

Revealing the spatiotemporal pattern of urban vibrancy at the urban agglomeration scale: Evidence from the Pearl River Delta, China

Yuxiao Jiang^{a,b}, Zongyao Sun^c, Di Wei^{b,d}, Pengjun Zhao^{a,e}, Linchuan Yang^a, Yi Lu^{b,*}

^a Department of Urban and Rural Planning, Southwest Jiaotong University, Chengdu, Sichuan Province, China

^b Department of Architecture and Civil Engineering, City University of Hong Kong, Hong Kong

^c Faculty of Architecture and City Planning, Kunming University of Science and Technology, Kunming, Yunnan Province, China

^d School of Architecture and Urban Planning, Huazhong University of Science and Technology, Wuhan, China

^e School of Urban Planning and Design, Peking University Shenzhen Graduate School, China

ARTICLE INFO

Handling Editor: Dr. Y.D. Wei

Keywords:

Urban vibrancy
Intensity of vibrancy variation
Coefficient of variation
Geographically weighted regression
Spatiotemporal analysis
Urban vitality

ABSTRACT

Urban vibrancy research has largely focused on city-scale analysis, leaving urban agglomeration-level vibrancy underexplored. Using location-based service (LBS) data from the Pearl River Delta (PRD), China, this study quantified urban vibrancy through four indicators: density, variation intensity, day-night tide, and holiday-weekday tide. OLS and GWR models were employed to examine the relationships between built environment factors and urban vibrancy. The findings revealed distinct vibrancy patterns between core cities and fringe areas: core cities exhibited higher vibrancy density with lower temporal fluctuations than fringe areas. OLS results revealed that road density and distance to railway stations significantly influenced vibrancy density and variation intensity, while population density and GDP density were strongly linked to vibrancy density. Residential POI and NDVI significantly affected variation intensity. The GWR model highlighted spatial heterogeneity in how built environment factors impact vibrancy. This study provides insights into spatiotemporal vibrancy at the urban agglomeration scale, offering guidance for optimizing built environments to support balanced regional development.

1. Introduction

1.1. The concept of urban vibrancy

As a reflection of human activities, urban vibrancy is receiving considerable attention from numerous scholars of urban studies due to its positive benefits on the resilience, social sustainability, residents' well-being, and innovation capacity of cities (Jacobs, 1961; Montgomery, 1998; Niu, Li, Li et al., 2022). Urban vitality was first mentioned in Jane Jacobs' book *"The Death and Life of Great American Cities"*, in which pedestrian flows and human activities were summarized as urban vitality or vibrancy (Jacobs, 1961). In recent decades, the rapid pace of global urbanization has led to various challenges in major cities, including urban sprawl, traffic congestion, the rise of suburban bedroom communities, and jobs-housing imbalances (Wei & Ewing, 2018). These issues have contributed to the uneven distribution of urban vibrancy within and between cities, as well as a decline in the quality of

life for residents in certain urban areas (Zhang, Li, Wu, et al., 2021; Zhang & Zhao, 2021). To address the abovementioned issues, scholars have suggested improving urban vibrancy and social interaction through planning interventions, such as enhancing the sense of place (Lynch, 1960) and street aesthetics (Ashihara, 1983), increasing public space (Gehl, 2011) and building a walking-friendly neighborhood (Frumkin, 2004). These initiatives have alleviated urban problems to some extent and facilitated urban vibrancy.

1.2. Measuring urban vibrancy

Urban vibrancy, despite being a multidimensional concept, is generally understood as the level of human activity and interaction within an urban environment. A well-designed urban environment that supports and stimulates various human activities is generally regarded as a key to enhancing urban vibrancy (L. Chen, Zhao, Xiao, & Lu, 2022; Y. Chen, Yu, Shu, Yang, & Wang, 2023). Scholars usually evaluate urban

* Corresponding author. Department of Architecture and Civil Engineering, City University of Hong Kong, Hong Kong.

E-mail addresses: yuxijiang8-c@my.cityu.edu.hk (Y. Jiang), sun_zongyao@163.com (Z. Sun), diwei3-c@my.cityu.edu.hk (D. Wei), pengjun.zhao@pku.edu.cn (P. Zhao), yanglc0125@swjtu.edu.cn (L. Yang), yilu24@cityu.edu.hk (Y. Lu).

<https://doi.org/10.1016/j.apgeog.2025.103694>

Received 15 August 2024; Received in revised form 27 April 2025; Accepted 9 June 2025

Available online 24 June 2025

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vibrancy through urban physical environment exposure (Delclos-Alió & Miralles-Guasch, 2018; Xia et al., 2020) and human activity density (Humphrey, Jensen, Small et al., 2019). Early methods relied on field observations and surveys, which provided detailed insights but were labor-intensive and could not capture large-scale spatiotemporal dynamics (Sallis, Cerin, Conway et al., 2016; Sung & Lee, 2015).

