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Elaborating Spatiotemporal Associations Between the Built Environment and Urban Vibrancy: A Case of Guangzhou City, China

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Abstract: This study applies multi-source datasets (i.e., Baidu Heat Map data, points of interest (POIs) data, and floor area and land use data) and geographically and temporally weighted regression (GTWR) models to elaborate the spatiotemporal relationships between the built environment and urban vibrancy on both weekdays and weekends, using Guangzhou City as a case. First, we verified the spatially and temporally nonstationary nature of the built environment correlates, which have been largely ignored in previous studies based on local regression techniques. The spatially and temporally heterogeneous effects of the built environment on urban vibrancy are then presented and visualized, based on the GTWR results. We found that the elasticity of location (i.e., distance), land use mix (i.e., diversity), building intensity and numbers of POIs with various functions (i.e., density) are different across time (2-h intervals within a day) and space (grids), due to people's everyday lifestyle, time-space constraints, and geographical context (e.g., spatial structure). The findings highlight the importance of a better understanding of the local geography on the spatiotemporal relationships for urban planners and local governments so as to put forward decision-making support for fostering and maintaining urban vibrancy.

Keywords: urban vibrancy; Baidu Heat Map (BHM); built environment; heterogeneity; geographically and temporally weighted regression

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1 Introduction

Urban vibrancy, a concept first defined by Jacobs (1961) as street life over a 24-h period, describes human activities and their interactions with spatial entities over time and space. It also means the capacity of urban places to meet people's 'vital and biological requirements' (Lynch, 1984). As a reflection of the attraction of a place, urban vibrancy has been widely regarded as an essential element for attracting human and economic capital, achieving urban quality of life, and improving people's subjective feelings of urban places (Lynch, 1984; Hall and Pfeiffer, 2000; Glaeser, 2011; Lan et al., 2020). Thus, fostering and maintaining urban vibrancy has been a subject of intense research across disciplines, sectors, and scales (Landry, 2012). With the increasing prevalence of urban sprawl and emerging phenomenon of urban shrinkage (Handy et al., 2005; Ewing and Cervero, 2010; Barrington-Leigh and Millard-Ball, 2015; Jin et al., 2017), a better understanding of the re-

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lationship between the built environment and urban vibrancy is of exceptional importance for urban planners and local governments so as to put forward decision-making support for future urban sustainable development.

In studying urban vibrancy, however, its quantitative evaluation remains a challenging issue due to a lack of appropriate data (Wang et al., 2015a; Wu et al., 2018; Huang et al., 2020). In previous studies, anecdotal observations of human activities at micro-scale units (e.g., street blocks and neighborhood) and numerous qualitative theories have been proposed regarding the assessment of urban vibrancy and its associations with specific features of built environment (Jacobs, 1961; Gehl, 1987; Lynch, 1984). The qualitative data collected from a small sample size, while useful, are static information and inadequate for capturing the city-wide and fast-changing urban dynamics (Wang et al., 2015a; Chai et al., 2016; Wu et al., 2018). In the e-society (Loo and Wang, 2017), the widespread adoption of mobile phones and a variety of location-based service have enriched spatial big data (Graham et al., 2013; Wang and Loo, 2019). Recently, user-generated content (UGC) with geospatial information have become a valuable source of large-scale and real-time information in human behavior research (Goodchild, 2007; Batty, 2013). Since around 2010, UGC, such as mobile phone signaling data, GPS trajectory data, social media check-in data (e.g., Sina Weibo, Twitter, Flickr), Wi-Fi access point data, location-based service data, and public transport smart card data, have been widely used to investigate urban vibrancy and its dynamics at an unprecedentedly fine spatiotemporal scale (Qin et al., 2014; Zheng and Zhou, 2017; He et al., 2018; Kim, 2018; Delclòs-Alió et al., 2019; Sun et al., 2019; Wang et al., 2020a; Xia et al., 2020). Specifically, the spatial density and/or diversity of human activities, as proxies of vibrancy, have been evaluated by such single-source and/or multi-source datasets (Wang et al., 2015a; Jin et al., 2017; Zhen et al., 2017; Long and Huang, 2019; Huang et al., 2020; Ta et al., 2020; Xia et al., 2020).

On the basis of urban vibrancy evaluation, a handful of studies have been conducted to examine how built environment contributes to urban vibrancy (Jin et al., 2017; He et al., 2018; Ye et al., 2018; Long and Huang, 2019; Huang et al., 2020; Ta et al., 2020; Xia et al., 2020). In general, many empirical studies confirmed that high density and mixed land use can foster and maintain urban vibrancy in an area. Methodologically, points of interest (POIs) which mark the locations of facilities and infrastructures in different sectors have emerged as useful and powerful tools to reflect the urban built environment (Yue et al., 2017; He et al., 2018; Zeng et al., 2018; Xia et al., 2020). Besides, global regression techniques (e.g., multiple linear regression) have been mostly developed in unveiling the quantitative relationship between the built environment and urban vibrancy.

However, these non-spatially statistical methods ignored the fact that built environment and urban vibrancy tended to be spatially clustered and correlated (Wang et al., 2015b; Wu et al., 2018; Wang et al., 2020b; Yang et al., 2021). In her pioneering work, Jacobs (1961) stated that 'liveness and variety attract more liveliness; deadness and monotony repel life'. Therefore, it is reasonable to expect the spatially heterogeneous effects of the built environment on urban vibrancy. Moreover, human activity shows high degrees of temporal regularity due to time-space constraints (Timmermans et al., 2002; Schwanen and Kwan, 2008). In Time Geography, people's everyday life is constituted by a sequence of various activity chains performed at different places in a 24-h period (Loo and Wang, 2018). For instance, on a typical weekday, people are often at their workplace during daytime hours and staying at their residence during the night. Thus, it is also reasonable to believe that the associations between the built environment and urban vibrancy should be temporally heterogeneous. Therefore, the regression results may be problematic when location and time, as the two determinants of urban vibrancy, are not controlled. And the inaccurate estimation may offer erroneous implications for urban practice. Based on this understanding, this study takes a step further to investigate and visualize the spatiotemporal relationships between the built environment and urban vibrancy. In spite of the fundamental importance, research on such relationships and their spatiotemporal heterogeneity is far from enough.

