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Investigating the spatiotemporal pattern of urban vibrancy and its determinants: Spatial big data analyses in Beijing, China

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ABSTRACT

Investigating urban vibrancy and factors that impact urban vibrancy aids the understanding of urban land use policies, provides solid foundation for scientific urban planning. The boom in information and communication technologies and the advancement of big data extraction provides new sources of data and make it possible to measure and analyze urban vibrancy at a finer spatial and temporal scale. This study aims to portray the spatiotemporal variation patterns of urban vibrancy in 24 h and investigate the potential influence mechanism of it. The central districts of Beijing consisting of 135 subdistricts are selected as the study area. Massive and spontaneous geo-tagged check-in data released from social media platforms has attracted increasing attentions in urban vibrancy studies because it reflects well people's activities at a certain time, which is a good proxy for urban vibrancy. This study hence uses the check-in data from Weibo, the largest microblogging platform in China, to proxy urban vibrancy. We also extract from multisource spatial big data to explore potential determinants of urban vibrancy. This study seeks to reveal the global and local varying impacts of different factors on urban vibrancy by employ spatial lag model (SLM) and multiscale geographically weighted regression (MGWR) model. Results show that the increase in the number of different point of interests (POIs) improves urban vibrancy. Their effects on vibrancy vary at different times but have no obvious spatial scale variation. Splitting effect and attraction effect of land use diversity are introduced to explain its significantly negative effect on the intensity and fluctuation of urban vibrancy. It requires the wisdom of urban planners to balance these two effects of land use diversity in the process of urban construction. The guidance strategy of "highlighting the main functions and enriching the auxiliary functions" is helpful to build vibrant cities. Socioeconomical conditions, location and accessibility have different spatial scale effects on urban vibrancy at subdistrict level. These findings enable us to have a deeper understanding of the variation patterns and influence mechanism of urban vibrancy in China's megacities and benefit the urban land use policy research and management community.

1. Introduction

In the last two decades, China has undergone dramatic increase in both urban population and built-up areas (He et al., 2018; Huang et al., 2017; Wang et al., 2012). Such rapid urban development causes scholars to worry about the disorderly urban sprawl in some areas might lead to inefficiency of creating vibrant urban spaces (Batty, 2016; Jin et al., 2017; Xia et al., 2020). The government has also noticed the potential problems in the process of urbanization and proposes to improve urban vibrancy as an important strategic task in the 13th Five-year Plan. Since Jacobs (1961) put forward the concept of urban vibrancy, it has attracted extensive scholarly attentions from different disciplines, such as urban planning, social sciences and geographical information sciences (Delclos-Alio et al., 2019; Gehl, 1971; Klemek, 2007; Maas, 1984; Montgomery, 1998; Sung and Lee, 2015). Researchers generally believe that urban vibrancy reflects the interaction between the various daily human activities and existing urban facilities, which plays a critical role in promoting comprehensive, coordinated, and sustainable urban development (Kang, 2020; Li et al., 2020b; Mouratidis and Poortinga, 2020; Wu et al., 2018a). Vibrant urban spaces tend to support diverse

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human activities and facilitate social interactions, bring a diversity of benefits, such as improving the people's subjective feelings of urban life, attracting investment and talents, enhancing economic competitiveness, and achieving social sustainability (Meng and Xing, 2019; Pinquart and Sorensen, 2000; Zhang et al., 2020). On the contrary, the lack of urban vibrancy may lead to a series of socioeconomic issues and become serious impediments to urban development (Jin et al., 2017; Li et al., 2020b; Woodworth and Wallace, 2017). The studies on urban vibrancy will help urban planners and decision-makers make effective plans to achieve sustainable urban development (Laman et al., 2019; Meng and Xing, 2019). Hence it is imperative for urban scholars to understand the patterns of urban vibrancy and identify the factors that affect urban vibrancy, especially at finer spatial scales.

Data availability used to be the primary issue for quantitative analysis of urban vibrancy (Sung and Lee, 2015; Ye et al., 2018). Most scholars conducted their investigations of urban vibrancy at the scale of the neighborhood through qualitative methods, such as field observations and interviews (Filion and Hammond, 2003; Powe, 2012; Ravenscroft, 2000). However, with the rapid development of information and communication technologies, many data sources emerge to provide previously unavailable information about urban dynamics and open up new opportunities in the studies of urban vibrancy (Garcia-Palomares et al., 2018). In the era of big data, internet users are not only recipients of information but also producers of vast amounts of data. With the permission of users, many social media apps can collect tremendous amount of information along with accurate locational information when they post a message, leaving so-called "digital geographic footprints" (Garcia-Palomares et al., 2018; Tu et al., 2020). The digital geographic footprints are intermingled with their offline daily life and provide new ways of investigating the interaction between human activities and urban environments (Blanford et al., 2015; Garcia-Palomares et al., 2018; Shelton et al., 2015). Compared with traditional data derived from statistical census and surveys, these geo-tagged big data show significant advantages for us to further investigate urban vibrancy because it contains large sample size and have high penetration with strong timeliness (Li et al., 2020b; Xia et al., 2020; Ye et al., 2018). With geo-tagged social media, large-scale and fine-grained datasets become more readily available. These datasets open a new chapter in urban studies in the big data era that could advance the theoretical understanding and practical management of sustainable urban development through the investigation of the highly dynamic but ultimately consistent urban vibrancy. Many recent studies have tried to analyze spatial big data from different sources to further explore urban vibrancy (Delclos-Alio et al., 2019; Lu et al., 2019; Meng and Xing, 2019; Tang et al., 2018; Wu et al., 2018a; Zeng et al., 2018). Our current study follows suit the trend of scholarly work but attempt to provide a more in-depth analysis of urban vibrancy with advanced spatiotemporal analytical techniques to contribute to the scientific understanding of sustainable urban development.

This article aims to further the understanding of the spatiotemporal variation pattern of urban vibrancy at subdistrict level and explore the relationship between urban vibrancy and its determinants. In addition to explore the potential mechanisms of urban vibrancy, this study also proposes that such mechanisms might vary in space. Specifically, this study attempts to make contributions to urban studies in several ways. First, we analyze and distinguish the physical features and socioeconomic attributions of spatial big data from different sources based on our own investigation and reference to previous studies (Huang et al., 2020; Li et al., 2020a; Tu et al., 2020). This is the foundation to choose more reliable indicators to represent urban vibrancy. Because urban vibrancy is a people-centered rather than material-centered concept, the indicators used to measure urban vibrancy should be able to reflect the intensity of human activities directly. Social media data serves the purpose well. Second, dynamics and variability are two prominent features of urban vibrancy, and the spatial and temporal snapshots of human activities show the varied aspects of daily life in cities. The distinct feature of this study is that we divide 24-hour into 12 slots (2 h per slot) rather than simply regarding a whole day as a snapshot of cities, which could accurately reflect the complex and changeable urban vibrancy from a more subtle time scale. Third, we try to summarize the influencing factors of urban vibrancy into a more systematic research framework and take into consideration both spatial autocorrelation and spatial heterogeneity in empirical analysis so that the analytical paradigm can be applied to other urban settings as well. In this study, we propose that the determinants of urban vibrancy might include four aspects: land function, socioeconomic conditions, accessibility, and location. In terms of empirical research, spatial autoregression model is applied to control the influence of potential spatial autocorrelation. To deal with possible spatially varying relationship between urban vibrancy and its determinants, we employ the multiscale geographically weighted regression (MGWR) to address both the scale effect and locational effect of influencing factors. MGWR could improve the estimation efficiency and accuracy, and its result gives the influence scale of different explanatory variables (Fotheringham et al., 2017; Li and Fotheringham, 2020; Yu et al., 2020). The application of MGWR will deepen our understanding of influence mechanism of urban vibrancy in a more holistic way.

The remainder of this article is organized as follows. Section 2 reviews the relevant literature of urban vibrancy and introduces the research framework. Section 3 gives a detailed description of the study area, data sources and empirical methods. Section 4 reports and analyzes the study results, with specific attention to spatial and temporal variation of urban vibrancy and the impacts of its determinants. The last section concludes this study and discusses future work.

2. Literature review

2.1. The definition and measurement of urban vibrancy

Urban vibrancy, also known as urban vitality, describes the attraction, diversity and accessibility of a place and it is recently used in city performance assessment (He et al., 2018; Wu et al., 2018a). It is regarded as a broad and complicated concept with rich meanings (Long and Huang, 2019; Xia et al., 2020; Ye et al., 2018; Zhang et al., 2020). In her book *The Death and Life of Great American Cities*, Jacobs (1961) was the first to provide a synthesized view on urban vibrancy based on her own experiences and observations. She claimed that the interaction between human activities, especially pedestrian activities, and urban facilities constitute the diversity of urban life, which is the main reflection of urban vibrancy (Delclos-Alio et al., 2019; Jacobs, 1961; Sung and Lee, 2015). Gehl (1971) described urban vibrancy as the feeling that a place is populated and used. Subsequently, Maas (1984) added that urban vibrancy arises from a variety of unique socioeconomic opportunities and a dense pedestrian population. In Montgomery's paper, urban vibrancy was conceptualized and measured as "the extent to which a place feels alive or lively" (Montgomery, 1998). In recent studies, Dougal et al. (2015) and Huang et al. (2020) described urban vibrancy as the spillover effects that arise in urban contexts from the endogenous interactions of the people living in the city. Based on these studies, we find that no matter how the definition changes, researchers generally emphasize that the essence of urban vibrancy is the interaction between people and things, and human activities are the most important manifestation.

With data and methodological limitations, early studies on urban vibrancy mainly focused on anecdotal observations of limited number of streets or subdistricts and qualitative analysis. Since the late 1990 s, different indicators, such as population density, employment rate, housing price and urban services from census and survey data were widely used as proxies for urban vibrancy (Harvey, 2001; Huang et al., 2020; Nicodemus, 2013; Wu et al., 2018b). However, the traditional field surveys and urban datasets are static information, often small in sample size with slow updating. These data sets do not have the ability to

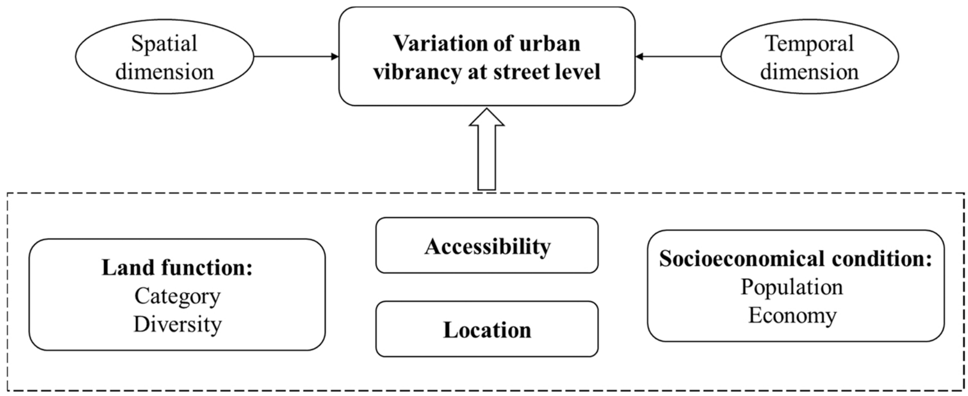


Fig. 1. Four aspects of influencing factors of spatiotemporal urban vibrancy.

capture the rapidly changing urban dynamics in the modern megacities.

The rapid development of telecommunication technologies and the blend of social media to everyday social life enable human activities to be captured on a more frequent time scale and at a finer spatial scale. This brings huge transformations of measurement of urban vibrancy. First, due to the advance of data acquisition technologies, the study area could expand from a few subdistricts to the whole city or area. Second, the intensity of human activities in an area rather than subjective assessment of the surrounding environment can be acquired through mining geotagged big data such as telecommunication or social media data. As a result, an increasing number of studies employ such datasets to represent and measure urban vibrancy, such as pedestrian traffic records (Kim, 2020), the mobile phone records (Li et al., 2020b; Tang et al., 2018; Yue et al., 2017) and social media data (Garcia-Palomares et al., 2018; Meng and Xing, 2019; Wu et al., 2018a). Although there are concerns about biased representativeness of geotagged big data, previous studies have shown the stability of human activities behind massive data and general consistency of multisource big data (Garcia-Palomares et al., 2018; Song et al., 2010).

In addition to these types of big data that is closely related to human activities, some other types of big data are also used in the existing studies, such as the number of small catering businesses (Xia et al., 2020; Ye et al., 2018), nighttime light value (Lan et al., 2020) and points of interest (POI) (Tu et al., 2020). In this study, however, we do not use these datasets to represent urban vibrancy. For one thing, these datasets mainly reflect the material spaces or land functions that are primarily inanimate (Wu et al., 2018a; Zhang et al., 2020). Using these datasets might not portray underlying urban vibrancy well. For example, the intensity of people's activities of a small shop is generally lower than that of a large supermarket, while they might have the same number of POIs. For another, these data lacks the variation at temporal dimension and it is difficult to reflect the 24-hour dynamic of urban vibrancy (Ye et al., 2018). For these reasons, we adopt to present urban vibrancy in this study using the Weibo check-in records and the number of check-ins at subdistrict level. The widely popular Weibo check-in records provide an excellent proxy for the vibrancy intensity (Li et al., 2020a; Xiao et al., 2018; Zeng et al., 2017). Check-ins on social media applications and platforms not only documents the real-time geographical locations of users but also indicates people's collective activities and mobility patterns (Chen et al., 2019).

2.2. The influencing factors and mechanism of urban vibrancy

Urban vibrancy represents a vivid level of urban development. A city with higher urban vibrancy tends to attract more people, more investment, and develop better and more sustainably (Huang et al., 2020; Mouratidis and Poortinga, 2020). For this matter, urban planners and decision-makers often incline to devise planning policies aiming at improving urban vibrancy. It is hence critical to understand what factors have impacts on urban vibrancy and how these factors impact urban vibrancy.