With the advent of urban big data, some researchers have measured urban vitality with various big data sources such as social media data (Williams, Xu, Tan, Foster, & Chen, 2019), street view image data (Yin, Cheng, Wang et al., 2015), location-based data (Zhao et al., 2011), night light data (Wu et al., 2022), and multisource urban big data (Niu et al., 2022). These data enable fine-grained spatiotemporal analyses of urban vibrancy (Calabrese et al., 2014). In this context, urban vibrancy measurement can be categorized into two dimensions: human activity intensity (e.g., walking behavior, population aggregation) and vibrancy potential (e.g., night-time light). Empirical studies have employed pedestrian volume (Jiang, Chen, Grekousis et al., 2021), nighttime light data (Wu et al., 2022), and small catering businesses as proxies of urban vibrancy (Xia et al., 2020). However, these static indicators fail to capture the dynamic nature of urban vibrancy, particularly its temporal changes and fluctuations.

1.3. Temporal dimension of urban vibrancy

The temporal dimension of urban vibrancy introduces significant complexity, as cities exhibit distinct activity patterns during different times of the day, week, and year (Mouratidis & Poortinga, 2020). For example, urban vibrancy during peak hours is characterized by heightened commercial and transportation activity, while holidays often see a shift toward recreational and leisure activities (Balsas, 2019). This temporal variation is particularly pronounced in high-density urban areas, where built environment features, population behavior, and external conditions interact to produce spatiotemporal heterogeneity (Xia et al., 2020).

Recent studies have begun to explore these temporal variations, evolving from single time-point assessments (e.g., point of interest (POI) data) (Jin, Long, Sun et al., 2017) or a period of time (e.g., nighttime light data) (Wu et al., 2022) to multi-timestamp approaches using mobile phone signaling data (Chen, Zhao, et al., 2022). This progression has enabled researchers to examine short-term fluctuations, such as diurnal or holiday effects, as well as long-term trends, such as demographic changes and infrastructure developments.

Several recent studies have adopted advanced methods to examine temporal urban vibrancy. For example, Kim (2020) used functional principal component analysis to explore 24-h pedestrian traffic patterns in Seoul, while Chen, Zhao, et al. (2022) employed a geographically and temporally weighted regression (GTWR) model to analyze Shenzhen's urban vibrancy dynamics. Wang, Yue, et al. (2021) investigated the fluctuations throughout the day in population distribution using a Bayesian spatiotemporal model. These studies highlight the continuous spatial and temporal fluctuations of urban vibrancy (Zhong, Schlöpfer, Müller Arisona et al., 2017).

Understanding the fluctuating rhythms of urban vibrancy provides critical insights into human behavior and urban vitality characteristics (Ouyang, Fan, Wang et al., 2022). The 5D built environment framework, namely destination accessibility, distance to transit, design, density, and diversity, has been widely employed to evaluate built environment factors related to urban vibrancy and travel behaviors (Ewing & Cerro, 2010; Xiao & Liu, 2023). In addition to these dimensions, factors such as urban greenery level (Jiang, Liu, Ren et al., 2024; Yang, Lu, Cao, Wang, & Chen, 2025), and economic activity intensity (Jia et al., 2021) also been found to significantly influence urban vitality. However, studies examining temporal changes in urban vibrancy and their influencing factors remain limited. Existing research reveals that the relationship between urban vibrancy and built environment characteristics varies over time. Niu et al. (2022) found that commercial facilities had a

greater impact on vibrancy during weekdays while building density played a more critical role on weekends. Ouyang et al. (2022) demonstrated in West Shenzhen, vibrancy fluctuation was driven by educational and cultural facilities.

1.4. Research gap and our study

Although existing research has expanded our understanding of urban vibrancy, they have focused primarily on the neighborhood or urban level (Huang, Zhou, Li et al., 2019). While some studies have compared urban vibrancy between several large cities (Yue, Chen, Thy et al., 2021; A. Zhang, Li, Ma, & Guo, 2021), there is still a gap in understanding urban vibrancy at the urban agglomeration scale. The development of urban agglomeration has blurred the administrative boundaries of cities (Li et al., 2018), reshaped city and regional organization, and facilitated more active intraregional population movement (Taylor & Knox, 1995; Zhang, Su, Xiao, Jiang, & Wu, 2013). The emergence of urban agglomeration in developing countries induces new research demands. Using the Pearl River Delta (PRD) as an example, individuals can choose to work in Shenzhen while living in adjacent cities (e.g., Dongguan and Huizhou) due to the expensive housing prices of Shenzhen and the convenient transportation system of the PRD. Thus, focusing on the urban vibrancy within Shenzhen alone cannot represent the real human activities within the region. Hence, it remains a challenge to investigate the spatial-temporal pattern of urban vibrancy within urban agglomeration through the lens of the microscale.