This article introduces multi-source datasets (i.e., Baidu Heat Map data, POIs data, floor area and land use data) to study urban vibrancy and the associated environmental correlates. In particular, we are interested in how location (i.e., distance), land use mix (i.e., diversity), building intensity and numbers of POIs with various functions (i.e., density) contribute to urban vibrancy. Using Guangzhou City, China as a case study, we aim to 1) verify the spatially and temporally heterogeneous effects of the built environment on urban vibrancy; 2) explore the spatiotemporal relationships between the built environment and urban vibrancy, and particularly; 3) visualize the associated environmental correlates across time and space. These variables can well represent Jacobs's ideas on built environment planning (Jacobs, 1961), and have been frequently tested in previous studies (Yue et al., 2017; Wu et al., 2018; Ye et al., 2018; Long and Huang, 2019; Huang et al., 2020; Ta et al., 2020; Xia et al., 2020). Existing studies indicate that human behaviors are different on weekdays, weekends, and holidays due to different levels of time-space constraints (Wang et al., 2015b, 2020b; Wu et al., 2018). As a city accommodating a large number of floating people who return home during holidays, Guangzhou City shows obviously different population distribution on holidays and non-holidays. Therefore, in this study, we also differentiate between urban vibrancy and the associated environmental correlates on weekdays and weekends. Our study can provide insights for urban planning and design.

This study contributes to the literature in the following two aspects: 1) Theoretically, this study contributes to the wide discussion on the relationships between the built environment and urban vibrancy by revealing the spatiotemporal heterogeneity. 2) Methodologically, Baidu Heat Index (BHI) derived from the Baidu Heat Map (BHM) was introduced to capture the real-time urban vibrancy and its dynamics. Compared to social media check-in data which has been widely used in studying urban vibrancy, BHM enjoys a much larger size of users and thereby better measures urban vibrancy and its spatiotemporal dynamics (Wu and Ye, 2016; Yang et al., 2021). Furthermore, multi-source datasets have been combined to measure the 2-/3- dimensional built environment. Moreover, GTWR models have been applied to unveil the spatiotemporally nonstationary nature of the built environment correlates.

2 Materials and Methods

2.1 Study area

As the capital city of Guangdong Province located in the Pearl River Delta, Guangzhou is a representative example of the rapidly growing and large coastal cities of China. It covers an area of 7249 km^2 with a total population of over 15 million in 2019. Guangzhou City was selected as the research scope for this study. The selected areas include Liwan, Yuexiu, Tianhe, Haizhu, Baiyun, Huangpu, and Panyu districts, which cover the major urban areas of Guangzhou (Fig. 1). Among them, the central urban area, comprising Liwan, Yuexie, Tianhe, and Haizhu districts, enjoys the advantages of transport accessibility, scientific and technological innovations, and comprehensive service provisions, compared to other districts of Guangzhou City (Wei et al., 2021).

2.2 Data sources

2.2.1 Urban vibrancy: Baidu Heat Map (BHM) data

As the largest search engine and website in China, Baidu provides a variety of location-based service (e.g., Baidu Search, Baidu Map, Baidu Weather). Since 2011, Baidu has begun to provide access to aggregated information on the spatial distribution of Baidu App users via the public service BHM. According to its official definition, BHM is a digital map in which the geographical location information of Baidu App users at a certain time point are projected and different colors are used to show the user distribution in a region (Li et al., 2019; Wang and Chang, 2020; Yang et al., 2021). As a measure of population density, BHM data have been widely used to measure the movement of people across urban space and urban vibrancy (Wu and Ye, 2016; Yang et al., 2021). Compared with the conventional population density derived from the Census data which does not vary within a day, BHM updates every 15 minutes capturing the real-time dynamic information about crowd distribution. With several hundred million Baidu mobile application users (Wang and Loo, 2019), BHM data have great potential to provide significant information regarding population density across time and space (Li et al., 2019; Wang and Chang, 2020; Yang et al., 2021). Fig. 2 illustrates an example of a BHM of Guangzhou City at 18:00 on December 4, 2019. Totally, 252 BHMs were collected. Adopted from Tan et al. (2016) and Yang et al. (2021), BHMs were loaded into ArcGIS 10.3, and BHI, a measure of population density, was calculated based on the pixel data of each unit (0.1 km × 0.1 km) and the quantitative relationship between color and population density as defined by BHM. At the community level, we also compared the