The majority of the studies regard land function as a primary impacting factor on urban vibrancy (Garcia-Palomares et al., 2018; Li et al., 2020b; Lu et al., 2019; Sung and Lee, 2015; Tu et al., 2020; Wu et al., 2018a). Different types of land function provide different services for people, which is closely related to the daily human activities, therefore affect urban vibrancy (Axhausen et al., 2002; Wu et al., 2020). Because different urban activities depend on specific land functions, urban land function types have significant impacts on urban vibrancy in both the short and long terms. From the long-term perspective, Huang et al. (2017) found that the change of employment subcenters significantly affect population distribution, which could change the spatial distribution of urban vibrancy. For daily dynamics of urban life, Wu et al. (2018a) classified land use into four categories: consumption-related, housing-related, traffic-related and others. They analyzed these categories' impacts on urban vibrancy. Similarly, Garcia-Palomares et al. (2018) divided land use into ten types, including residential, office, retail, transport, park, education, culture, health care, industry and others. Zhang et al. (2020) found that green space offers positive externalities to streets' vibrancy.

Mixed land function, which means diversity of urban form, is regarded as a key strategy to promote urban vibrancy and sustainability (Yue et al., 2017). Many urban development theories, including networked city, new urbanism, and smart growth suggest that mixed land use is a basic feature of a vibrant city (Meng and Xing, 2019; Smith, 2002; Tranos and Nijkamp, 2015; Zhang et al., 2020). In general, mixed land use makes the subdistricts more vibrant and provides urban residents with more opportunities and diverse experiences in daily life, work, and recreation, thereby cultivating urban vibrancy (Wu et al., 2018b; Ye et al., 2018). Still, there are also studies reporting that mixed land use might not serve the purpose of promoting urban vibrancy. For instance, De Nadai et al. (2016) showed no significant correlation between the diversity of land functions and urban vibrancy in Italian cities. In Tang et al. (2018)'s study, they found that the functional mixing degree has a negative effect on urban vibrancy during the working hours of a day. The mixed land function's effects on urban vibrancy in megacities seem to depend on specific cities, ceteris paribus.

Other than land functions, three other categories have been identified in the literature that might impact urban vibrancy (Garcia-Palomares et al., 2018; Li et al., 2019, 2020b, 2021; Lu et al., 2019; Tu et al., 2017; Wu et al., 2018a): socioeconomical conditions, accessibility, and location (Fig. 1). Socioeconomical conditions, represented by population and economic status, are directly related with urban vibrancy. This often means larger population and economic size boost urban vibrancy. Accessibility is usually expressed by traffic conditions, which plays an important role in the interaction between urban residents and land functions. If a city's transportation system is poor, the city tends to be less vibrant. Location measures the closeness to urban center

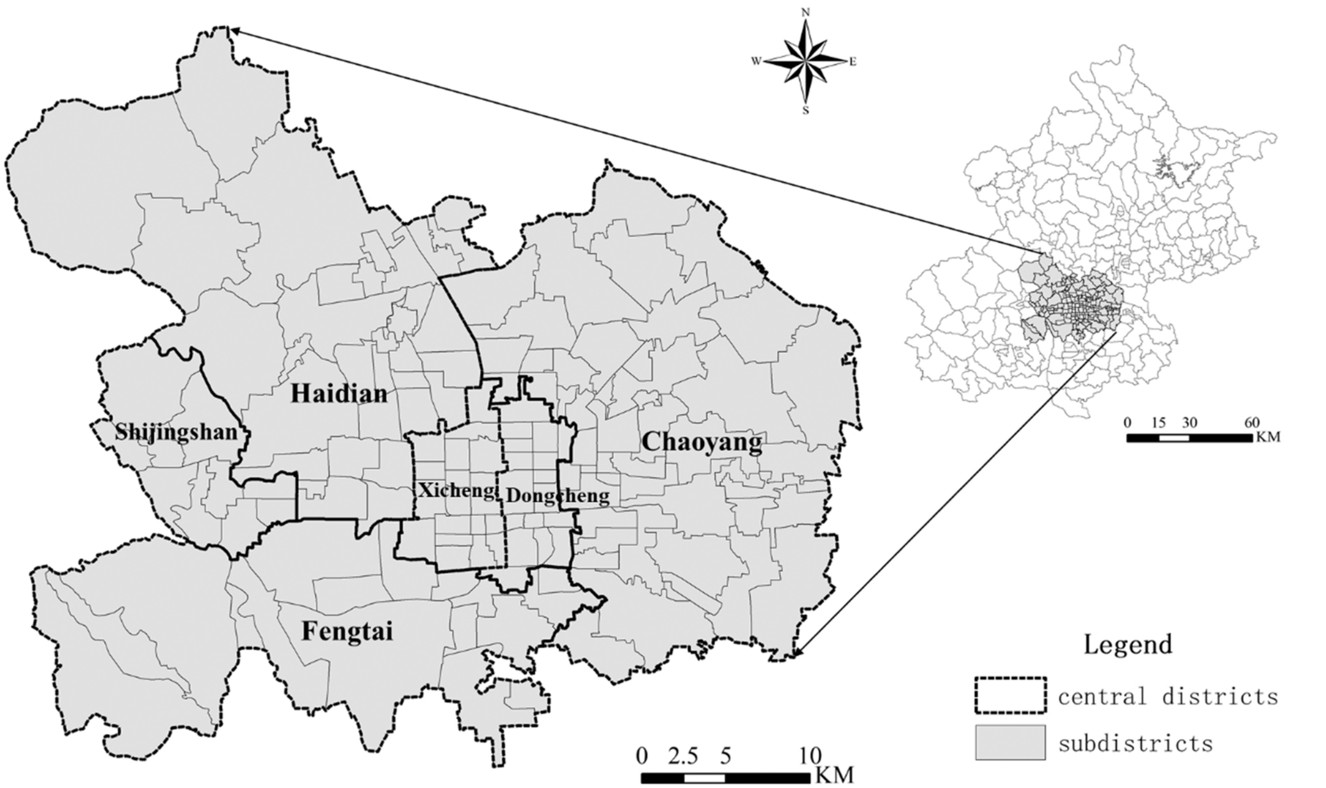


Fig. 2. Research area: the central six districts of Beijing.

(Garcia-Palomares et al., 2018; Wu et al., 2018a). Although the spatial layouts of different cities vary greatly, the central area of the city, usually the central business district or administrative center often has the highest urban vibrancy. Locations that are farther away from the center tend to be less vibrant.

3. Data and methodology

3.1. Research area

As the capital city of China, Beijing is a highly developed cities with high urban vibrancy. Since the late-1970 s, Beijing's population and economy have been growing rapidly, and great changes have taken place in the urban layout. Beijing often serves as a role model for other cities in China, particularly in the processes of urban development, urban planning and policy making (Huang et al., 2017). Due to data availability, in this study we focus on the central urban area in Beijing. The research area includes six districts, namely Dongcheng, Xicheng, Chaoyang, Haidian, Fengtai and Shijingshan (Fig. 2). With 8.4% of the land area, these districts of Beijing have 54.1% of the total population and 70.5% of Beijing's GDP in 2018, which provides an excellent setting for understanding urban vibrancy and how the listed factors impact urban vibrancy.

Administrative division and artificial grid division are two common spatial scales that are widely used in recent studies (Li et al., 2019, 2020b; Wu et al., 2018a; Yue et al., 2017). In this study, we use the subdistrict (*Xiangzhen/Jiedao*) as the basic spatial analysis unit. In China, administrative divisions are the basic elements of government management. Different subdistricts usually contain common urban functions but different authority relationship and institutional conditions of urban development. Research on urban vibrancy at subdistrict level might provide more operable results. For comparison purposes, our study also attempted grid division with a 1 km by 1 km dimension. The results are not ideal and factors and urban vibrancy cannot be clearly associated. From a policy perspective, using grid division tends to be subjective and is difficult to evaluate the analysis results of different sizes of the grid. In addition, a grid usually covers parts of a subdistrict or covers different subdistricts, which brings difficulties to the implementation of policies at a specific subdistrict. The study hence focuses only on analysis based on subdistrict administrative units. There are 135 subdistricts in the six central districts of Beijing (Fig. 2). The data is acquired from the Beijing Platform for Common Geospaital Information Services (http://beijing.tianditu.gov.cn/).

3.2. Data

In this study, Weibo check-in data is used to represent urban vibrancy, and the influencing factors are extracted from the point of interest (POI) data, extrapolated from the 1 km grid population and GDP data, and road network data. The check-in records are acquired from Sina Weibo (https://open.weibo.com/). Sina Weibo is the largest microblogging website in China. It has more than 500 million monthly active users. To avoid the impact of special events, such as new semesters or holidays, we select the week from September 23 to September 29 as the study period. We obtain a total of 192,160 pieces of check-in records in this week and then divide them into 12 time slots (2 h per slot) according to the release time. Check-ins in each time slot refers to the total number (sum) of check-ins released in this period during the 7 days. The point of interest (POI) data reflects urban land use at a finer granularity thus is regarded as a good proxy for land function. We acquired 125,324 POIs from Baidu Map (http://map.baidu.com/), one of China's largest online map service providers. The raw POI data contains many types, including catering service (CS), shopping service (SS), recreation and entertainment (RE), corporate business (CB), financial service (FS), scientific research and education (SE), medical and health (MH), government and administration (GA), accommodation and residence (AR), and tourist attraction and green space (TG). Following common practices (Li et al., 2020b; Tang et al., 2018; Wu et al., 2018a), we categorize these POIs into 4 subcategories: consumption-related POI (CPOI), occupation-related POI (OPOI), housing-related POI (HPOI),

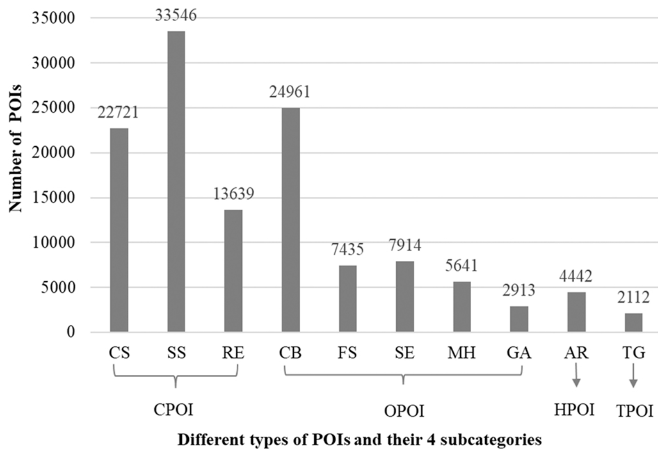


Fig. 3. The number of different types of POIs and their 4 subcategories.

Table 1
Explanation and summary statistics of the variables.

Variables	Explanation	Min	Max	Mean	SD
CI	number of check-ins in a week	78	6376	1423	1214
CPOI	number of consumption-related POIs	2	2295	518	413
OPOI	number of occupation-related POIs	0	2794	362	346
HPOI	number of housing-related POIs	0	138	33	29
TPOI	number of tourism-related POIs	0	245	16	41
SDI	Simpson diversity index of POIs	0.000	0.652	0.506	0.069
POP	number of residents	5657	517,904	89,915	84,704
GDP	number of GDP [10,000 yuan]	52,123	5645,161	1134,108	970,401
ROAD	length of the road network [m]	17,256	831,225	121,812	114,149
DIST2TAM	distance to Tian'anmen Square [m]	815	30,450	10,393	6308

and tourism-related POI (TPOI) according to residents' common daily activities. Fig. 3 shows the details of the POIs in different categories. Population and GDP are the most direct indicators of socioeconomic conditions. Unfortunately, population and GDP data at subdistrict level are not readily available. Instead, 1 km grid population and GDP data in 2015 are extracted from Resource and Environment Science and Data Center of Chinese Academy of Sciences (http://www.resdc.cn) (Liu et al., 2005), which serves as an adequate substitute for subdistrict population and GDP levels. Road network information is calculated from Open Street Map (OSM). Map overlay operation produces road network length for each subdistrict.

Based on the four categories of POIs, we calculate a Simpson diversity index (SDI).

as the indicator of land function diversity as follows:

$$D = 1 - \sum_{i=1}^{S} P_i^2$$

where S is the number of POI category and P_i represents the proportion of the number of the ith category POI to the total number of POIs. SDI measures the probability that two POIs randomly selected from the pool of POIs belong to the same categories. It takes into account POI richness and evenness and is a fine indicator of land function diversity (Yue et al., 2017). In addition, the distance from spatial centroid of each subdistrict to the Tiananmen Square (39°54′N, 116°23′E) is measured to represent the location of these spatial units. Table 1 lists the detailed explanations and summary statistics of the variables used in the study. After preliminary exploration of the data, when modeling the relationship of the urban vibrancy and its influencing factors, we apply natural logarithmic transform of these variables, except for Simpson diversity index, to approximate the linear relationship and reduce potential multicollinearity.

3.3. Methodology

To explore the spatiotemporal distribution patterns, the kernel density estimation (KDE) approach is often used to transform discrete check-ins into a continuous surface of urban vibrancy (Meng and Xing, 2019; Tang et al., 2018; Wu et al., 2018a). By providing a space weight function with optimal bandwidth, the KDE approach could eliminate the local noise to a certain degree and produce smooth distribution surfaces (Rizwan et al., 2018). According to Silverman (2018), the KDE takes the form:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right)$$

where $f(x)$ refers to the KDE function at a location with the observation value x,h denotes the bandwidth and k is the kernel function. In this study, we adopt the quadratic kernel function with a bandwidth of 100 m to generate smooth hot spots of check-ins. In addition, it is expected that urban vibrancy shows significant spatial autocorrelation pattern. The Moran's Index of urban vibrancy and the associated Moran's scatterplot (Anselin, 1988, 1995a; Le Gallo and Ertur, 2003; Yu and Wei, 2008) will be employed to examine the spatial autocorrelation pattern of urban vibrancy. The details of spatial autocorrelation measurement and detection are described in many previous studies (Kang, 2020; Li et al., 2020b; Lu et al., 2019; Tu et al., 2017; Xia et al., 2020; Zhang et al., 2020) and will not be repeated here.