To fill the abovementioned research gaps, this study conducts fine-grained analyses of urban vibrancy patterns at the urban agglomeration scale to provide deep insights into human activities on such a large spatial scale. Furthermore, we explore the spatial-temporal patterns of urban vibrancy by analyzing the vibrancy density and vibrancy variation intensity. The administrative boundary at the city level may not fit real human flows due to a large amount of cross-city movement (Zhang, Fang, Zhou et al., 2020). In such a context, using a fine-grained spatial unit is warranted. Therefore, we use a 2 km × 2 km grid as the unit of analysis to study the spatial-temporal urban vitality pattern and its connection with the built environment. Daily human-activity data during weekdays and holidays in the PRD are acquired from Tencent location big data, which is the largest Chinese social media platform. Our study offers a refined understanding of dynamic human activities within urban agglomerations and provides practical guidance for optimizing the built environment to promote balanced vibrancy.

To visually clarify the theoretical gaps and research innovations addressed in this study, we developed a conceptual framework (Fig. 1). This framework not only summarizes the limitations of previous studies and highlights the emerging research needs brought about by urban agglomeration development, but also explicitly emphasizes two major extensions: shifting the research scale from the single-city level to the urban agglomeration scale and broadening the research content from spatial network structures to human activities and urban vibrancy. By doing so, our study captures a finer-grained and more dynamic understanding of urban agglomerations beyond administrative boundaries.

2. Methods

2.1. Study area and data sources

The PRD region is one of China's three major urban agglomerations, covering a total land area of 55,369 km² (Fig. 2). It comprises two subprovincial cities, Guangzhou and Shenzhen, along with seven prefecture-level cities: Foshan, Zhaoqing, Dongguan, Huizhou, Zhuhai, Zhongshan, and Jiangmen (Zhao et al., 2017). In 2020, the PRD had a total population of 78.01 million, which accounted for 61.9 % of Guangdong Province (National Bureau of Statistics of China, 2020). Integrating Hong Kong SAR and Macau SAR, the Chinese government initiated the Greater Bay Area (GBA) to build a top-tier megaregion with