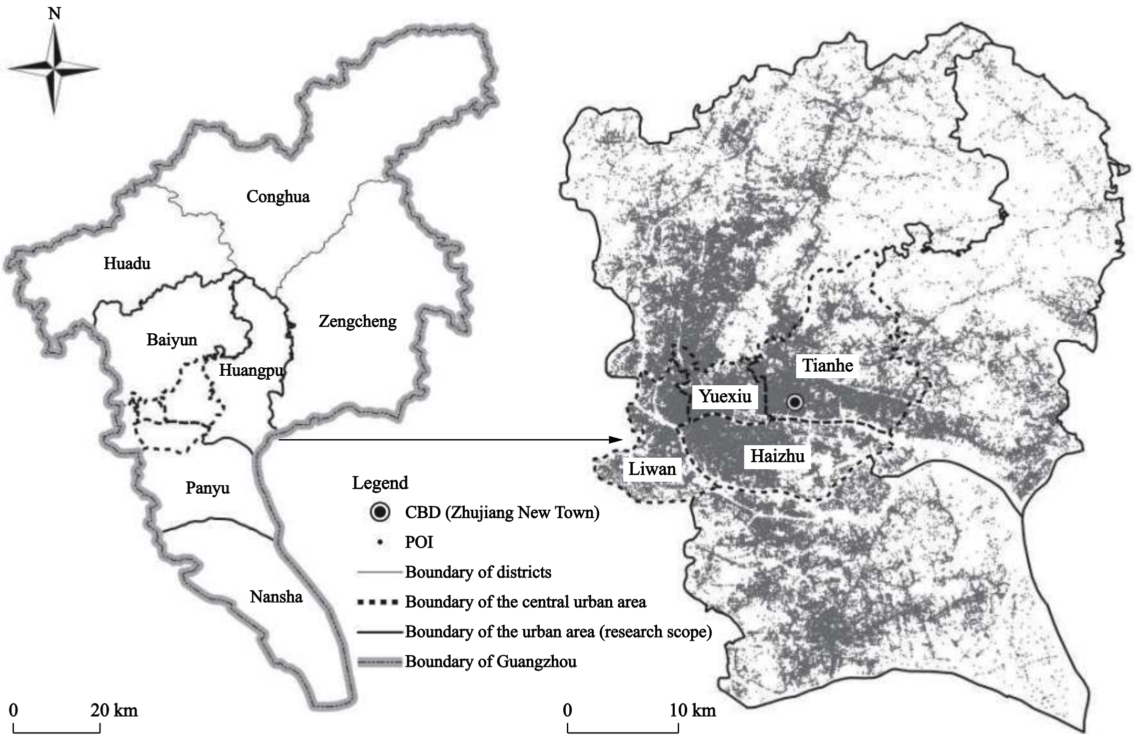

Fig. 1 Map of Guangzhou City, China and the distribution of points of interest (POIs)

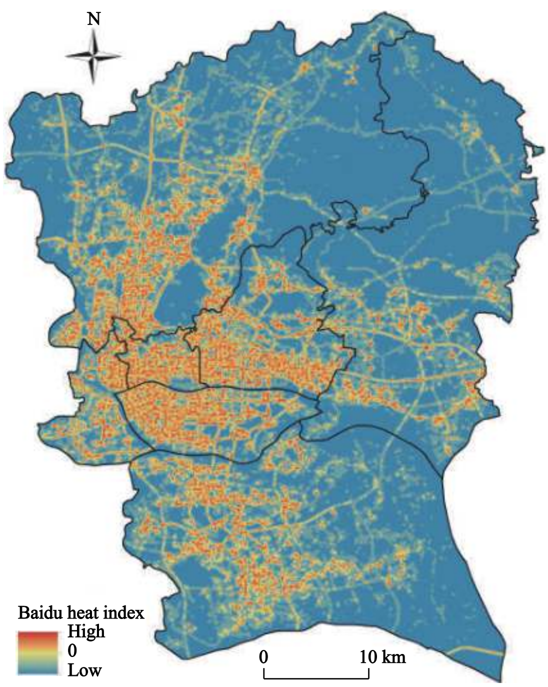

Fig. 2 An example of a Baidu Heat Map of Guangzhou City

BHI at 11:00 pm (when the vast majority of people are staying at home) to the population density derived from the recent Census data and found that the two variables have a significantly high level of correlation (0.90), suggesting that using BHI is acceptable for measuring urban vibrancy and its spatiotemporal dynamics. Noted that the validity of BHI as a proxy for urban vibrancy depends on our definition of the seminal definition by Jacobs (1961) that urban vibrancy is the presence of street life over a 24-hour period.

2.2.2 Built environment

The built environment characteristics are represented by POIs data, floor area and land use data. POIs data measure both the intensity and diversity of activity destinations (He et al., 2018; Yang et al., 2021). Compared with land-use data, POIs data have much finer statistical granularity and thus show greater flexibility for studying at various scales. Moreover, human activity can be better presented by their interactions with POIs rather than by land-use type (Loo and Wang, 2018). In this study, POIs data obtained from AutoNavi, a popular web-mapping platform and location-based service provider in China, are used to reflect the built environment. A total of 344 829 POIs in Guangzhou City in 2018 were collected. According to the classification of AutoNavi, POIs were classified into 12 types. These 12 types were further grouped into consumption-related POIs (CPOI), housing-related POIs (HPOI), traffic-related POIs (TPOI), and other POIs (OPOI), as shown in Table 1.

Table 1 Four categories of points of interest (POIs)

Category	Original types of POIs
CPOI	Shopping service, catering service, life service, recreation and entertainment service, accommodation service
HPOI	Residential district (community names, apartments, residential quarter, *etc.*)
TPOI	Traffic service (road, stations, bus stop, subway station, airport, harbor, *etc.*)
OPOI	Corporate business, medical and health service, financial service, education service, government and administrations

Note that POI data are count data that do not differentiate the size of a facility, which affects its capacity to satisfy people's activity requirements. For example, a shopping mall will provide more shopping opportunities than a convenience store does, thereby influencing people's choices of shopping destination in a vastly different manner. We expect the introduction of total floor area, as a measurement of 3-dimensional built environment can help mitigate this drawback (Yang et al., 2021). The information on floor area and land use of Guangzhou City were collected from the 2020 Survey of Urbanization Evaluation, which is provided by the local planning administrative department with the land use and floor area map in a vector graphics file format.