To explore the relationships between influencing factors and urban vibrancy and the potential varying effects of those influencing factors, this study adopts a full spatial strategy at both global and local levels that provide complementary evidence to investigate urban vibrancy and its influencing factors. At the global level, a spatial autoregressive model will be applied to the data for a general understanding of how those factors impact urban vibrancy during the 24-hour period. At the local level, a multiscale geographically weighted regression approach is employed to investigate the factors' potential varying effects.

3.3.1. Spatial autoregression models (SAM)

It is common to use the ordinary least square estimator (OLS) for global regression to explore relationships between variables (Garcia-Palomares et al., 2018; Huang et al., 2020; Li et al., 2019, 2020b; Meng and Xing, 2019). However, the existence of spatial autocorrelation in the regression residuals violates the independence assumption in traditional empirical analysis. Anselin, 1988, 2003; Anselin et al., 1996, among many others, proposed the maximum likelihood estimator as an alternative since it is not restricted by independent regression residuals. Based on the possible sources of spatial autocorrelation in regression residuals, there are two types of spatial autoregression models that are often considered in empirical studies (Yu and Wei, 2008). If the source is primarily from a spatially autocorrelated dependent variable, we have a spatial lag specification. If, however, spatial autocorrelation in the residual is from omitted but spatially autocorrelated explanatory variables, then we will have a spatial error specification. The general formula for the spatial autoregressive model takes the following form:

$$y = \rho W_1 y + \beta X + \lambda W_2 \varepsilon + \quad \mu$$

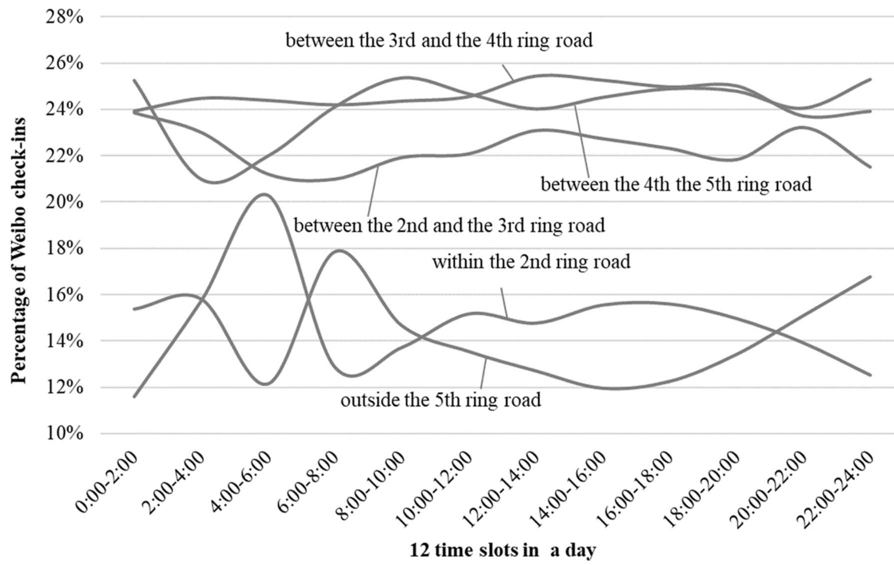


Fig. 4. 24-hour's variation of check-ins between different ring roads.

where y denotes the dependent variable, W_1 and W_2 denote two spatial weight matrices describing the influence intensity among different spatial units for the dependent variable and error terms, respectively. Although W_1 and W_2 do not have to be the same. In practice, they often take the same form. W_1y is the spatially lagged dependent variable, and ρ is the coefficient of W_1y. X refers to a matrix of independent variables and a constant term, β is the coefficient vector of independent variables, and ε is the error term that is spatially autocorrelated; λ is the coefficient of the spatial error, $W_2\,\varepsilon$, and μ is a well-behaved error term.

As argued in Anselin (1988), the Lagrange Multiplier (LM) robust diagnostic tests based on ordinary least square (OLS) residuals can help choose a more appropriate model. The model that has a larger and significant robust LM statistics often is the more appropriate specification. Since the residuals of the spatial autoregressive models are no longer independent, the adjusted R^2 cannot be used to test the goodness-of-fit for the model. Instead, the spatial autoregressive model is estimated via maximum likelihood estimator, the likelihood-based Information Criteria, such as the Akaike Information Criterion (AIC) is used to test the goodness-of-fit and comparison among the models. The model with smaller AIC is considered the better fit for the data (Yu and Wei, 2008). We employ the spdep package (Bivand et al., 2013) in R (https://www.r-project.org/) to conduct LM tests and estimate the coefficients of variables via spatial lag model.

3.3.2. *Multiscale geographically weighted regression (MGWR)*

Global regression assumes that the impact of independent variables on dependent variables, represented by the variables' coefficients, are constant over space. However, spatial nonstationarity is a common phenomenon in spatial processes and the relationship between variables likely changes with location. Geographically weighted regression (GWR) has often been applied to address spatial nonstationarity directly (Fotheringham et al., 2002; Li et al., 2020b; Tu et al., 2020; Yu, 2006; Zhang et al., 2020). GWR is a local regression model that allows variables' coefficients to vary spatially. Traditional GWR assumes that all the processes being modeled operate at the same spatial scale, which might not reflect the complexity of the real world. Fotheringham and colleagues proposed the multiscale geographically weighted regression (MGWR) to deal with the scale effect of different explanatory variables (Fotheringham et al., 2017). MGWR relaxes the assumption of fixed scale by allowing the conditional relationships between dependent variable and independent variables to vary at different spatial scales. MGWR model formulation can be described as follows.

$$y_i = \sum_{j=0}^{m} \beta_{bwj}(u_i, v_i)x_{ij} + \varepsilon_i$$

where bwj in β_{bwj} indicates the bandwidth used for calibration of the jth conditional relationship. In this study, bisquare kernel function and AICc are often used to select the optimal bandwidth. Proportional change in the residual sum of squares (SOC_{RSS}) is adopted as the termination criterion of successive iterations. The graphical user interface (GUI) developed for MGWR (Oshan et al., 2019) is available on this website (https://sgsup.asu.edu/sparc/multiscale-gwr) and is used for our current study. More details about MGWR can be found in Fotheringham et al. (2017) and Yu et al. (2020).

4. Results and discussion

4.1. *Spatiotemporal distribution of urban vibrancy*

Using the Weibo check-in data, the study first explores the 24-hour's variation of urban vibrancy between different ring roads since Beijing has a distinctive ring-road defined center-periphery spatial structure (Fig. 2). By converting the discrete Weibo check-in data using kernel density estimation (KDE) to continuous smooth surfaces, we can detect potential urban vibrancy "hot spots." The results are in Figs. 4 and 5.

The urban vibrancy in the different subdistricts varies quite a lot in different time periods (Fig. 4). Urban vibrancy within the 2nd ring road and outside the 5th ring road vary most dramatically, followed by the vibrancy between the 4th and 5th ring road and between the 2nd and 3rd ring road. Inside the 2nd ring road is the historical center of Beijing (the Forbidden City) and many central governmental agencies. This location typically attracts less population flow (except for tourists) than the other parts of the city because of its specific functions. On the other hand, there are many places outside the 5th ring road that have not been fully developed. This makes the density of urban activities in these two areas relatively low. Urban vibrancy between the 3rd and 4th ring road, the sandwiched interlayer of Beijing's central districts, shows the smallest change over the 24-hour period. Urban vibrancy within the 3rd ring road, including within the 2nd ring road and between the 2nd and 3rd ring road, presents the trend of "up-steady-down" pattern from morning to night. It is worth noting that the changes of these two regions are not synchronous. The stable phase with high vibrancy between 2nd and 3rd ring road lasts for a long time (from 9:00–21:00). While urban vibrancy within the 2nd ring road increases later in the morning and

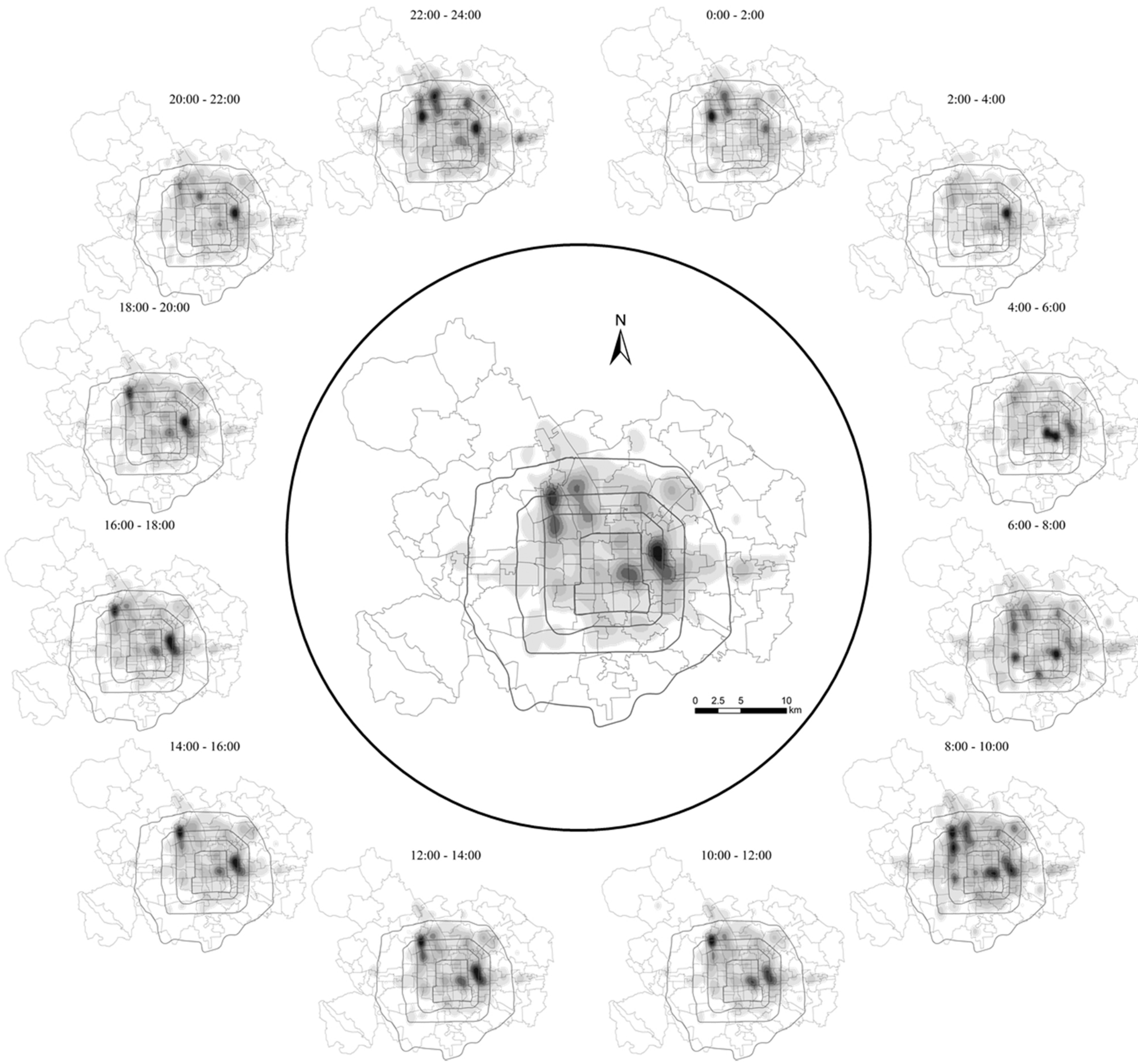


Fig. 5. Kernel density estimation results of the check-ins for 24 h and at different times.

decline earlier in the afternoon, leading to a relatively transient high-value duration. Compared with urban vibrancy within the 3rd ring road, urban vibrancy outside the 4th ring road shows a reverse trend of "down-steady-up" trend. But the turning points of vibrancy in these two regions also appear at different times. The temporal variation of urban vibrancy between different ring roads enables us to portray tide-like mobility patterns of people's activities in Beijing's central district during a typical day. People started to flow into urban center from the periphery during the daytime and flow out to the periphery at night, suggesting a typical separation pattern between work and residence in supercities in China. Historically, Beijing has adopted a spatial growth pattern of edge-expansion. Through the construction of the ring roads, Beijing continues to expand outward around the traditional central area where the Forbidden City locates. This spatial growth pattern leads to a distinctive ring-road defined center-periphery urban structure. The peak and valley of variation curve reflect the changes of human activities between different ring roads. The results agree well with the modern urban dynamics of a well-connected and ringed supercity like Beijing.

After using the KDE to convert discrete check-ins points into smooth surfaces and visualize them with hot spot map (Fig. 5), we can observe the temporal evolution of urban vibrancy from a finer spatial granularity. It can be seen from Fig. 5 that the spatial distribution pattern of people's activities changes at different time slots but remains relatively stable. The subdistricts with high urban vibrancy are mainly located within the 4th ring road, especially in the middle of Dongcheng, the west of Chaoyang and the northeast of Haidian districts. These subdistricts are the locations of science and technology industrial parks, central business district, and foreign embassies. From a temporal perspective, urban vibrancy is relatively low during typical sleeping times (0:00 – 6:00) and then gradually increase from 6:00 a.m. to 10:00 a.m. After that, the spatial patterns of people's activities keep relatively stable during the working hours in the afternoon. These results suggest that overall, the change of distribution patterns of urban vibrancy is closely associated with different types of residents' daily activities. Vibrant urban space is people-active urban space. Sustainable urban land use should be people-oriented land use pattern that not only balance the needs of both the land and the people, but also maximize the benefits for both.