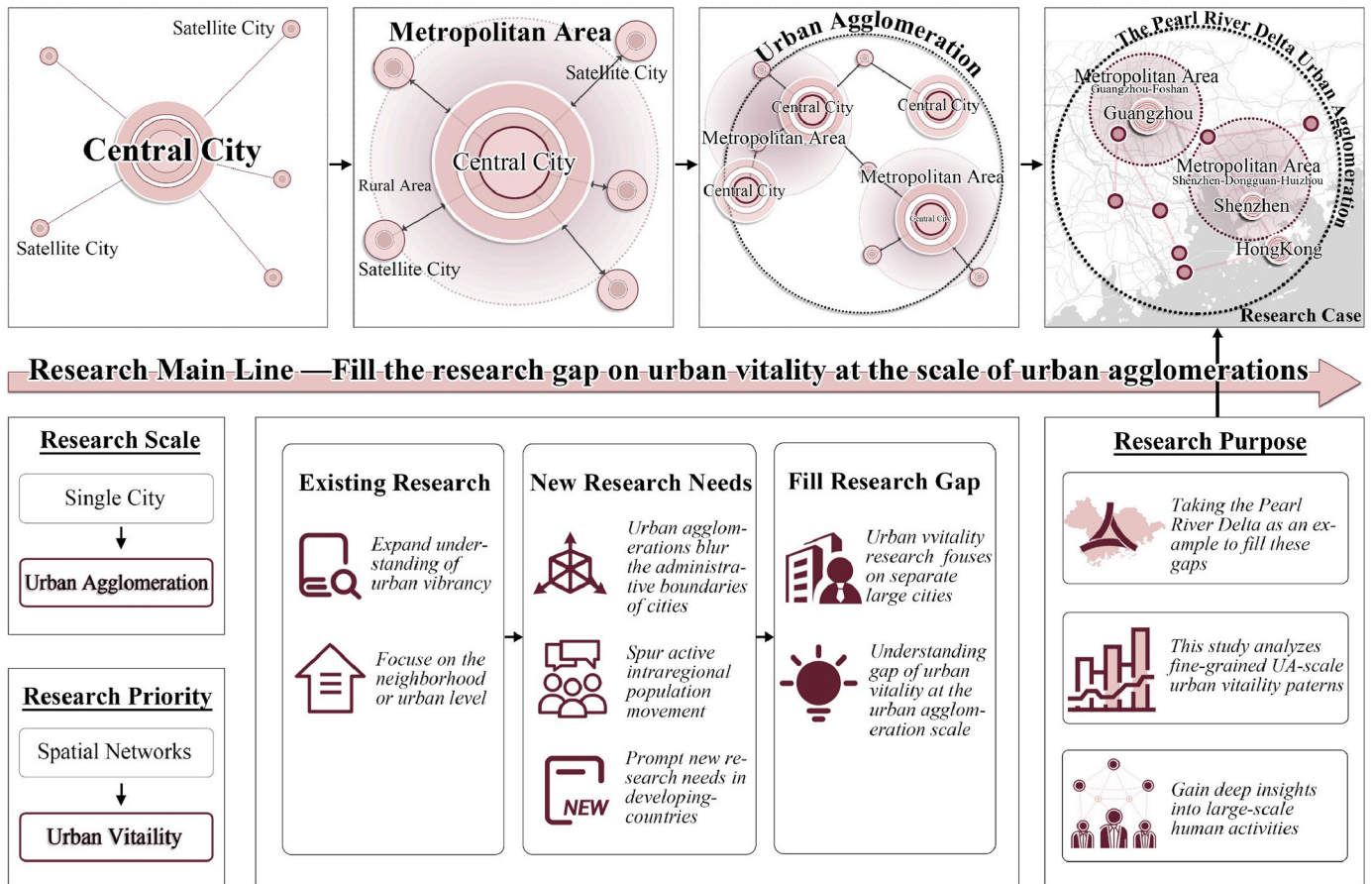


Fig. 1. Conceptual framework illustrating the research gap and innovation in studying urban vibrancy at the urban agglomeration scale.

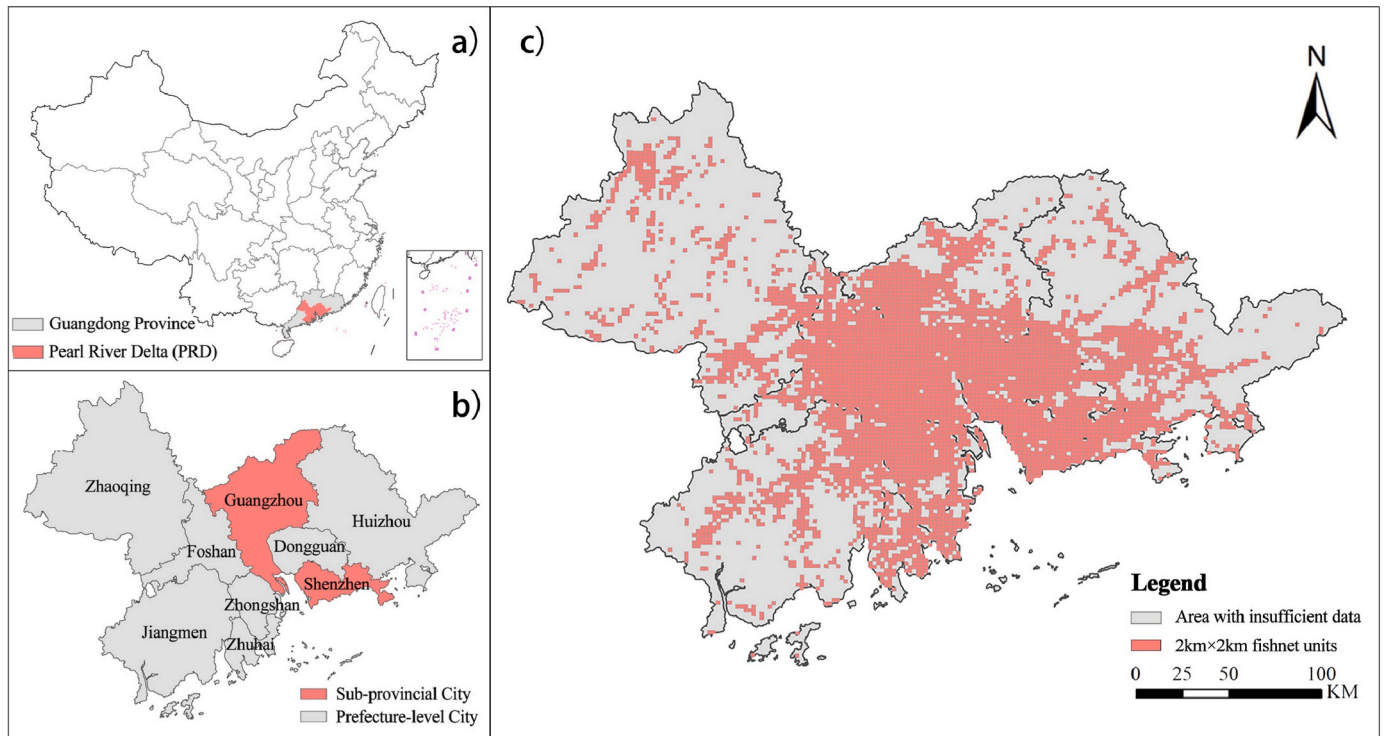


Fig. 2. a) Location of Pearl River Delta, China. b) The nine cities within the PRD region. c) Study area with a fishnet of 2×2 km grids.

high population density, industry-leading clusters, and competitive economic activities (Yu et al., 2023). As a vital part of the GBA, the PRD's economic output in 2020 surpassed 10 trillion yuan, accounting for 83 % of the GBA (Statistics Bureau of Guangdong Province, 2020).