2.3 Research design

2.3.1 Spatiotemporal unit

Choosing an appropriate spatial unit is important due to the uncertain geographic context problem (Kwan, 2012). When the unit of analysis is too big or small, the geographical disparity of urban vibrancy may be masked (Wu et al., 2018; Wang et al., 2020a). In previous studies, a grid size of 0.5–2.0 km is usually used at the city scale (Wang et al., 2020a). Considering that a positioning error of about 0.1–1.0 km may exist when the phone signal or WiFi is not good, a 1 km × 1 km grid is used as the spatial unit to reflect urban vibrancy on a fine scale. Accordingly, Guangzhou City can be divided into 6565 grids.

For the temporal analysis, dividing a day into twelve 2-h time periods have been widely used in previous behavior studies (Zheng and Zhou, 2017; Wu et al., 2018). We also adopted this approach and examined the temporal dynamics of urban vibrancy in 2-h intervals within a day.

The average BHI in each spatiotemporal unit (i.e., a grid during 2-h interval) were used as the dependent variable (Table 2). The independent variables refer to the built environment of each grid, including two categories, namely, POIs-related variables and other variables. POIs-related variables include CPOI, HPOI, TPOI, and OPOI, while other variables consisting of location, land use mix, and building intensity.

2.3.2 Modelling approaches

To understand the spatially and temporally heterogeneous effects of the built environment on urban vibrancy,

Table 2 Variable definition and sample statistics in Guangzhou City

Variable name	Variable definition	Mean	SD
Dependent variable (urban vibrancy)			
Weekday vibrancy	Average Baidu Heat Index (BHI) in a grid during 2-h interval on a weekday	107.68	227.32
Weekend vibrancy	Average BHI in a grid during 2-h interval on a weekend	149.49	352.79
Independent variable (built environment)			
Location	Straight line distance from grid center to the CBD (Zhujiang New Town) / km	18.43	7.80
Land use mix	The proportion of the six major land use types (i.e., commercial, residential, industrial, municipal administration, education, and public open space), calculated with the adapted entropy method by Song et al. (2013)	0.61	0.16
Building intensity	Total floor area in the grid / million m^2	0.17	0.18
CPOI	Number of consumption-related POIs in a grid / (counts / km^2)	57.99	115.50
HPOI	Number of housing-related POIs in a grid / (counts / km^2)	17.23	35.58
TPOI	Number of traffic-related POIs in a grid / (counts / km^2)	19.26	40.81
OPOI	Number of other POIs in a grid / (counts / km^2)	85.40	159.58

geographically and temporally weighted regression (GTWR) is adopted in this study. As a temporal extension of geographically weighted regression (GWR), GTWR examines the local relationship between independent and dependent variables in the time-space dimension (Huang et al., 2010). Compared to GWR which captures spatial nonstationarity (Brunsdon et al., 1996), GTWR provides excellent advantages in simultaneously addressing spatial and temporal heterogeneity. Given the nature of spatiotemporal dynamics, as discussed above, GTWR is chosen to model the relationship between the built environment and urban vibrancy. Specifically, the GWTR model can be defined as follows:

$$y_i = \beta_0(u_i, v_i, t_i) + \beta_1(u_i, v_i, t_i)x_{i1} + \beta_2(u_i, v_i, t_i)x_{i2} + \ldots + \beta_k(u_i, v_i, t_i)x_{ik} + \varepsilon_i \tag{1}$$

where the dependent variable y_i refers to the urban vibrancy in spatiotemporal unit i on a weekday (or a weekend). (u_i, v_i, t_i) is the coordinates of unit i in the time-space dimension (u_i, v_i and t_i are the longitude, latitude and time, respectively). x_{ik} denotes the kth variable (k = 7) for unit i, and β_k (u_i, v_i, t_i) represents a set of parameter values at unit i. β_0 (u_i, v_i, t_i) is the intercept value, while ε_i is the unobservable disturbance term of unit i. Noted that the dependent variable and independent variables are transformed by logarithm to conform to the normality assumption. Specifically, ln (x+1) was adopted in the logarithmic transformation because some variables have values below 1. The estimated parameter can be explained as 'elasticity', a measurement of the percentage changes of one variable in response to a change in another (Yang et al., 2018).

GTWR model estimates the local regression coefficients based on a weighting matrix built upon space-time distances between observed unit i and other observations (Huang et al., 2010):

$$\beta(u_i, v_i, t_i) = \left[x^T W(u_i, v_i, t_i)x\right]^{-1} x^T W(u_i, v_i, t_i)y \tag{2}$$

where the weighting matrix W (u_i, v_i, t_i) is an $n \times n$ diagonal matrix, i.e., diag (W_{i1}, W_{i2},…W_{ij},…W_{in}). W_{ij} ($1 \le j \le n$) refers to the space-time distance decay function, determined by the space-time distance (d^{st}) and bandwidth h. The main assumption is that the closer measurements to unit i in the space-time coordinate system have higher weight in predicting β_k. By contrast, the GWR model only considers the spatial distance and models the variety of spatial relationship (Brunsdon et al., 1996). According to Huang et al (2010), the space-time distance d_{ij}^{st} is defined as:

$$d_{ij}^{st} = \sqrt{\gamma\left[(u_i - u_j)^2 + (v_i - v_j)^2\right] + \delta(t_i - t_j)^2} \tag{3}$$

where γ and δ are the weights for harmonizing the influence of differing units between space and time. In this study, a common Gaussian distance decay functions and Euclidean distance are adopted to calculate the weighting matrix with the greatest efficiency:

$$W_{ij} = \exp\left[-\frac{\left(d_{ij}^{st}\right)^2}{h^2}\right] \tag{4}$$

where h denotes a nonnegative parameter named the space-time bandwidth, which can be acquired via the use of Akaike information criterion (AIC) (Hurvich et al., 1998):

$$AIC = 2k + n\ln(RSS) \tag{5}$$

where k is the number of estimated parameters in the model (k = 7), n refers to the number of units, and RSS is the Root-Sum-Squares. AIC deals with the trade-off between the goodness of fit and the simplicity of the model. For model comparison, the lower the value for AIC, the better the fit of the model (Hurvich et al., 1998).