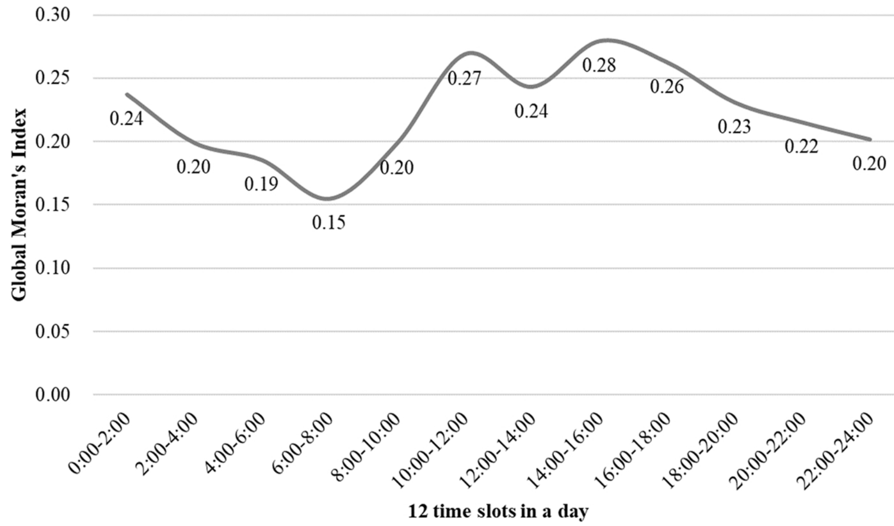


Fig. 6. Global Moran's Index of urban vibrancy at different times.

4.2. Spatial autocorrelation analysis of urban vibrancy

Fig. 6 shows the values of global Moran's Index at different time slots. Tests suggest that the pattern is significantly different from random, which agrees with our hypothesis that urban vibrancy in Beijing is spatially autocorrelated. The change of global Moran's Index from early morning to late night presents the trend of "wave-like up and down." This likely reflects people's regular daily activities. People generally live in the peripheries of the central districts while work and relax in the central areas. Before 8:00 in the morning, people's activities are relatively scattered, and the degree of spatial autocorrelation is relatively low. Then with the influx of workers and tourists to the core area, the intensity of people's activities begins to climb in these subdistricts, resulting in the increase of spatial autocorrelated urban vibrancy. After a short fluctuation at noon, people begin to flow out, which leads to the decline of spatial autocorrelation.

The results of local Moran's Index in Fig. 7 show the spatiotemporal clusters or outliers of subdistricts with different urban vibrancy than the neighborhoods. First, the global spatial autocorrelation of urban vibrancy mentioned above could be interpreted by the local patterns of spatial association (Yu and Wei, 2008). Specifically, among the four types of local spatial pattern (the High-High (HH), High-Low (HL), Low-Low (LL), and Low-High (LH)), the number of HH clusters changes most dramatically in 24 h, which dominates the variation process of global Moran's Index. Although the other three types exist in some time slots, their number is too small to have a significant impact on the global spatial association. Second, the HH clusters are mainly distributed in the north of the central subdistricts of Beijing, especially in the north central subdistricts between the 2nd and the 5th ring road. In contrast, most of the southern subdistricts are not significant and the only one LL cluster, Changxindian Subdistrict, is also in the south. Such distribution pattern is the result of a differentiated district zoning policy. According to *the urban master plan of Beijing (2016–2035)*, Haidian District in the northwest of the city, is expected to become the core area of the national science and technology innovation center. The eastern and northern parts of Chaoyang District should be built into a first-class business center and international exchange center. Universities, science and technology parks, business districts and embassies are mainly located in these subdistricts and create higher urban vibrancy. Fengtai District in the south is zoned as the Capital's service provision area and it is less likely for whole markets and transportation hubs to bring people there and generate high urban vibrancy. Due to the protection of ancient buildings and the existence of government offices within the 2nd ring road, it is also less likely to form a high-high cluster of urban vibrancy within the 2nd ring road (Fig. 7).

4.3. Temporal variation of the impact of determinants

Urban residents' activities change over the course of a day, which leads to the variation of urban vibrancy. It is necessary and meaningful to explore how determinants affect urban vibrancy at different time periods. Regression analysis is well suited for such task. Variance inflation factors (VIF) of independent variables are calculated to detect multicollinearity before the regression analysis. The result shows that except for the number of residents (POP), all other explanatory variables have a VIF value less than 10. So variable POP is removed from our model. Next, we conduct the traditional OLS estimation for all 12 time slots and test the spatial autocorrelation of the residuals. Consequently, except for 6:00–8:00 in the morning, the residuals of the other 11 time slots show significant positive spatial autocorrelation based on the Lagrange Multiplier (LM) tests (Table 2). Based on the Robust Lagrange Multiplier test, the spatial lag model (SLM) turns out to be a more appropriate specification to interpret the spatial autocorrelation of the residuals (Table 2). The results of SLM for the 12 time slots and the Lagrange Multiplier tests are reported in Table 2. For significant variables, temporal variations of their coefficients are visualized in Fig. 8 so that we can analyze their impacts on urban vibrancy more intuitively.

As illustrated in Table 2, the estimated coefficients of variables and their significance levels have great differences in these 12 time slots. The impact of consumption-related POIs (CPOI) is generally not significant except for 2:00 a.m. to 4:00 a.m., which is the active nightlife period for the young. It can be seen in Fig. 5 that high values of urban vibrancy during this period is in the east of Chaoyang District, where the famous Sanlitun Bar Street in Beijing is located. Occupation-related POI (OPOI), housing-related POI (HPOI) and tourism-related POI (TPOI) tend to have significant positive effects on urban vibrancy in most of the time slots. The common feature of these three POIs is that people usually spend a relatively long time there. In Fig. 8, the fluctuation of the OPOI curve is monotonous, with only one peak at 11:00, while the TPOI curve fluctuates dramatically and has many peaks and troughs. Working time of office workers is fixed but the time when people appear in tourist attractions is relatively random, which brings difficulties to capture the temporal regularity. For HPOI, the coefficients fluctuate in the shape of "W." Two troughs appear at 2:00–4:00 in the morning and 16:00–18:00 in the afternoon, which are the times for most people to sleep or socialize outside. These results can roughly depict a typical picture of people's daily activities in megacities. Office workers are the main body of urban residents, and the route of their daily activities are usually "home-

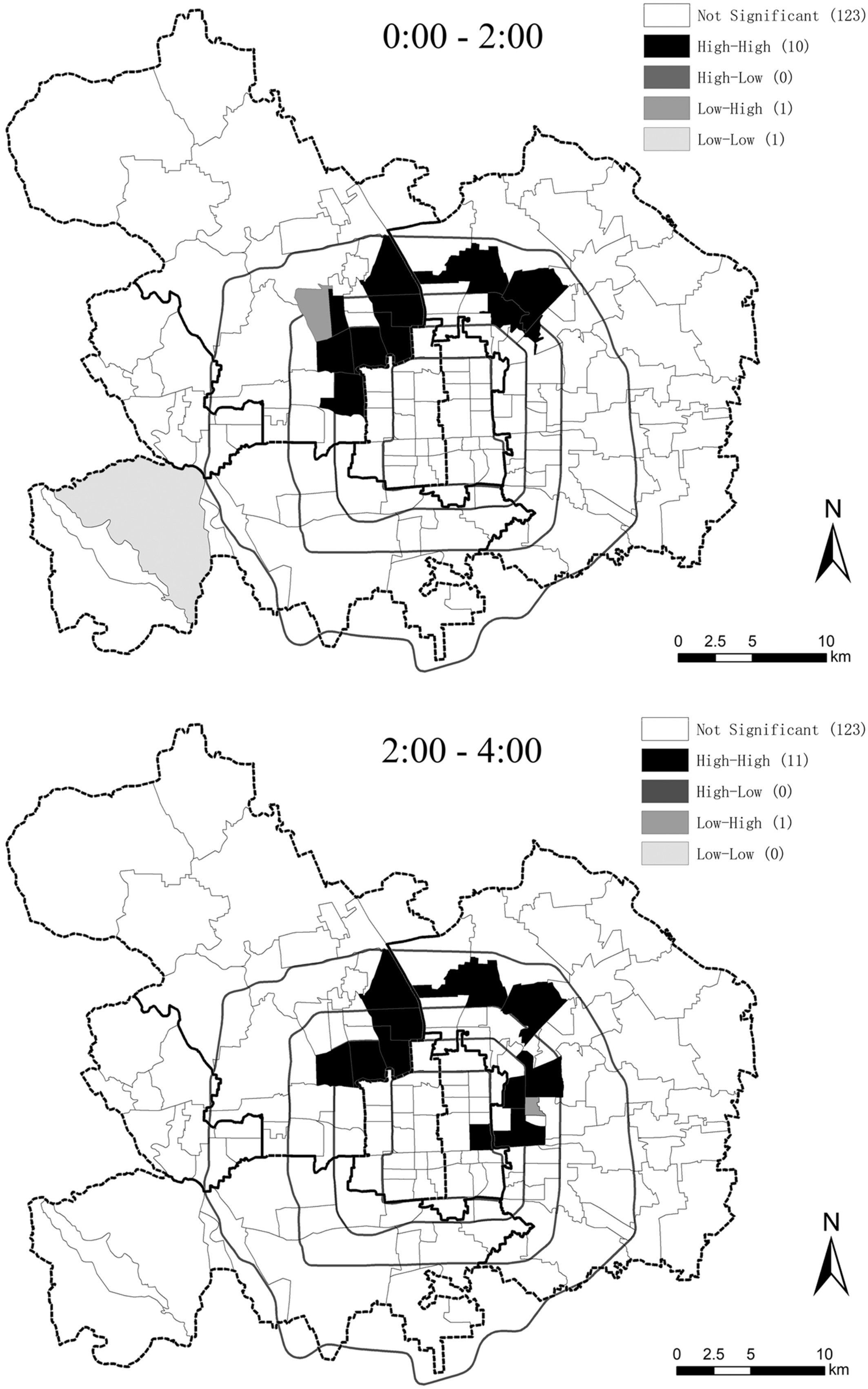
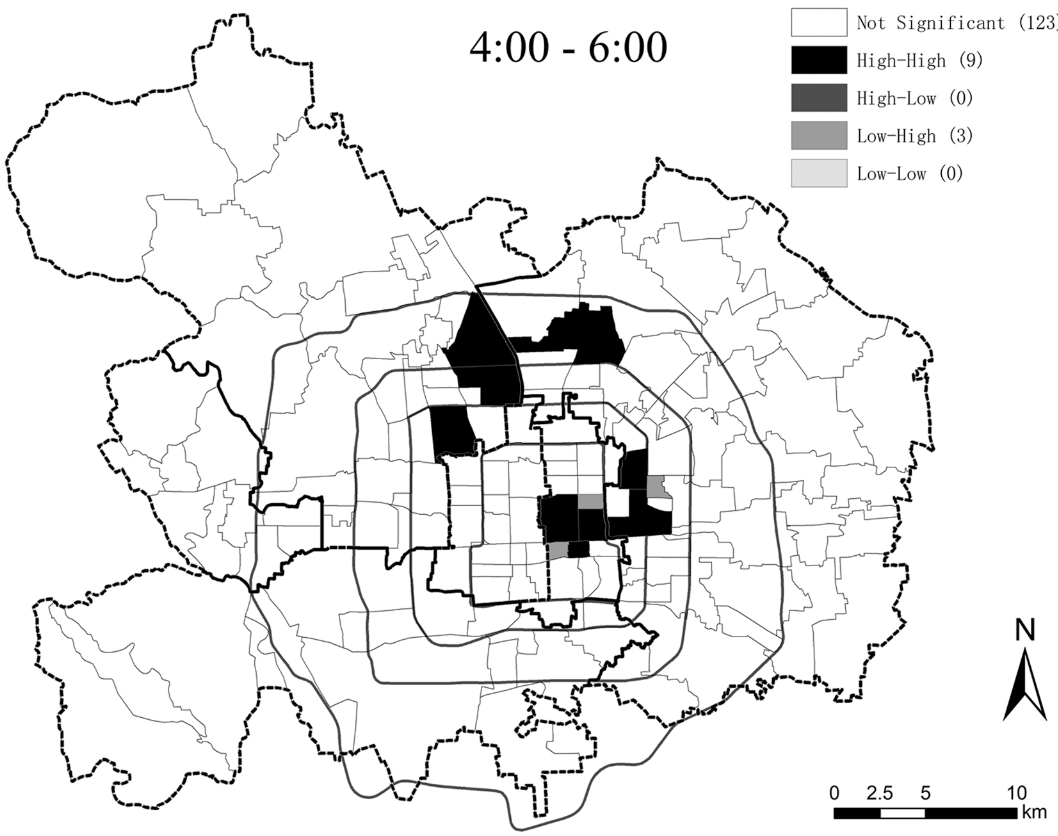


Fig. 7. Local Moran's I of urban vibrancy at different times.