The PRD is characterized by rapid urbanization, high population mobility, and diverse socio-economic activities (Wei, Wang, Jiang et al., 2024). As a globally significant manufacturing and trade hub, the region hosts dense transportation networks and industrial clusters that foster vibrant economic interactions (Hui, Li, Chen et al., 2020). The PRD is characterized by substantial cross-boundary commuting and inter-city interactions, with distinct spatiotemporal dynamics in human activity patterns.

The data we used to measure the urban vibrancy of the PRD were obtained from Tencent location-based services (LBS), which is the largest location service provider in China and consists of various mobile phone applications owned by Tencent (Liu, Huang, Li et al., 2021). The Tencent LBS data collects the absolute number of location-sensing activities in real time through Tencent-owned location-based applications, such as WeChat, Didi, and QQ Map. With over 1.2 billion user communities and fine-grained spatiotemporal granularity, Tencent LBS data has emerged as a valuable resource for revealing spatiotemporal human activities with high probability (Hui et al., 2020).

2.2. Analysis framework

In this research, we conducted an exploratory spatial analysis of regional vitality indicators and their associations with built environment characteristics under the extended 5D framework using OLS and GWR models. The global and local spatial autocorrelations of collective vitality indicators were examined. Fig. 3 illustrates the main analysis framework.

2.3. Indicators of regional vibrancy aggregation

We created many 2×2 km grids covering the PRD to gather the Tencent LBS data. Grids in which the aggregated Tencent observations were less than 50 (i.e., mostly forests, farmlands, or other large natural areas) were discarded, which left 5227 grids in total. Each grid aggregated real-time Tencent location-sensing activities, serving as proxies

for urban vibrancy.

We sampled the Tencent LBS data on a national holiday (May 1, 2019) and a weekday (May 6, 2019) in the PRD through the Tencent Heatmap API (<https://heat.qq.com>) and obtained the Tencent data every hour. Considering the inaccuracy of mobile phone signaling data after midnight (e.g., some people turn off their phones while sleeping), active Tencent data from 6:00 a.m. to 23:59 a.m., i.e., 18 data points per day, remained. The raw dataset consisted of grid ID, grid coordinates, and numbers of human activities for 18 timestamps (Table 1). The raw data was anonymized and did not include any personal information about the users, ensuring the protection of personal privacy.

To explore the population aggregation pattern, we used four indicators, i.e., urban vibrancy density (UVD), coefficient of variation (CV), vibrancy tide between holiday and weekday (VT_{hw}), and vibrancy tide between daytime and nighttime (VT_{dn}). UVD was considered a proxy for urban vibrancy using the average human activity density of each grid during active times (6:00–23:59). High UVD represented high daily human activity in the grids. Previous studies focused on the changes at different timestamps, which overlooked the magnitude of changes in total duration (Mu et al., 2021). Hence, the CV of all-day data was used to present the degree of dispersion within each grid (Bedeian & Mossholder, 2000). The CV was calculated as follows:

$$CV = \frac{\sigma}{\mu} \quad (1)$$

where σ and μ denote the standard deviation and mean value of 18-time-stamp data, respectively.

To better observe urban vibrancy in different time periods, we established two vibrancy tidal density (VT) indicators, i.e., VT_{hw} and VT_{dn} . VT_{hw} represents the disparities in UVD between holidays and weekdays. A positive value of VT_{hw} indicated that daily human activity intensity was higher on holidays than on weekdays. Similarly, VT_{dn} represents the disparities in UVD between daytime (7:00–17:59) and nighttime (18:00–23:59). A positive value of VT_{dn} indicated stronger urban vibrancy during the daytime, while a negative value indicated stronger vibrancy during the nighttime, and the disparities were positively associated with the absolute value of VT. VT_{hw} and VT_{dn} were calculated as follows:

