advanced Systematic Literature Review on Spatiotemporal Analyses of Twitter Data. *Transactions in GIS*, 19(6), 809–834. https://doi.org/10.1111/tgis.12132

Sun, Y., and Paule, J. D. G. (2017). Spatial analysis of users-generated ratings of yelp venues. *Open Geospatial Data, Software and Standards*, 2(1), 5. https://doi.org/10.1186/s40965-017-0020-9

Tsou, M.-H. (2015) Research challenges and opportunities in mapping social media and Big Data. *Cartography and Geographic Information Science*, 42(sup1), 70–74. https://doi.org/10.1080/15230406.2015.1059251

Tu, W., Cao, J., Yue, Y., Shaw, S.-L., Zhou, M., Wang, Z., Chang, X., Xu, Y. and Li, Q. (2017) Coupling mobile phone and social media data: a new approach to understanding urban functions and diurnal patterns. *International Journal of Geographical Information Science*, 31(12), 2331–2358. https://doi.org/10.1080/13658816.2017.1356464

Tukey, J. W. (1962) The Future of Data Analysis. *Annals of the Institute of Statistical Mathematics*, 33(1), 1–67.

Wan, N., Zhan, F. B., Lu, Y. and Tiefenbacher, J. P. (2012) Access to healthcare and disparities in colorectal cancer survival in Texas. *Health & Place*, 18(2), 321–329. https://doi.org/10.1016/j.healthplace.2011.10.007

Yu, K. and Lee, S. (2017). An Analysis of Factors Affecting the Agglomeration of Food Industry in Seoul Using Geographically Weighted Regression Model. *Journal of The Korean Regional Development Association*, 29(2), 189–210.

Zhai, S., Xu, X., Yang, L., Zhou, M. and Zhang, L. (2015). Mapping the popularity of urban restaurants using social media data. *Applied Geography*, *63*, 113–120. https://doi.org/10.1016/j.apgeog.2015.06.006

Zukin, S. (2009) *Naked City: The Death and Life of Authentic Urban Places*. New York , New York: Oxford University Press.

Zukin, S., Trujillo, V., Frase, P., Jackson, D., Recuber, T. and Walker, A. (2009) New Retail Capital and Neighborhood Change: Boutiques and Gentrification in New York City. *City & Community*, 8(1), 47–64. https://doi.org/10.1111/j.1540-6040.2009.01269.x

Zukin, S., Lindeman, S., and Hurson, L. (2017) The omnivore's neighborhood? Online restaurant reviews, race, and gentrification. *Journal of Consumer Culture*, 17(3), 459–479. https://doi.org/10.1177/1469540515611203