3 Results

3.1 Model fit specifics

Prior to estimating each regression model, a Pearson correlation analysis and a variance inflation factor test were conducted. Results suggest that correlation between independent variables are low (below 0.40) and/or statistically insignificant and multicollinearity is not a problem in this study. Table 3 summarizes the performance statistics of OLS, GWR, and GTWR models for explaining the variations in urban vibrancy on weekdays and weekends, respectively. In all three models, all built environment variables listed in Table 2 are significant at the 1% level and exhibit the expected signs. Generally, being closer to the CBD, having higher levels of building intensity and land use mix, and concentrating more POIs of various functions contribute to urban vibrancy.

Table 3 Performance of OLS, GWR, and GTWR models in Guangzhou City

Performance statistics	Weekday vibrancy			Weekend vibrancy		
	OLS	GWR	GTWR	OLS	GWR	GTWR
R^2	0.396	0.513	0.754	0.348	0.474	0.736
Adjusted R^2	0.394	0.460	0.731	0.346	0.416	0.711
AIC	–6154.953	–6009.452	–5311.210	–7067.941	–6925.521	–4186.150

Notes: Ordinary least squares (OLS), Geographically weighted regression (GWR), Geographically and temporally weighted regression (GTWR), Akaike information criterion (AIC)

However, it is important to note that the performance statistics vary significantly among the OLS, GWR, and GTWR models. Specifically, GTWR models have the highest explanatory power, explaining 73.1% and 71.1% of the variations in urban vibrancy on weekdays and weekends, respectively. On the contrary, OLS models explain the lowest percentages of the variations (39.4% and 34.6% respectively). Besides, GTWR models also have the lowest values of AIC. The comparisons confirm our hypothesis that the evolution of urban vibrancy is influenced by built environment variables that are heterogeneous across both time and space. Moreover, the Moran's *I* values of urban vibrancy for weekdays and weekends are 0.495 and 0.459 (P-value < 0.001), respectively, suggesting that urban vibrancy has positive spatial autocorrelation and noticeable features of spatial clustering. Moran's *I* index has been widely adopted as a measure of spatial autocorrelation (Huang et al., 2010; Wu et al., 2018a).Based on this, it is reasonable to believe that ignoring the spatial and temporal effects on urban vibrancy would lead to biased estimates of the associated environmental correlates at the local level. Therefore, it is important for urban planners and city governments to have a better understanding of the local geography on the spatiotemporal relationships between the built environment and urban vibrancy, which enables the formulation of more pertinent, targeted and effective strategies/actions in fostering and maintaining urban vibrancy.

3.2 Spatiotemporal associations between the built environment and urban vibrancy

Tables 4 and 5 summarize the GTWR results for urban vibrancy on weekdays and weekends, respectively. Obviously, the regression coefficients vary in the time-space dimension, as shown in their quartile distribution. Generally, the variation trends, signs, and degrees of built environment variables are roughly the same on weekdays and weekends. We compared the estimation and interpretation of coefficients based on their median values here. Compared to the mean, the median is proved to be more robust to extremely large or small values.

The total floor area plays a dominant role in contributing to urban vibrancy, suggesting that increasing building intensity is an effective tool in attracting people and their associated activities. This result is consistent with the findings of earlier studies that the concentration of activity opportunities makes a place more attractive (Jacobs, 1961; Ye et al., 2018). Land use mix is the

Table 4 Geographically and temporally weighted regression (GTWR) results on associations between built environment and urban vibrancy on weekdays in Guangzhou City

Variable	Min.	Lower quartile	Median	Upper quartile	Max.
Location	–9.924	–3.054	–0.234	0.013	0.928
Land use mix	–3.677	–0.138	0.314	2.965	5.636
Building intensity	–1.611	–0.009	1.425	4.864	7.275
CPOI	–3.257	–0.027	0.182	2.533	4.466
HPOI	–2.990	–0.019	0.078	1.621	1.628
TPOI	–4.279	–0.024	0.189	2.895	5.309
OPOI	–2.006	–0.035	0.016	0.053	1.231

Note: The meaning of CPOI, HPOI, TPOl and OPOl are same as in Table 2

Table 5 Geographically and temporally weighted regression (GTWR) results on associations between built environment and urban vibrancy on weekends

Variable	Min.	Lower quartile	Median	Upper quartile	Max.
Location	–9.133	–3.591	–0.132	0.360	1.900
Land use mix	–3.104	–0.213	0.561	3.060	5.815
Building intensity	–1.825	–0.003	1.768	5.602	7.869
CPOI	–3.031	–0.034	0.198	2.063	4.045
HPOI	–2.024	–0.026	0.129	1.753	3.187
TPOI	–3.288	–0.029	0.173	2.655	3.505
OPOI	–2.825	–0.044	0.022	0.057	1.756

Note: The meaning of CPOI, HPOI, TPOl and OPOl are same as in Table 2

second most statically positive factor in accounting for urban vibrancy, further verifying that diversity of activity opportunities is highly associated with urban vibrancy (Jacobs, 1961; Ta et al., 2020). High level of land use mix refers to a combination of commercial, residential, institutional, or industrial use, which can offer more attractions to people. Thus, great potential exists to improve urban vibrancy through enhancing land use mix. With negative signs, location is the third most statistically significant factor in influencing urban vibrancy. As distance to the city center increase, the urban vibrancy decrease, all else being equal. This finding coincides with the observations in earlier studies of Guangzhou's strong urban center in its monocentric spatial structure (Xu and Yeh, 2003). The positive signs of the densities of POIs with various functions suggest that the concentration of either four types of activity opportunities contributes to urban vibrancy. Specifically, CPOI and TPOI have greater impacts on urban vibrancy compared to HPOI and OPOI, suggesting that entertainment and transportation facilities are of importance for Guangzhou people's daily lives. The local differences of these key associated environmental correlates (i.e., location, land use mix, building intensity, CPOI and TPOI) in the time-space dimension are visualized and analyzed in the following section.