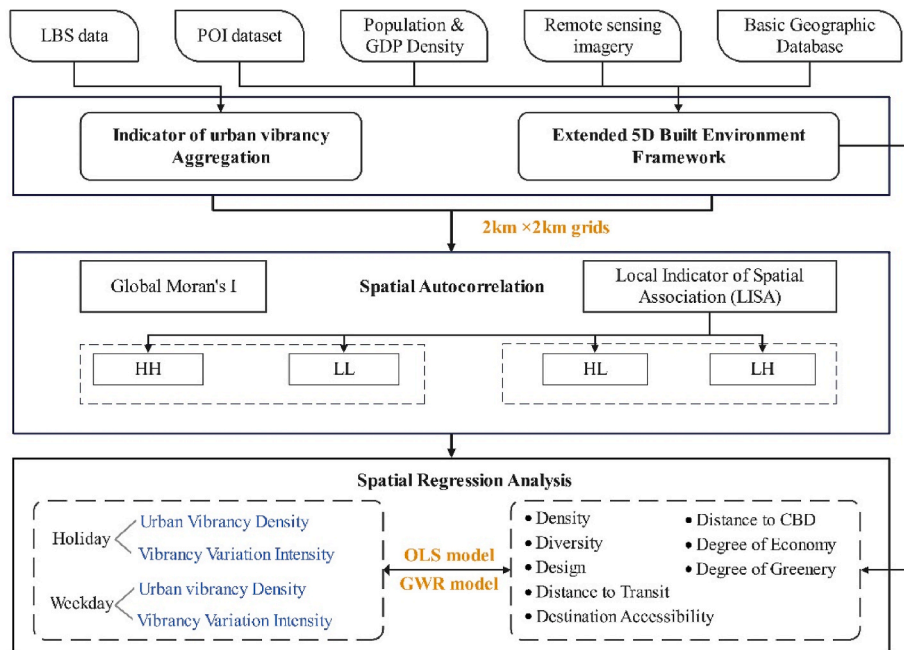


Fig. 3. The main analysis framework for characterizing spatiotemporal patterns of urban vitality and investigating its association with built environment elements.

Table 1

One-day example of the Tencent LBS raw dataset.

Grid ID	Grid coordinates		Numbers of human activities in each grid for 18 timestamps (from 6:00 a.m. to the next 0:00 a.m.)							
	Longitude	Latitude	06:00	07:00	08:00	...	21:00	22:00	23:00	
1	114.635932	23.229227	0	1	0	...	0	0	0	
2	112.060171	23.610967	3	0	0	...	0	54	5	
3	114.002894	23.729929	2	1	6	...	23	19	4	
...	...	...	...	...	...	...	...	...	...	
5226	113.938389	22.575968	15	11	6	...	24	62	30	
5227	113.200949	22.660003	8	9	13	...	14	21	24	

$$VT_{hw} = UVD_{holiday} - UVD_{weekday} \quad (2)$$

$$VT_{dn} = UVD_{daytime} - UVD_{nighttime} \quad (3)$$

where $UVD_{holiday}$ and $UVD_{weekday}$ denote the average human activity (UVD) in each grid during a holiday and weekday, respectively. $UVD_{daytime}$ denotes the UVD in each grid during the daytime (7:00–17:59). $UVD_{nighttime}$ represents the UVD in each grid during the nighttime (18:00–23:59).

2.4. Built environment characteristics

The built environment factors were assessed using the 5D framework, namely diversity, design, destination accessibility, density, and distance to transit. The 5D framework is a well-established evaluation model commonly used in studies examining the relationship between vibrancy and the built environment (Ewing & Cervero, 2001). We added three elements that may affect human activity, i.e., the density of the spatial economy, degree of greenery, and distance to the central business district (CBD), to build an extended 5D framework for this study (Yang et al., 2024).

Density was quantified as the population density within each grid. This population density was determined using WorldPop data (<https://www.worldpop.org>) with a ~3-arc second resolution (Tatem, 2017). Destination accessibility and diversity were measured by POIs. We retrieved the POI data from Gaode Map through its API (<https://lbs.amap.com>). In this study, the original POI dataset with twenty categories was reclassified into four categories, i.e., commercial, residential, recreational and public service. The destination accessibility was calculated according to the number of POIs with the abovementioned four categories in each grid. In addition, distance to major employment centers in the Greater Bay Area is also categorized under destination accessibility. To analyze the impact of major economic centers on urban vibrancy, we identified the CBDs of the four key central cities in the region: Central in Hong Kong, Central Plaza in Macao, Futian in Shenzhen, and Tianhe in Guangzhou. The shortest distance from each grid within the PRD to these four CBDs was calculated to represent the distance to the CBD.

Diversity was calculated using the entropy score of the four categories of POI data as follows (Chen, Lu, et al., 2022; Shannon, 1948):

$$POI_{mix} = - \sum_{i=1}^n p_i \ln p_i \quad (4)$$

where n represents the total POI categories in the grid and p_i represents the ratio of the i th category. A higher POI_{mix} index indicates that the grid has better diversity.