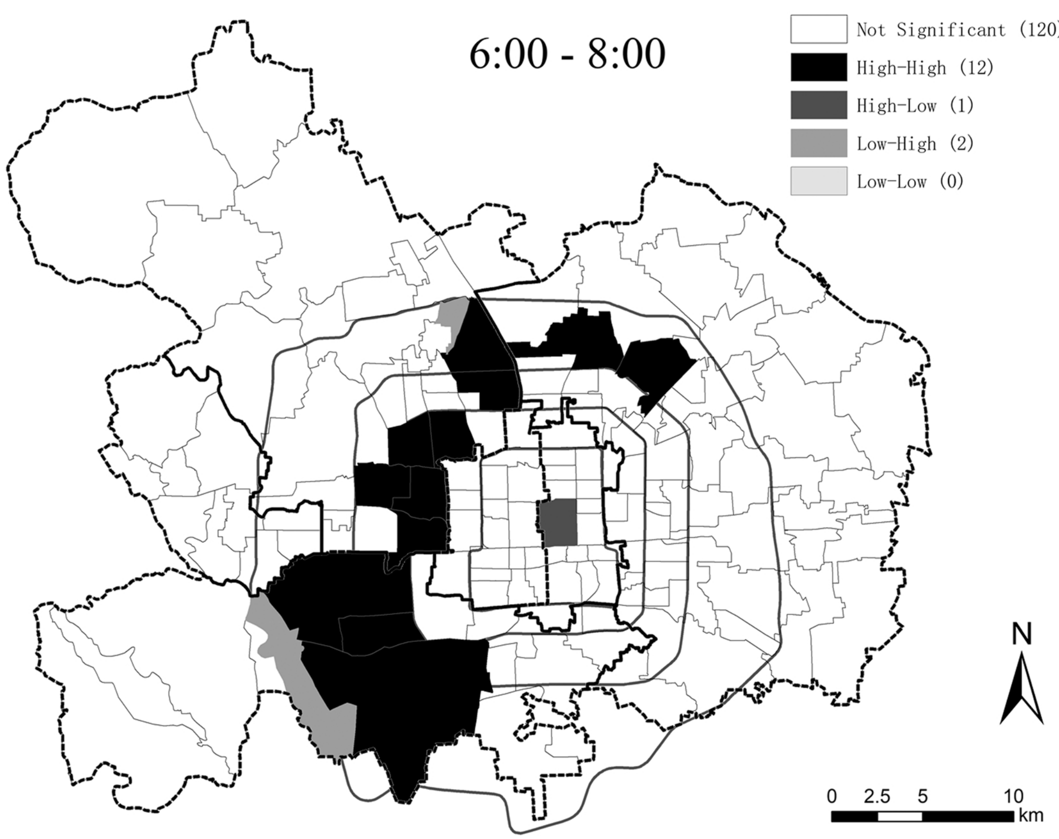
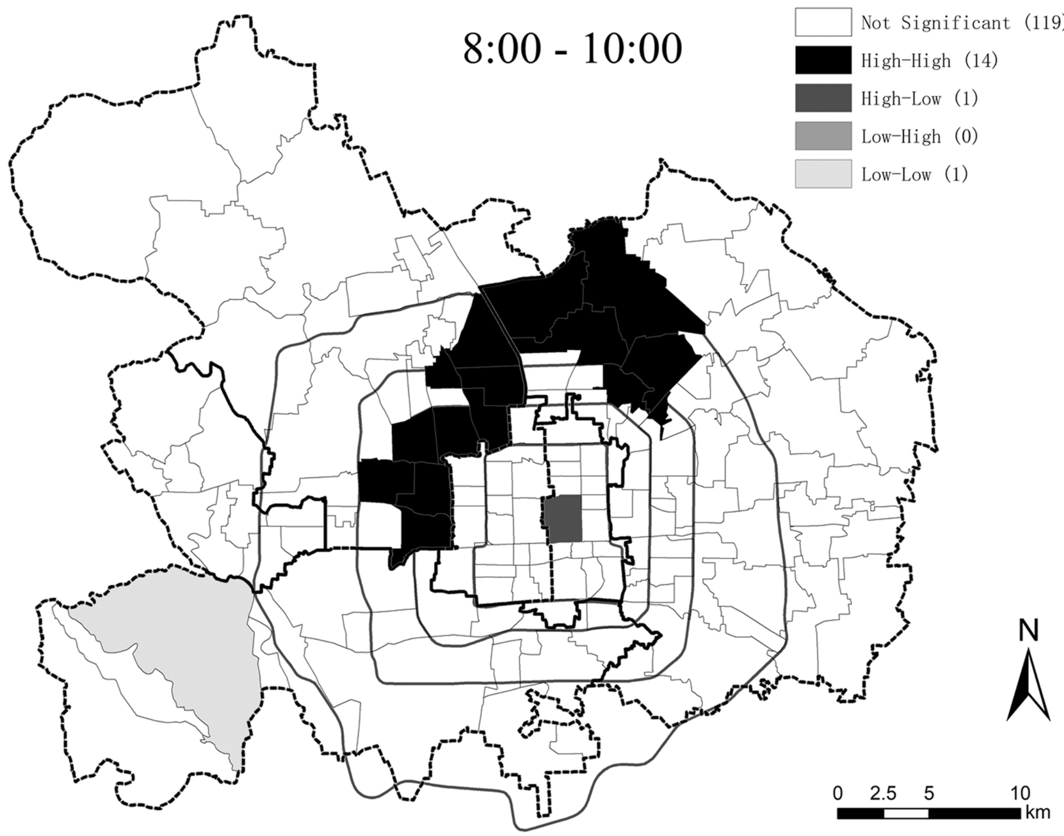
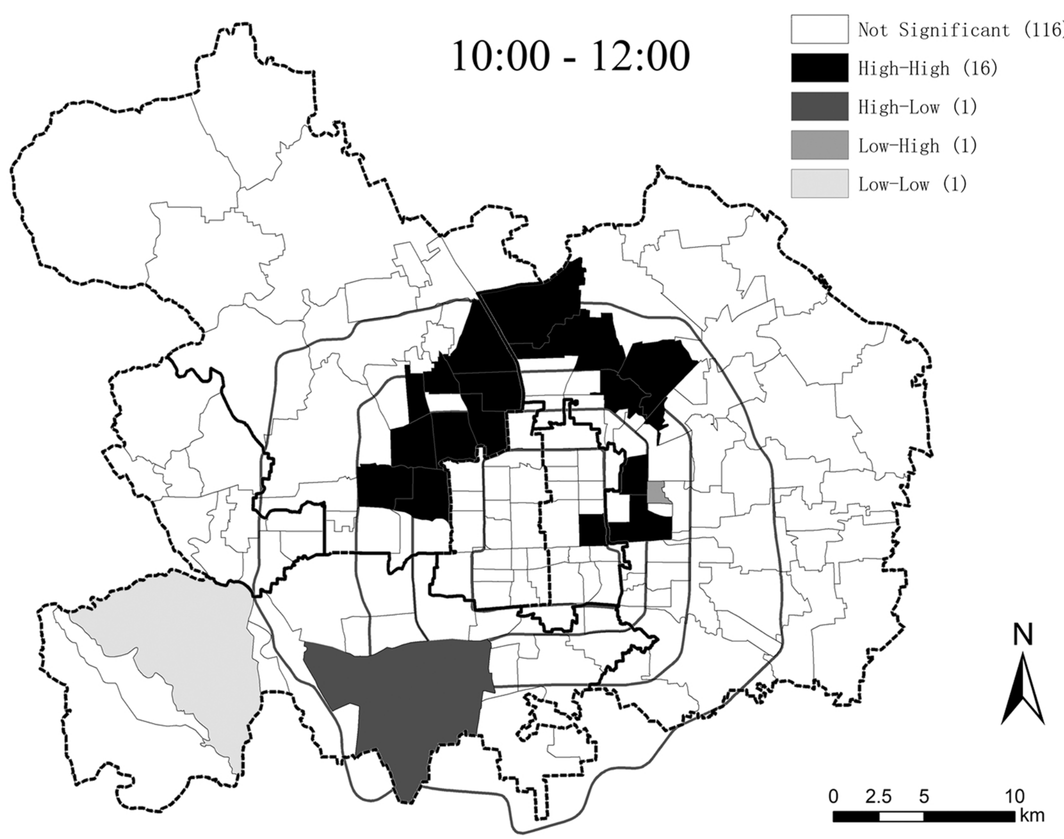


Fig. 7. (*continued*).





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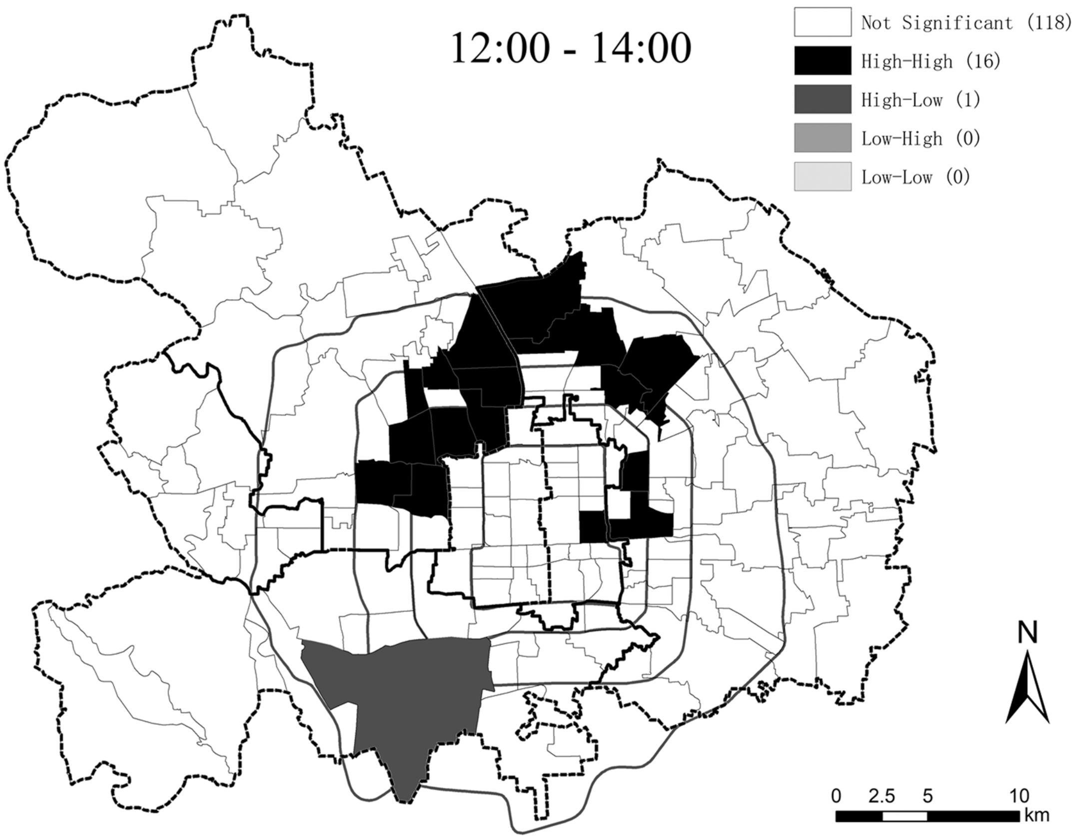