3.3 Visualization of the key built environment correlates

Figs. 3 and 4 show the average temporal and spatial change tendencies of the coefficient, using their median values of each temporal and spatial unit respectively.

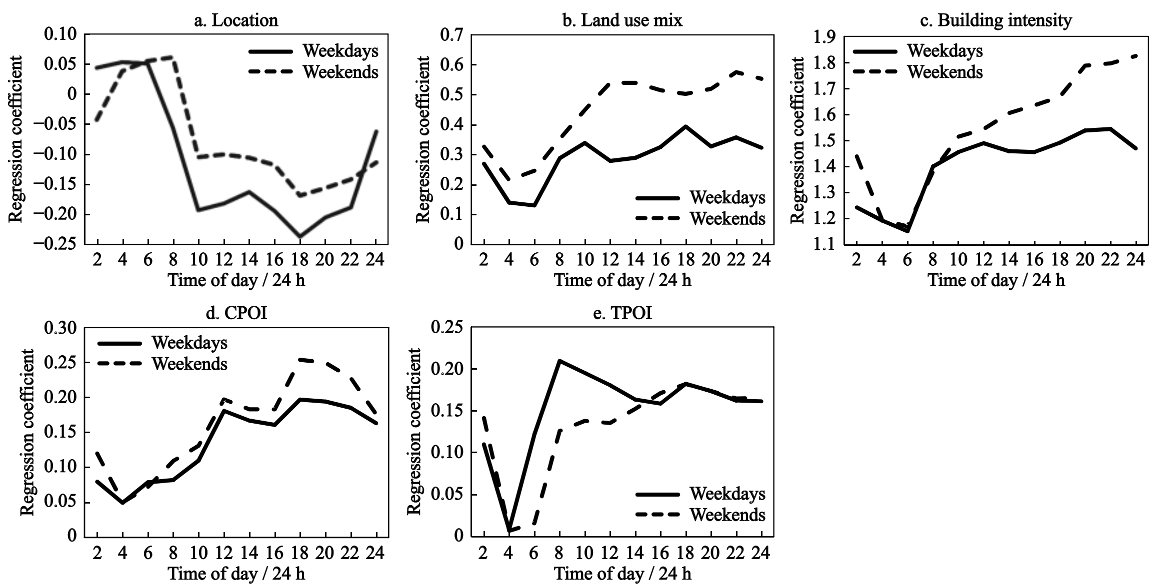

Fig. 3 Temporal trends of key built environment correlates of urban vibrancy on weekdays and weekends. The meaning of CPOI and TPOI are same as in Table 2