Considering that the PRD is an urban agglomeration instead of a particular city, we operationalized the shortest distance to the nearest railway station in each grid as the distance to transit. Design was assessed by measuring road density, which is defined as the total road length within each grid. The density of the spatial economy was measured on the basis of the average GDP in each grid. The GDP data were acquired from the China GDP spatial distribution dataset, which reflects the detailed spatial distribution of GDP across China with a 1 km

resolution (XU, 2017).

Previous studies have reported that high levels of urban greenery are beneficial for promoting social activities and urban vitality (Chen et al., 2025; He, Lu, Xie, & Helbich, 2021). For this study, the degree of greenery was collected in terms of the average normalized difference vegetation index (NDVI) within each grid. We acquired cloud-free Sentinel-2 remote sensing imagery to calculate the NDVI in April 2019. The NDVI was measured as follows:

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (5)$$

where NIR and Red refer to the reflectance in the near-infrared and infrared bands, respectively. The NDVI value ranges from -1 to 1 . Zero and negative NDVI values typically represent non-vegetated surfaces, such as water bodies, bare soil, or urban infrastructure. Positive NDVI values indicate the presence of vegetation, with higher values representing denser vegetation.

2.5. Spatial autocorrelation

We assessed the heterogeneity and dependence of the grids ($2 \text{ km} \times 2 \text{ km}$) by employing both global and local Moran's I statistics. The global Moran's I was used to examine whether the spatial distribution of urban vitality exhibits significant overall spatial autocorrelation, thereby identifying the presence of structured spatial patterns in the study area. This step provides the foundational judgment for further spatial analysis. The statistic was calculated as follows:

$$I = \frac{n \sum_i \sum_k w_{ik} (x_i - \bar{x})(x_k - \bar{x})}{(\sum_i \sum_k w_{ik}) \times \sum_i (x_i - \bar{x})^2} \quad (6)$$

where n denotes the number of $2 \text{ km} \times 2 \text{ km}$ grids; x_i and x_k represent the attribute values of i and k , respectively; and w_{ik} is the spatial weight matrix. The queen contiguity is applied as the spatial weight rule.

To further identify localized clustering patterns and spatial variations in urban vitality across multiple temporal contexts, including daytime versus nighttime and weekdays versus holidays, the local indicator of spatial association (LISA) was employed. While global Moran's I provides a summary measure of overall spatial autocorrelation, LISA reveals spatial heterogeneity by detecting specific clusters and outliers at the local level. Each grid was categorized as high-high (HH), high-low (HL), low-high (LH), or low-low (LL) based on the relationship between its value and those of its neighbors. The univariate LISA statistic was calculated as:

$$I_j = z_j \sum_{k=1}^n w_{jk} \times z_k \quad (7)$$

$$z_j = \frac{(X_j - \bar{X})}{\sigma} \quad (8)$$

where n is the number of grids; w_{jk} denotes the spatial weight between grid j and grid k ; X_j denotes the value of grid j ; and $\bar{X}$ and σ represent the mean value and standard deviation, respectively. Global Moran's I and LISA statistics were conducted using GeoDa (Version 1.14).

2.6. Spatial regression analysis

Initially, we examined the multicollinearity among explanatory variables on the basis of the variance inflation factor (VIF). The VIF of all variables was less than 4 except for recreational and public service POIs; thus, the POIs were excluded from the subsequent analysis.

Second, ordinary least square (OLS) regression models were adopted to examine the correlation between UVD and CV during holidays and weekdays. As a global regression framework, the OLS model assumes spatial stationarity in the associations between dependent and explanatory variables across the entire study area. While this assumption may oversimplify the spatial heterogeneity inherent in urban systems, the OLS model serves as a useful baseline to capture overall patterns and identify statistically significant predictors. Moreover, it provides a comparative reference for evaluating the added explanatory power of spatially explicit models such as geographically weighted regression (GWR). The OLS model is defined as follows:

$$y = X\beta + \varepsilon \quad (9)$$

where y is the dependent variable, β is a vector of the coefficients, X is the matrix of independent variables, and ε represents a vector of random error terms.

Third, we created four GWR models to investigate the association between the built environment and urban vibrancy patterns (UVD and CV during holidays and weekdays) and to measure spatial heterogeneity and spatial instability (Fotheringham et al., 1998). In comparison to the OLS model, the GWR model is capable of handling the local effects of spatial variables, resulting in greater accuracy (Zeng, Sun, Chen et al., 2021). The GWR model is expressed as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \quad i = 1, 2, \dots, n \quad (10)$$

where y_i denotes the dependent variable; $\beta_0(u_i, v_i)$ represents the constant of grid i ; $\beta_k(u_i, v_i)$ is the regression coefficient of the k -th parameter of grid i , reflecting the spatial analysis of the influence of different parameters on grid i ; p is the number of independent variables; (u_i, v_i) denotes the coordinates of grid i ; x_{ik} denotes the k -th value of grid i ; and ε_i represents the random error. OLS was conducted using GeoDa, and GWR was conducted using MGWR software (Oshan, Li, Kang, Wolf, & Fotheringham, 2019).