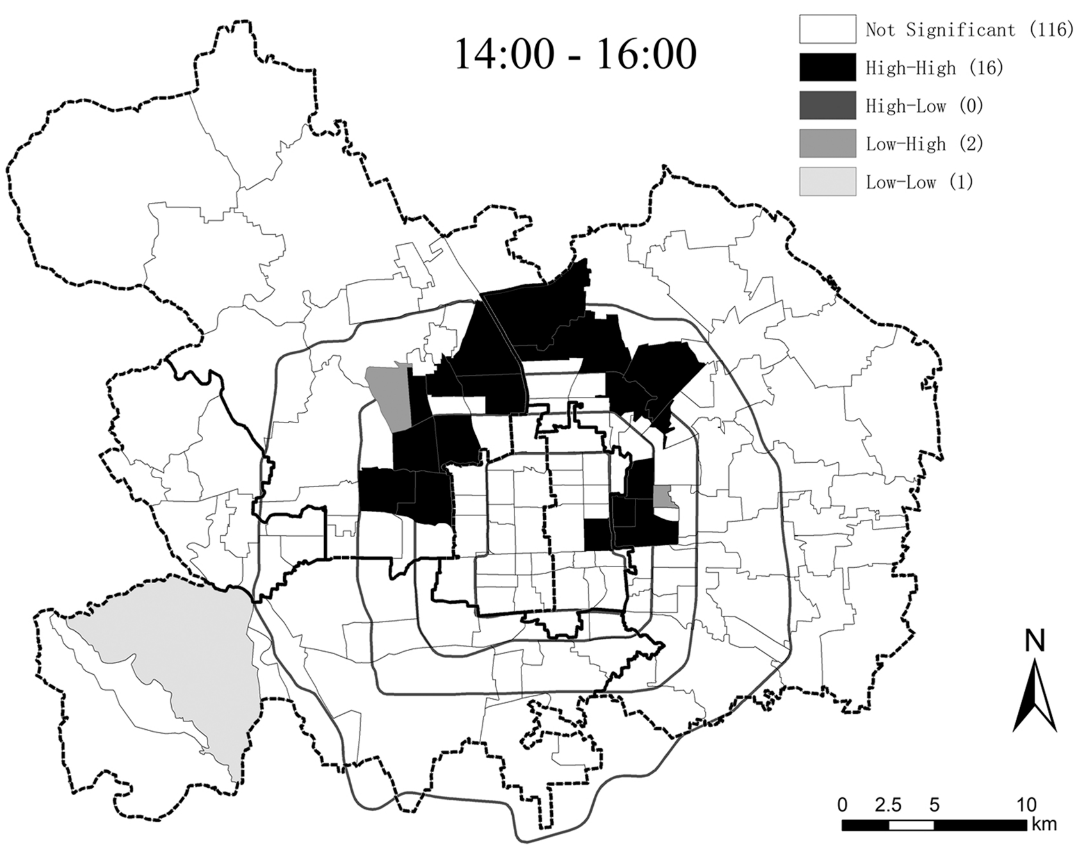

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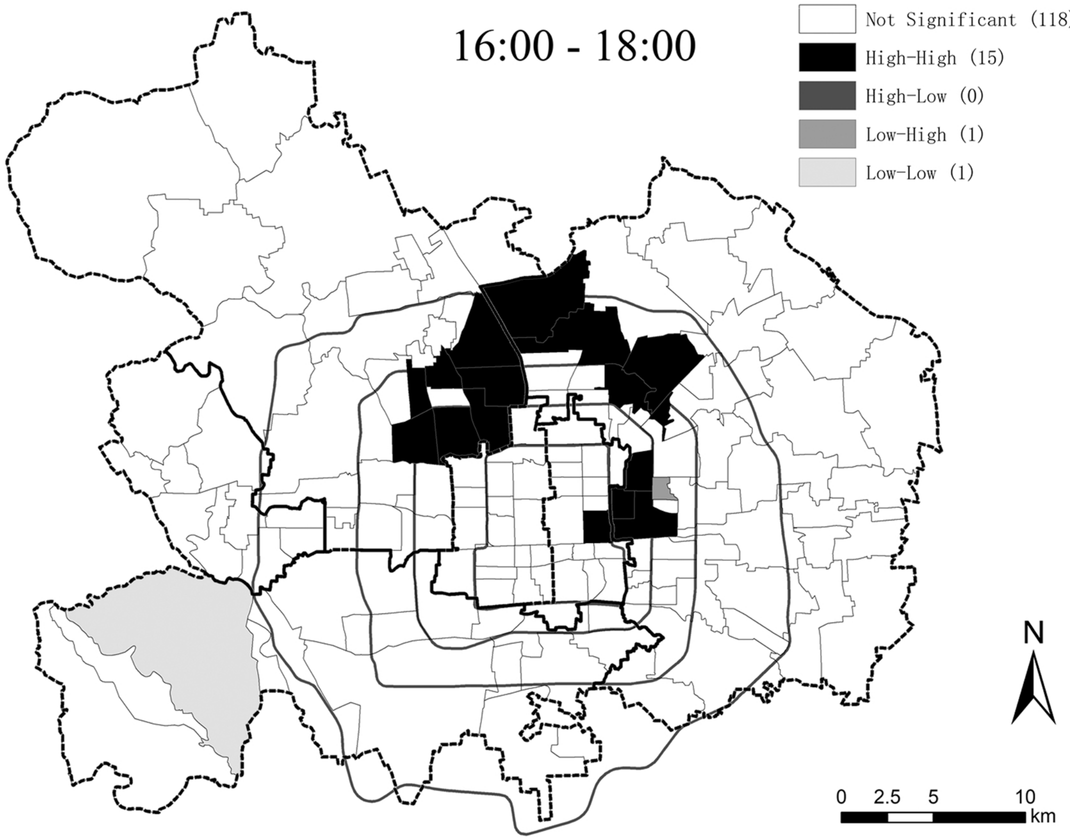

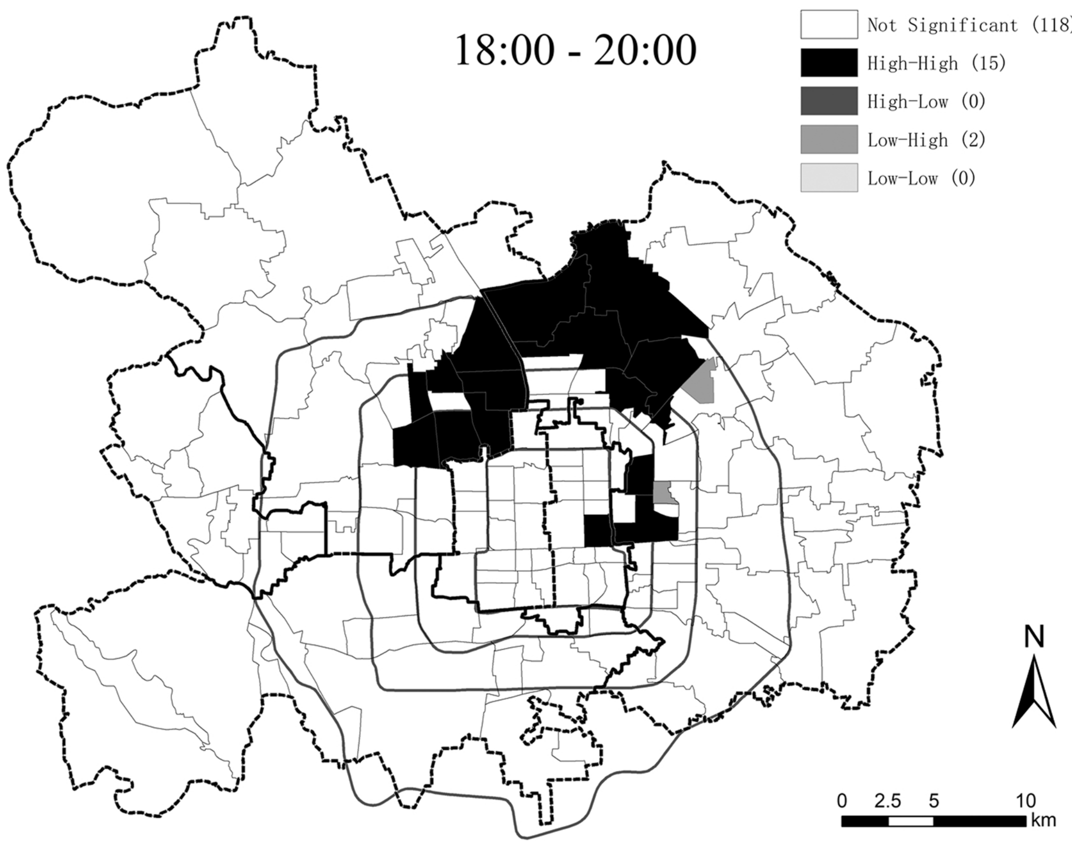

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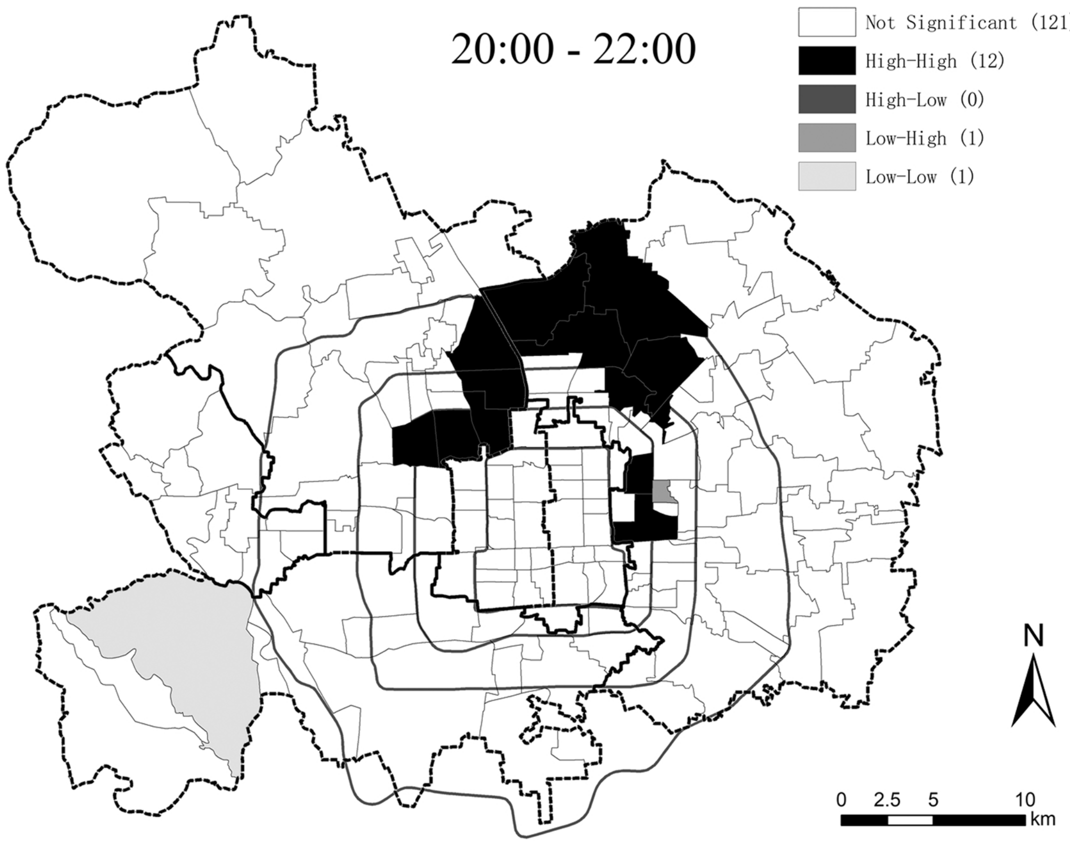


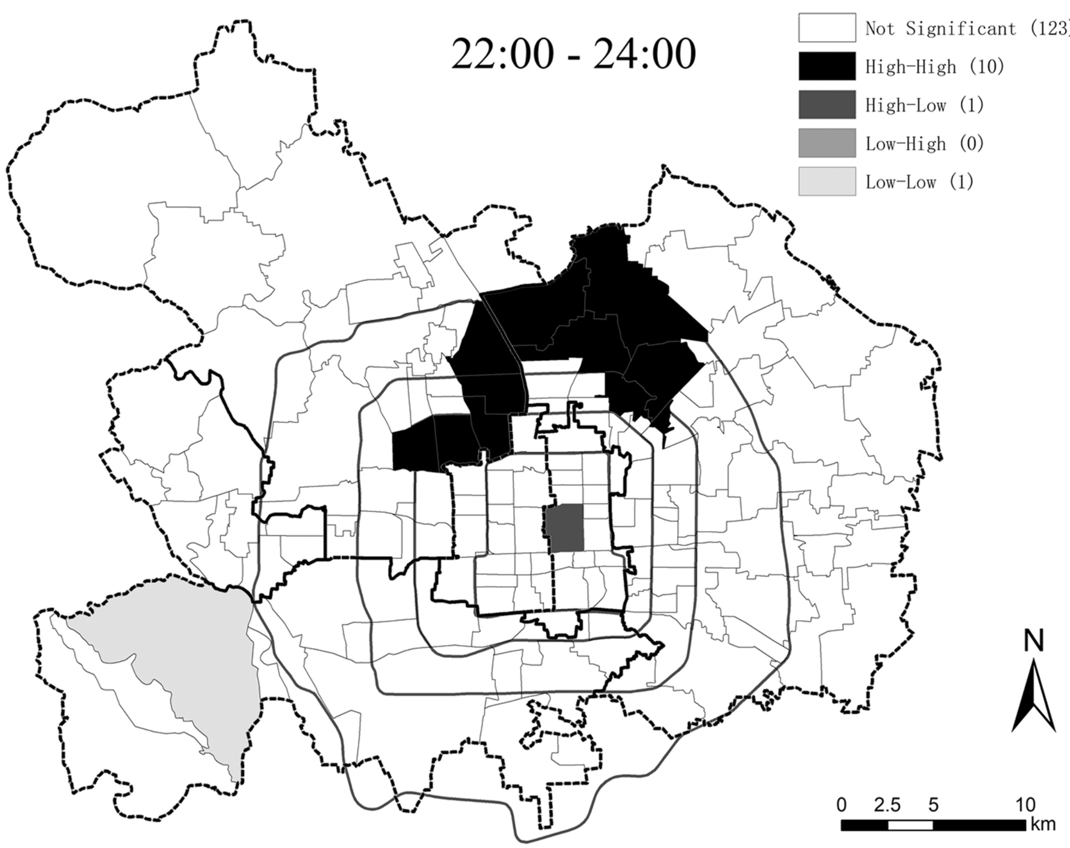


Fig. 7. (*continued*).

Table 2
Lagrange Multiplier tests and the estimated coefficients of variables for SLM and their significance levels.

Time Slots	CPOI	OPOI	HPOI	TPOI	SDI	GDP	DIST2TAM	ROAD	LMlag	LMerr	RLMlag	RLMerr
0:00–2:00	0.106	0.311 * *	0.312 * **	0.088 *	-4.737 * **	0.014	0.152	0.128	21.786 * **	20.709 * **	3.401 *	2.324
2:00–4:00	0.361 * *	0.262 * *	0.068	0.097 * *	-3.514 * **	-0.019	0.027	0.081	4.978 * *	3.478 *	1.541	0.041
4:00–6:00	0.090	0.293 * *	0.172	0.056	-2.998 * **	0.003	-0.181	0.251	5.747 * **	2.353	3.749 *	0.355
6:00–8:00	0.034	0.314 * **	0.301 * **	0.067	-3.453 * **	-0.112	0.097	0.322 * *	0.950	0.129	0.983	0.950
8:00–10:00	-0.055	0.475 * **	0.244 * *	0.108 * **	-4.716 * **	0.017	0.016	0.213	7.088 * **	5.663 * *	1.893	0.469
10:00–12:00	-0.048	0.610 * **	0.142	0.097 * *	-4.913 * **	0.080	-0.038	0.146	14.807 * **	13.522 * **	3.000 *	1.715
12:00–14:00	0.075	0.562 * **	0.121	0.110 * **	-4.245 * **	0.061	0.008	0.079	8.462 * **	7.844 * **	1.727	1.109
14:00–16:00	-0.018	0.536 * **	0.175 *	0.120 * **	-5.188 * **	0.051	-0.014	0.080	16.467 * **	9.243 * **	7.241 * **	0.017
16:00–18:00	0.133	0.513 * **	0.065	0.114 * **	-4.722 * **	0.069	-0.074	0.126	22.683 * **	16.588 * **	7.054 * **	0.958
18:00–20:00	0.167	0.429 * **	0.152	0.116 * **	-4.931 * **	0.036	0.031	0.096	5.831 * *	4.075 * *	1.962	0.206
20:00–22:00	0.112	0.352 * **	0.234 * *	0.074 *	-4.315 * **	0.071	0.086	0.102	9.228 * **	4.590 * *	4.641 * *	0.002
22:00–24:00	0.010	0.324 * **	0.322 * **	0.081 * *	-5.169 * **	0.032	0.118	0.189	12.395 * **	10.841 * **	2.713 *	1.159

Notes: ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

workplace-consumption place-home." In the morning, they leave homes for the workplaces and spend the whole morning there. After a short break at noon, they continued to work in the office until around 18:00. Going home directly or going to consumption places for shopping, dining and entertainment are two main choices for them after work.