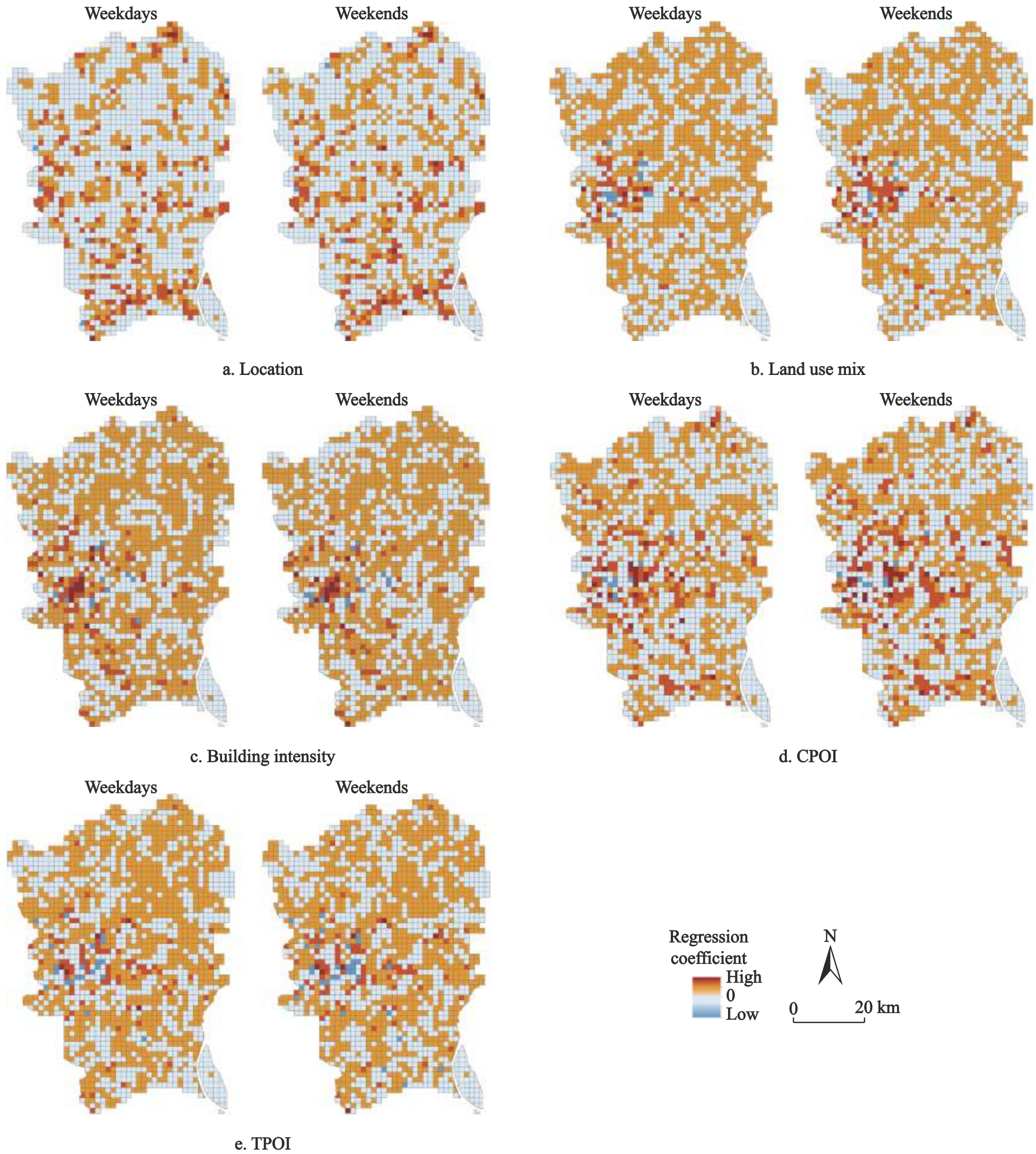

Fig. 4 Spatial distribution of key built environment correlates of urban vibrancy on weekdays and weekends in Guangzhou City. The meaning of CPOI and TPOI are same as in Table 2

The differences of these key associated environmental correlates between weekdays and weekends are also illustrated. For the temporal variations, the solid and dashed lines represent weekdays and weekends respectively (Fig. 3). For the spatial variation, on the basis of Jenks natural breaks classification we manually set zero as a threshold to distinguish between the positive and negative effects (Fig. 4).

Temporally, the variation trends of location for weekdays and weekends are similar. However, the degrees of location are different. Specifically, during 8:00–22:00, location has greater negative elasticity on weekdays than on weekends as the dashed line is located above the solid line. By contrast, the dashed line is located below the solid line in other 2-h intervals. This result can be related to the urban spatial structure development of Guangzhou City. Based on the spatial policy of 'expansion in the south, optimization in the north, advance in the east, and linkage in the west' since 2000, Guangzhou City has experienced rapid urban expansion (Xu and Yeh, 2003). As expected, a polycentric spatial structure will be formed to accommodate the growing urban population and their activities. However, other than a relatively dispersion of residence, there is still a high concentration of activity opportunities in relation to employment, leisure and recreation, and various civil obligations in the central urban area. Therefore, on weekdays, most people are busy at work and their employment activities mainly happened in the central urban area. And their non-employment activities are more likely to be organized around the workplace during the daytime. This fact also explains a 'dip' of location appearing during nighttime hours. Spatially, the relatively monocentric structure leads to the mostly negative effects of location on urban vibrancy. It is interesting to note 'pockets' of positive values at each district center on both weekdays and weekends. These areas with relatively higher concentrations of activity opportunities in the district are attractive to residents nearby. However, these areas are still far from the CBD and central urban area regarding urban vibrancy. Urban spatial structure, typically characterized by monocentric or polycentric development patterns, has been confirmed by some previous studies to have significant effects on urban vibrancy (Chen et al., 2019; Wang, 2021). The existence of multiple urban subcenters can lead to a greater diversity of urban amenities and hence can attract people to dine out, do shopping, or recreate, thus generating persistent vibrancy. Therefore, to achieve a high level of polycentric spatial structure that is beneficial to urban vibrancy, the city government should pay more attention to the comprehensive development of these areas through well-equipped urban amenities and facilities.

With higher degrees of effects on weekends than on weekdays, the temporally variation trends of land use mix, building intensity, and CPOI for weekdays and weekends are similar. The results further suggest that greater potential exists to improve the capacity of these built environment variables for urban vibrancy on weekends than on weekdays. Specifically, the peak values appear during nighttime hours (i.e., 18:00–22:00) when people are typically engaging in leisure, entertainment, and dinner parties (Wang et al., 2015b; 2020). Therefore, places with higher level of land use mix, building intensity, and consumption-related facilities can better satisfy people's various activity requirements and thus become more attractive. The fact that higher coefficients of land use mix, building intensity, and CPOI on the weekends than those on weekdays is also consistent with people's everyday lifestyle. Typically, most people face fewer time-space constraints and thus have more time to conduct non-employment activities on weekends. In contrast, on weekdays, most people typically commute between their home and workplace and do little other than work. Spatially, the effects of land use mix, building intensity, and CPOI on urban vibrancy are mostly positive on both weekdays and weekends. It is also interesting to highlight that some grids in the old city area (i.e., Yuexiu, Liwan, and the southern Baiyun), which has almost the highest mixed function, tend to have the greatest elasticity of land use mix on urban vibrancy. In addition, the high elasticity of CPOI on urban vibrancy are mainly distributed in the CBD and other district center. This uneven spatial distribution of the parameter estimates also suggest that the associations between the built environment and urban vibrancy may be non-linear, which deserves further investigation.

For TPOI, the average temporal and spatial change tendencies and degrees of effects on urban vibrancy for weekdays and weekends are different. On weekdays, the peak values appear at 8:00–10:00 and 16:00–20:00 when people commute between home and workplace. The consistence between this temporal variation trend and the time characteristics of commuting is highly related to the increasingly prominent home-work separation during the formation of multi-center spatial structure in Guangzhou City. Because people usually face higher level of time-space constraints of trying to get to work on time during the morning peak hours than that during the evening peak hours, the highest value is at 8:00–10:00. In contrast, on weekends, people face relatively low level of time-space constraints during the morning peak hours and usually have non-employment activities near their residence; thus, TPOI has relatively low, although positive, elasticity on urban vibrancy, especially during the morning peak hour. Spatially, the effects of TPOI on urban vibrancy are also mostly positive on both weekdays and weekends. However, note that the effects are greater in grids with better public transport accessibility (particularly metro stations), confirming the important role of public transport in contributing to urban vibrancy (Wang et al., 2015b).