Simpson diversity index of POIs seems to have negative impact on urban vibrancy, regardless of which time of the day. This finding is different from some previous empirical studies, which argue that mixed land function is the primary generator of urban vibrancy (Jacobs, 1961; Yue et al., 2017), but also agrees with other studies (De Nadai et al., 2016, 2020; Tang et al., 2018). One of the potential issues for the possible negative impact of the mixed land function index might be attributed to the POI data we used in the study. While the POI data reflects well the mixture of land functions, it does not necessarily reflect well the scales of those mixed land functions. On the other hand, this negative effect might also be the result from the splitting effects of the mixed land functions of any subdistricts. Just as a river splits into many channels, splitting effect for a subdistrict with mixed land functions refers to that only part of the potentially active population is attracted to these places because of the dispersion of land functions.

Beijing, as the political as well as socioeconomic center of China, is a city with a high degree of administrative planning and management. Most of its subdistricts are highly specialized in certain land functions. For example, the names of College Road Subdistrict in Haidian District and Finance Road Subdistrict in Xicheng District reflect the main function of those subdistricts directly. These are where colleges and financial centers locate. The subdistricts with high degree of mixed land functions are usually located outside the 5th ring road and the intensity of human activities is generally lower there in most of the day. In addition, because of the diverse land functions, a subdistrict could have both splitting effect and attraction effect. These two effects influence urban vibrancy from different directions. The land functions, represented by apartments, shopping malls, workplaces, or green spaces, are developed to meet different demands of people. Multi-functional subdistricts could provide a variety of services, so they are able to attract a sustained flow of people over a long time. This long-term ability of diverse land functions to attract population influx is called attraction effect. On the other hand, the people attracted to these areas are only a small portion of the active population during a short period of time in a day because for any time slot, people's demands for urban functions are often specific. Except for the land functions that provide specific services, most of other land functions are running at idle. This splitting effect at the short term as in our study could dominate the influence on urban vibrancy. This might explain why we observe the significantly negative effect of land function diversity on urban vibrancy in the current study.

The impacts of socioeconomic conditions, represented by GDP, and the location of subdistricts (DIST2TAM) on urban vibrancy are not statistically significant anytime during the day. The significant positive impact of traffic accessibility (ROAD) only appears at 6:00 a.m. to 8:00 a.m., which is the morning rush hours for commuters. This is likely because all three factors are static measures that might not be directly related with the highly dynamic urban vibrancy at the fine geographical (subdistricts) and temporal (2 h per slot) levels.

4.4. Spatial differences of the impact of determinants

Considering the potential spatial non-stationarity and scale effect, we applied the MGWR model to investigate the spatial differences of the determinants' impacts on urban vibrancy. The diagnostic information of OLS regression, classical GWR model and MGWR model is reported in Table 3. The results suggest that MGWR model seems to perform the best with the smallest residual sum of squares, AIC and AICc and the largest Log-likelihood.

The bandwidths used in the GWR model or MGWR model can be regarded as the influence scales of different variables. Table 4 summarizes the differences of all variables' bandwidths between classical GWR

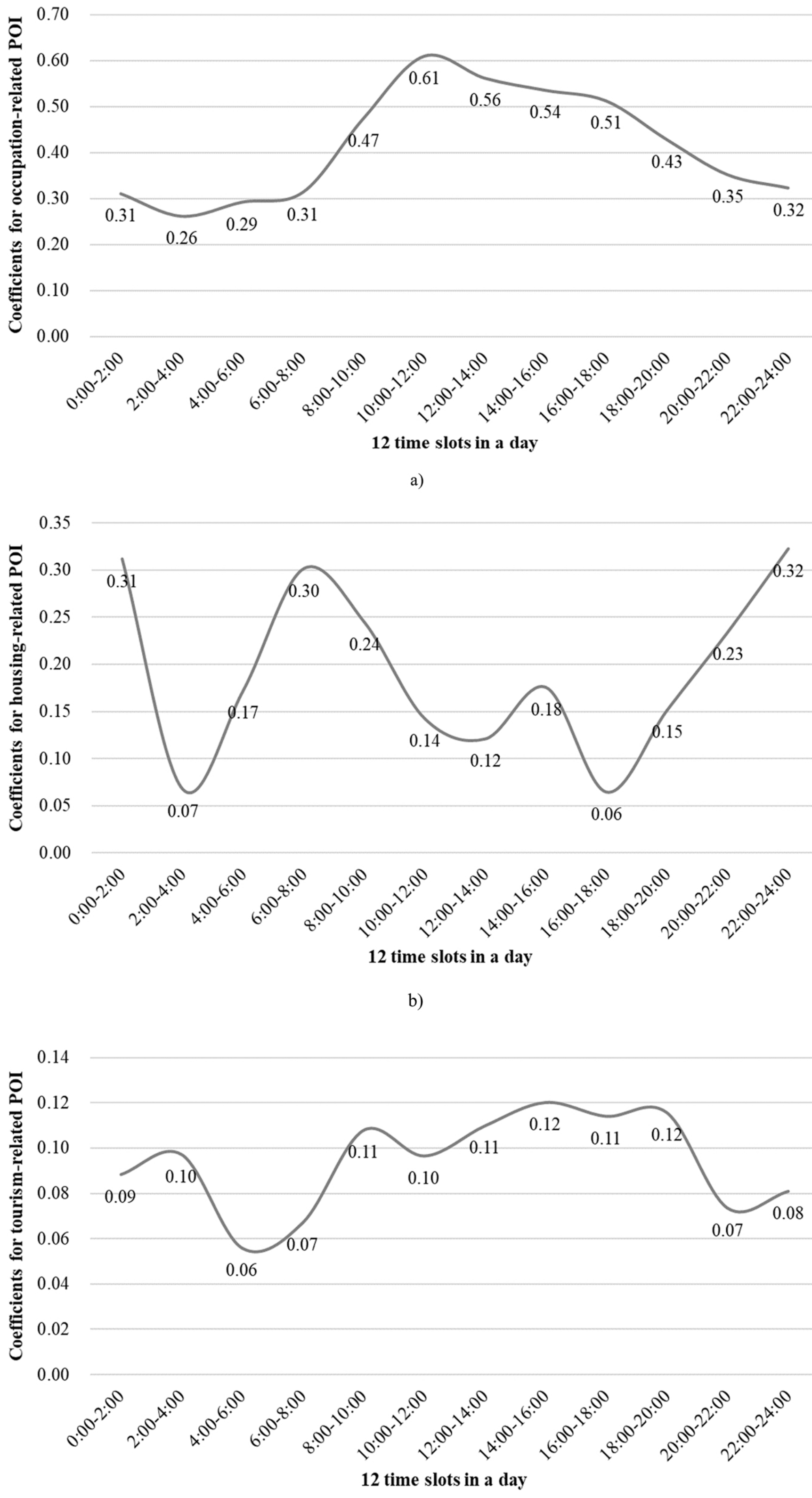


Fig. 8. Temporal variation of estimated SLM coefficients for a) OPOI, b) HPOI, c) TPOI.

model and MGWR model. The bandwidths of different variables are the same in GWR model and all the variables affect the urban vibrancy in the scope of 87 nearest neighbors (using the adaptive bandwidth approach). However, in MGWR model, influencing scales of different determinants on urban vibrancy are quite different. The parameter estimates associated with the CPOI and OPOI are global and optimal bandwidths of them are both 134 nearest neighbors (using the adaptive approach). This means the effects of CPOI and OPOI on vibrancy have no scale variation. The impacts of HPOI and TPOI vary slightly (bandwidths of 132 and 108 nearest neighbors, respectively). The other four variables

Table 3
Comparison between OLS, GWR and MGWR.

Diagnostic Information	OLS	GWR	MGWR
Residual sum of squares:	40.251	20.727	18.837
Log-likelihood:	-109.872	-65.071	-58.617
AIC:	237.744	193.737	183.949
AICc:	241.519	214.145	206.724

Table 4
Bandwidths of explanatory variables used in GWR and MGWR.

Variable	GWR	MGWR
CPOI	87	134
OPOI	87	134
HPOI	87	132
TPOI	87	108
SDI	87	43
GDP	87	59
DIST2TAM	87	45
ROAD	87	64

that have impacts on urban vibrancy vary quite differently in terms of spatial scales, with the bandwidths for the diversity of POIs being 43 nearest neighbors; GDP being 59 nearest neighbors; the distance to Tiananmen Square being 45 neighbors; and the length of road network being 64 neighbors. These results indicate that the local subdistrict vibrancy is mainly determined by diversity of land functions, socioeconomic condition, location, and accessibility rather than the number of various POIs, which further supports the modeling result from the global model that the dynamic urban vibrancy is likely globally related with the dynamic POIs, but locally related with more static measures.

In Fig. 9, we present the varying local parameter estimates from MGWR model for four variables with significant spatial scale variation to see their variations in the spatial scales more clearly.

The negative effect of the diversity of POIs (SDI) on subdistricts' vibrancy covers the entire research area. Negative effect appears in primarily two clusters, namely, subdistricts in Shijingshan and Fengtai District and subdistricts in the north of Chaoyang District. Chaoyang District has the largest population in Beijing and business office is one of its prime functions. Office workers have understandably predictable routes of daily activities in weekdays and their needs for other urban functions over the weekends are mainly met in other districts. The diversity of POIs has a stronger splitting effect on the urban vibrancy in Chaoyang. For subdistricts in Shijingshan and Fengtai Districts, they have a relatively small population and tourism-related POIs play important roles in generating vibrancy. Diversity of POIs weakens the positive impact of tourism-related POIs and reduces vibrancy in these subdistricts.

Regarding socioeconomical conditions, a subdistrict's GDP affect urban vibrancy negatively on both the west and east in the study area, whereas in the middle its effect is positive. With the urban expansion of Beijing, industrial and residential land use in city center gave way to traffic, commercial and social infrastructure (Huang et al., 2017). Urban vibrancy is generated in the interaction between people and land space and public amenities play an important role in this process. Compared with the central subdistricts, the western and eastern subdistricts have more industrial functions but less public service facilities. Although industrial land use can create massive GDP, it has negative impacts on urban vibrancy (Meng and Xing, 2019). In addition, large GDP is closely related to a large population size. Due to the lack of social infrastructure, excessive population inflow can bring crowding effect, which may cause a negative effect on urban vibrancy (Lan et al., 2020).

The local effects of the variable "the distance to Tiananmen Square" (DIST2TAM) are uniformly negative across the whole research area, indicating that a shorter distance of subdistrict to city center correlates a higher urban vibrancy. It can be seen from the coefficient's distribution pattern that except for some subdistricts in Haidian and Chaoyang District, the influence of geographical location tends to be stronger in the subdistricts further away from the city center. The subdistricts with relatively weak effect in Haidian and Chaoyang are the locations of famous colleges and central business district, respectively. Young people and high-income groups are the primary creators of local vibrancy, which makes the distance between these subdistricts and city center less important in promoting urban vibrancy there.

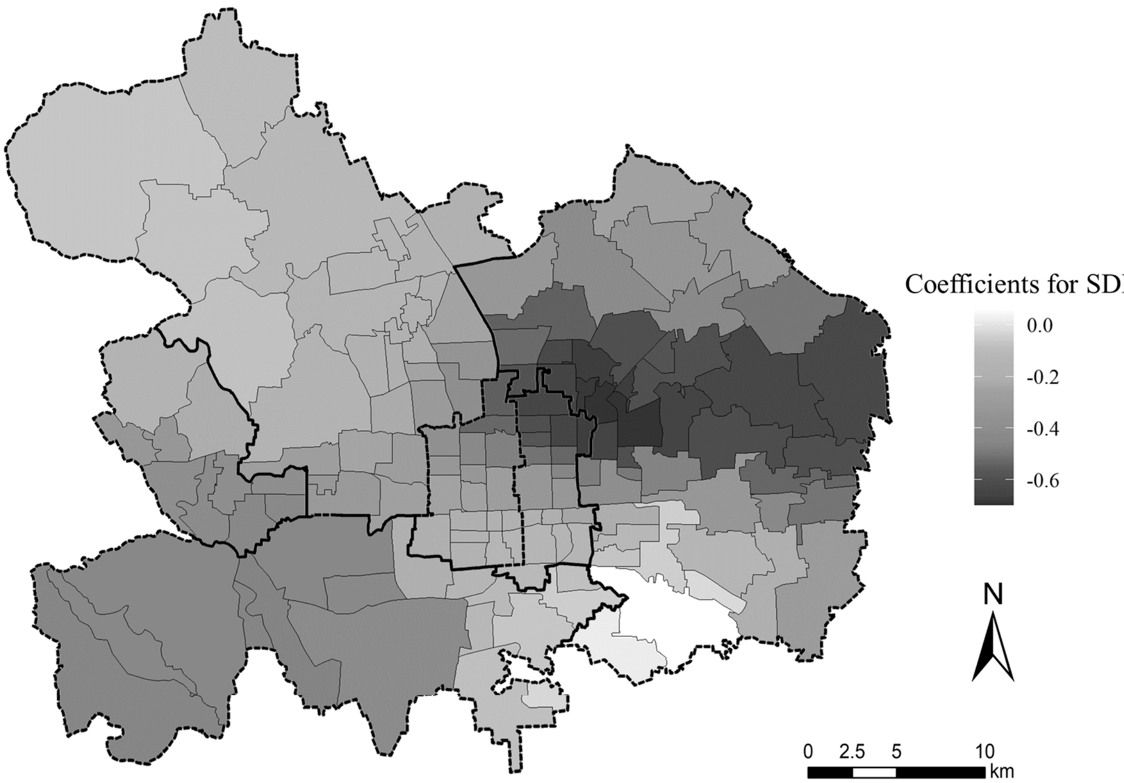
Traffic accessibility, represented by the length of road (ROAD), has positive impact on urban vibrancy globally. The spatial distribution of regression coefficients presents a typical sandwich structure with high values in the middle and low values on both sides. Next to the northern border of the central districts, there are two most populous residential communities in Beijing (Tiantongyuan and Huilongguan). In the south, most of the subdistricts in Fengtai District are the hubs of logistics transportation. The flow of population and commodities to the central areas is highly dependent on the traffic accessibility. The western subdistricts are mainly in ecological conservation areas and the intensity of human activities here is relatively low. To the east of Chaoyang District, the construction of Beijing municipal administrative center has efficiently transferred some residents' activities to Tongzhou District. Consequently, the dependence of traffic accessibility in these subdistricts is not as high as that in the central subdistricts.