4 Discussion and Conclusions

Using Guangzhou City as a case, this study elaborates the spatiotemporal relationships between the built environment and urban vibrancy by applying multi-source datasets and GTWR models. Previous studies have widely discussed the effects of the built environment on urban vibrancy; however, location and time as the two determinants of urban vibrancy have been extensively ignored in the global regression techniques. By comparing the model fit specifics of OLS, GWR, and GTWR models, we verified the spatial and temporal nonstationary nature of the built environment correlates. Based on the GTWR results, we summarized the spatially and temporally heterogeneous effects of the built environment on urban vibrancy based on quartile distribution of the local parameter estimates. Finally, the temporal and spatial patterns of these key associated environmental correlates (i.e., location, land use mix, building intensity, CPOI and TPOI) are visualized to show the details of the local geography of the spatiotemporal relationships between the built environment and urban vibrancy. Moreover, urban vibrancy and the associated environmental correlates on weekdays and weekends are differentiated in the analysis.

The spatially and temporally heterogeneous effects of the built environment on urban vibrancy, which can be well explained by people's everyday lifestyle and routine life rhythm, time-space constraints, and the geographical context (e.g., spatial structure), have important theoretical and policy implications. The existence of spatial and temporal non-stationarity implies that the assumption that the effects of the built environment on urban vibrancy are stationary across different time and space, which has been extensively assumed by the global regression models, is too ideal to be true. Given the complexity of the reality, ignoring spatiotemporal nonstationarity may lead to misestimation of the effects on urban vibrancy, thus generating ineffective or inefficient suggestions for interventions. In practice, the findings highlight the importance of a better understanding of the spatiotemporally heterogeneous effects of the built environment and avoiding 'one-size-fits-all' strategies/actions in intervening the built environment toward fostering and maintaining urban vibrancy. Meanwhile, urban practitioners can use the findings to understand the temporal and spatial patterns of aggregation of people, thereby informing urban spatial structure optimization, infrastructure allocation, and transportation management.

For example, some key built-environment variables, such as land use mix, building intensity, and TPOI, have obviously larger effects on urban vibrancy in the central urban area than the suburbs. This finding indicates that enhancing urban vibrancy through intervening the built environment may be more effective in these areas. By contrast, evidence also exists that a polycentric spatial structure is forming in Guangzhou, as shown by the dispersion of high-value effects of built environment variables including location and CPOI. This finding also suggests that to promote or sustain urban vibrancy in the outskirts, providing sufficient commercial amenities at the subcenters can be a feasible way. In the meantime, the effects (tendencies and degrees) of these built-environment variables on urban vibrancy vary across time (2-h intervals within a day) and are different between weekdays and weekends. This finding implies that some time-specific measures, such as transportation management measures, can be implemented to supplement the built-environment interventions.

Aside from the spatiotemporal heterogeneity, this study reveals the significant roles of some built environment variables, especially building intensity and land use mix, in influencing urban vibrancy. The confirmed effects of building intensity, which are in line with some previous studies (e.g., Tu et al., 2020; Huang et al., 2020), implies that even in China, where urban density is already high, pursuing compactness still has great potentials in enhancing urban vibrancy. Nevertheless, it is worth noting that in pursuing compactness, overconcentration should be avoided given its close association with some adversities, such as congestion and pollution (Li et al., 2019). Since the seminal work of Jacobs (1961), many studies have validated the significant effects of land use mix on urban vibrancy. However, as Yue et al. (2017) pointed out, high land use mix does not necessarily lead to high urban vibrancy. Selecting which method to measure land use mix and to what degree the mixed land uses are complementary to each other do matter (Yue et al., 2017). In this study, we use six major types of urban functions (as shown in Table 2) and an adapted entropy method (Song et al., 2013) to calculate the land use mix and reveal its significant effects; thus, the confirmed significant effects of land use mix in this study should be reliable. In practice, policies can be made to encourage the co-location of complementary urban functions to create meaningful land use mix, thus enhancing urban vibrancy.

It is recognized that this study also has some limitations, which highlight potential directions for future research. First, we measured urban vibrancy form the only perspective of attraction (i.e., density), ignoring the diversity perspective. Comprising different types of datasets to comprehensively measure urban vibrancy from both attraction and diversity perspectives (Ta et al., 2020) will help verify the results. Second, due to the data availability, we used the POI data in 2018, while the BHM data was collected in 2019. Fortunately, both built environment and human behavior pattern within a day can stay relatively stable within one year. Third, it is important to incorporate machine learning techniques (e.g., extreme gradient boosting) in examining the nonlinear, threshold, and spatiotemporal associations between the built environment and urban vibrancy, which provide guidance for urban planning. Fourth, more built environment variables (e.g., more detailed classification of POIs) and other control variables, which may influence urban vibrancy (e.g., weather condition and air pollution) (Sun et al., 2019), should be introduced into the analysis. Last but not the least, due to the scope of this study, we only use 1 km × 1 km grids to act as the spatial analysis units to measure the built environment (e.g., land use mix) and derive the BHI. However, as the modifiable areal unit problem (MAUP) (Kwan, 2012) suggests, the scale of spatial analysis units may influence the results. Hence, future studies are suggested to explore the relationships between the built environment and urban vibrancy with multiple spatial analysis units (e.g., 0.5 km × 0.5 km grids) and compare the results, thus examining the role of scale and validating the findings.

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