These diverse influences of the socioeconomic, physical, and infrastructure factors on urban vibrancy provide a complementary understanding of urban vibrancy dynamics in addition to the results presented by the global models. A clear message the MGWR model reveals is that any land use policies that aim to promote urban vibrancy need to consider the specific conditions of the subdistricts carefully. It seems at least at the subdistrict level, focusing on a particular land function might provide the best strategy for boosting its vibrancy during most of the day. On the other hand, while increasing road network density in a subdistrict will enhance its vibrancy, the effect might be limited if the majority of the residents in the subdistrict does not have a high demand for inter-subdistrict traffic.

5. Conclusions

Promoting urban vibrancy can bring great benefits to the healthy and sustainable development of cities. The rapid development of communication technologies enables us to utilize multi-source urban datasets to conduct more detailed and in-depth studies on urban vibrancy. In this study, we use the Weibo check-in data to represent the urban vibrancy at subdistrict level in central Beijing. Since similar geo-tagged social media data become increasingly available across the globe, similar studies can be applied to other cities to study the landscape of urban vibrancy and factors that impact urban vibrancy.

In our current study, we find that the spatial and temporal distribution characteristics of urban vibrancy at subdistrict level in Beijing show a typical spatial structure following the different ring-roads. As expected, urban vibrancy at subdistrict level exhibits strong spatial autocorrelation in most of the time periods during the day in our study. With explicit spatial effects taking into consideration, the study employs spatial lag autoregression model and multiscale geographically weighted regression model to investigate the relationship between urban vibrancy and its determinants. We believe this study contributes to the current literature of urban studies in three aspects. First, social media data could be a suitable proxy to measure urban vibrancy at the fine spatiotemporal scale. It is an advantage of people-centered spatial big data that material-centered data might not possess. By using Weibo check-in (or other geo-tagged social media) data, the dynamic distribution of urban vibrancy in Beijing can be visualized and analyzed in real time. Urban vibrancy in Beijing is closely related to the typical center-periphery structure of urban layout and the north-south difference of urban function orientation. Second, spatial analysis reveals that urban vibrancy at the subdistrict level is spatially autocorrelated. The



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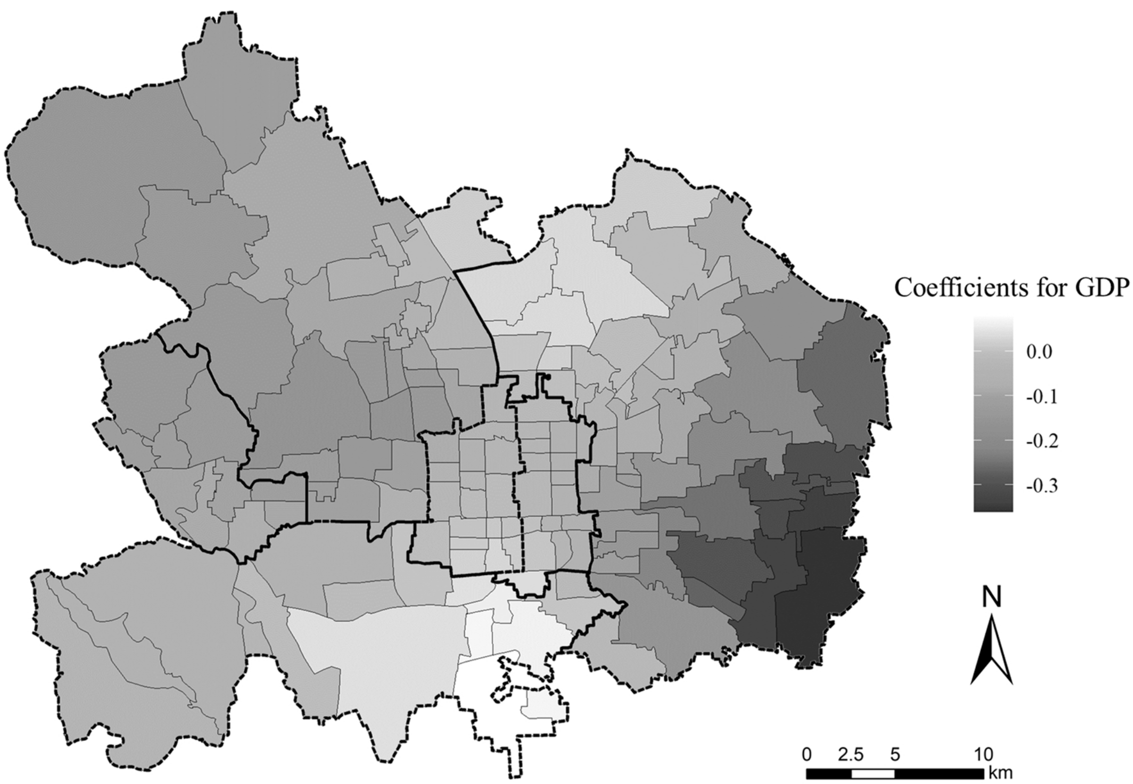
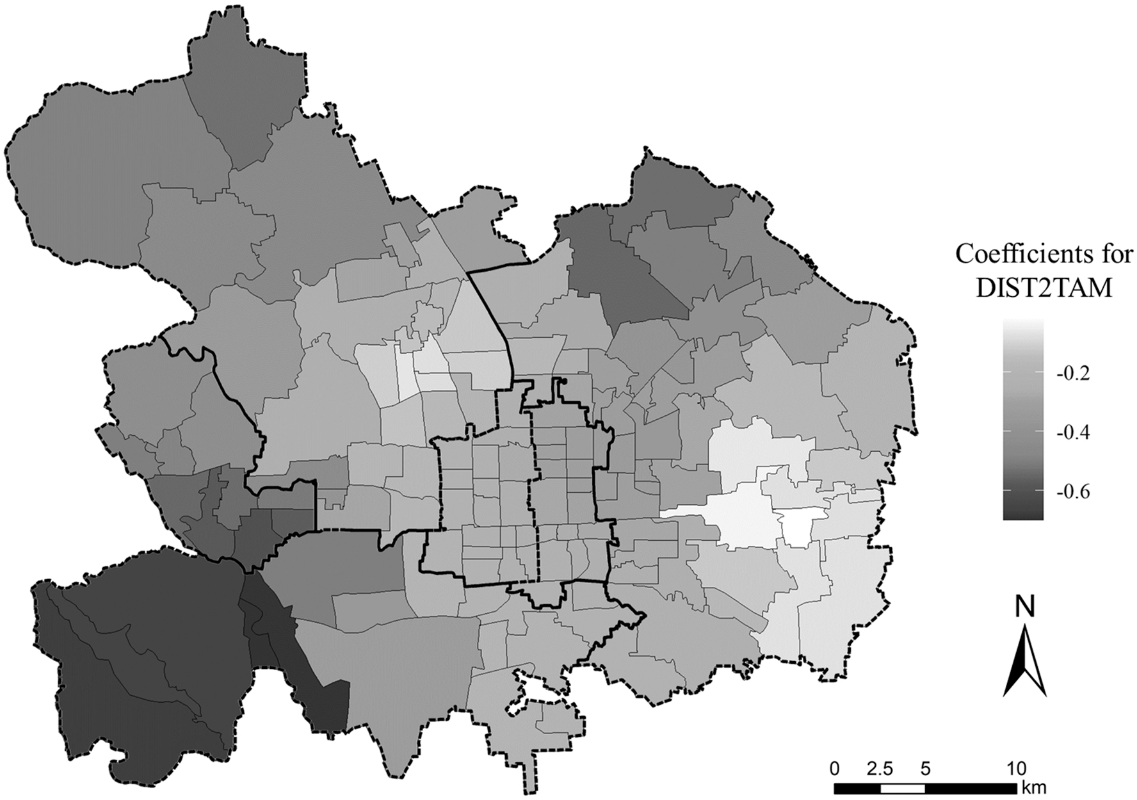


b)

Fig. 9. Spatial distribution of the estimated MGWR coefficients for a) SDI, b) GDP, c) DIST2TAM, d) ROAD.



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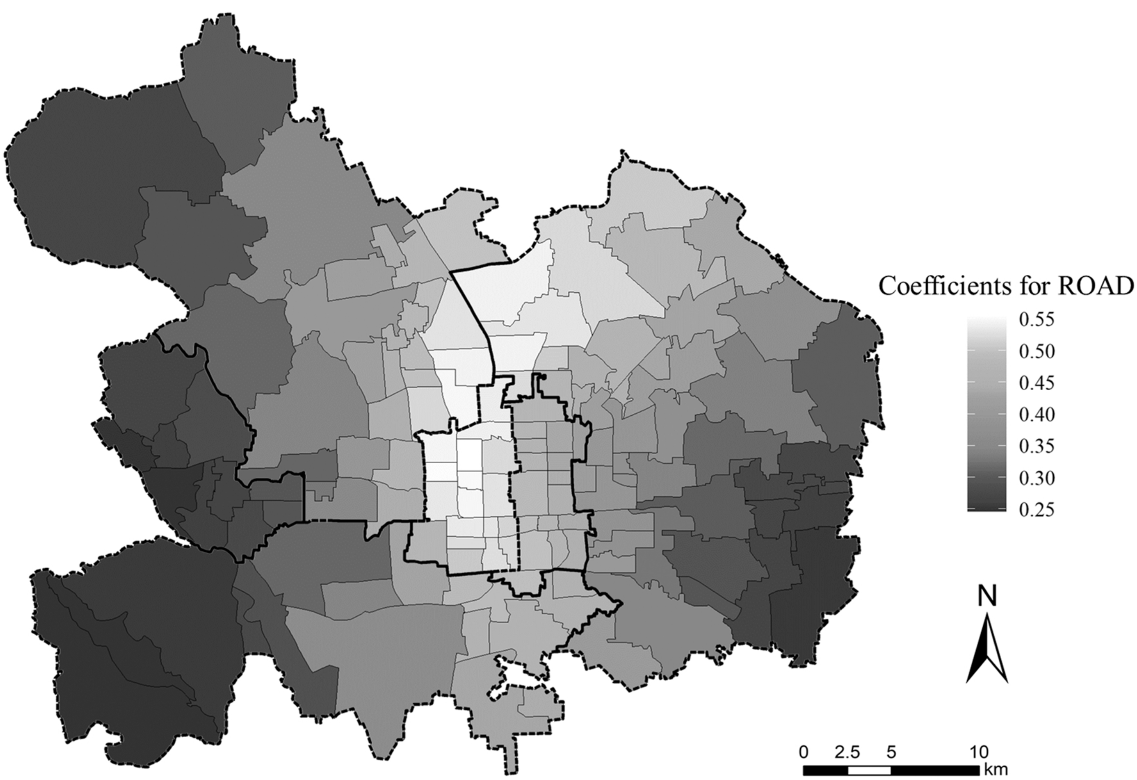

d)

Fig. 9. (*continued*).

existence of significantly positive spatial autocorrelation means that neighborhood vibrancy affects each other. The information provides important guidance for sustainable urban planning. Urban land use planning and management at the subdistrict level need close cooperation among immediate neighbors and a global master plan that governs the overall land use functions will serve the long run planning purpose well. Optimizing the layout of land functions to achieve the balance of the development interests among subdistricts requires the wisdom of urban managers and is the goal for long-term urban planning. Third, global and local regression analyses show the complex influence mechanism of urban vibrancy from temporal and spatial dimensions, respectively. The results show that promotion effects of POIs on vibrancy varies at different times but have no obvious spatial scale variation. Socioeconomical conditions, location and accessibility have different spatial scale effects on urban vibrancy at subdistrict level. Splitting effect and attraction effect of diverse land functions are the underlying mechanism to restrain the increase and fluctuation of urban vibrancy at subdistrict level. It suggests that the maintenance of urban vitality in a day relies on the appropriate allocation between main and auxiliary land functions. Rich land functions are the basis for promoting urban vibrancy. However, excessive pursuit of the diversity of land functions will weaken the attraction effect, which might be detrimental to the improvement of urban vibrancy in the long run.

Promoting urban vibrancy is one of the priorities of the government in China. This study takes Beijing as a case to broaden the scope of existing studies. Some findings verify the relevant theories of urban vibrancy, while some are inconsistent. The reasons are multifaceted, and it might closely relate to the urbanization with Chinese characteristics. For the practical significance of this study, we summarize it into two aspects. On the one hand, the discussion and application of social media data assist urban managers to construct guiding indicators to evaluate urban vibrancy. We argue that an appropriate proxy of urban vibrancy should be people-centered rather than material-centered. Therefore, the improvement of urban vibrancy should be committed to strengthen the interaction between resident activities and urban facilities, which is consistent with the concept of “compact cities”(Xu et al., 2020). On the other hand, the empirical findings provide assistance to policy maker to understand the spatiotemporal mechanism of urban vibrancy and enables them to make suitable planning and management decisions for the subdistricts’ land functions.

Urbanization in China is still a fast-ongoing process, and many cities are still undergoing early exploration stages of building vibrant cities. The land functions of subdistricts in these cities should be coordinated with local population and socioeconomic conditions. Furthermore, mining knowledge about the attraction and splitting effects of land function diversity aids to develop the strategy of “highlighting the main functions and enriching the auxiliary functions.” It is hoped that our study could provide a useful reference for future studies of urban vibrancy from a spatiotemporal analytical perspective. Our next research foci will be on the difference of urban vibrancy between weekdays and non-weekdays and testing whether splitting effect and attraction effect exist on larger spatial scales.

Declaration of Competing Interest

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

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