3. Results

3.1. Descriptive statistics

The descriptive statistics of the indicators of urban vitality and built environment variables are shown in Table 2. The average $UVD_{holiday}$ and $UVD_{weekday}$ within each grid were 111.14 (SD = 192.72) and 110.33 (SD = 198.82), respectively; that is, there were an average of ~111 people in each 2 km × 2 km area on holidays and ~110 on weekdays. The average $CV_{holiday}$ (M = 0.47, SD = 0.15) was higher than $CV_{weekday}$ (M = 0.41, SD = 0.16), indicating a stronger vibrancy level on holidays than on weekdays. In addition, there were significant spatial variations in the VT_{hw} across different grids, ranging from ~765 to ~386. The mean values of $VT_{dn,holiday}$ and $VT_{dn,weekday}$ were 2.36 (SD = 19.83) and -1.06 (SD = 12.65), respectively.

For the independent variables, the study area generally had high population density (M = 12392.29, SD = 23072.10), high GDP density (M = 192,701.21 thousand CNY, SD = 421,638.62), high road density (M = 22,386.80 m, SD = 17,477.55), and diversified POI use (M = 0.38, SD = 0.27). The area also had a convenient railway system with a short distance to the railway station (M = 12,063.92 m, SD = 10359.13). The average distance to the CBD and average NDVI were 59,240.43 m (SD = 42,163.86) and 0.35 (SD = 0.15), respectively. Regarding POIs,

Table 2

Statistics for all variables within the research area in the PRD sampled in 2018 (fishnet = 2 km × 2 km, N = 5227).

Variables (unit)	Min.	Max.	Mean	SD
Indicators of regional population aggregation				
$UVD_{holiday}$ (N)	2.78	2065.72	111.14	192.72
$UVD_{weekday}$ (N)	2.78	2381.67	110.33	198.82
$CV_{holiday}$	0.16	1.59	0.47	0.15
$CV_{weekday}$	0.12	1.91	0.41	0.16
VT_{hw} (N)	-765.61	386.94	0.82	44.00
$VT_{dn,holiday}$ (N)	-343.15	204.66	2.36	19.83
$VT_{dn,weekday}$ (N)	-166.38	298.74	-1.06	12.65
Independent variables				
Population density (N)	0	343,925.27	12,392.29	23,072.10
GDP density (thousand CNY)	0	9061.46	192,701.21	421,638.62
Road density (m)	0	115,877.51	22,386.80	17,477.55
POI mix (≥ 0)	0	0.76	0.38	0.27
Distance to railway station (m)	708.03	69,578.90	12,063.92	10,359.13
Distance to CBD (m)	816.94	203,737.61	59,240.43	37,645.22
NDVI	-0.14	0.77	0.35	0.15
Commercial POI (N)	0	1,95	126.86	267.90
Residential POI (N)	0	1,41	35.46	118.50

Note: POI = Point of interest; CBD = Central Business District; NDVI = Normalized difference vegetation index.

commercial centers outnumbered residential areas.

3.2. Disparities in urban vibrancy between holidays and weekdays

Utilizing the method described above, we estimated the urban vibrancy during holidays and weekdays in the PRD using Tencent LBS data (Fig. 4). There were similar spatial distribution patterns between $UVD_{holiday}$ and $UVD_{weekday}$ (Fig. 4a & b). Areas with the highest urban vibrancy density (UVD) ($UVD > 487.612$) were distributed in the Guangzhou-Foshan Metropolitan Area (GFMA) and the Shenzhen-Dongguan-Huizhou Metropolitan Area (SDHMA). Areas with medium UVD ($120.445 < UVD < 487.611$) appeared to be in the south of the PRD (Jiangmen, Zhongshan and Zhuhai) and core areas of counties in the PRD. In contrast, areas with the lowest UVD ($UVD < 120.444$) were mostly found in the less developed rural areas, including areas in the northwest and southwest of the PRD and the periphery of the GFMA. Overall, the spatial distribution pattern of UVD is closely associated with spatial location and regional development patterns. For instance, Guangzhou and Shenzhen, located in the alluvial plain of the PRD, feature high urbanization, economic vitality, talent attractiveness and educational resources (Hui et al., 2020). These features greatly increase the demographic attractiveness of the local and surrounding areas. The periphery of the PRD, which makes up over 60 % of the PRD territory, has relatively low development status. The weak industrial agglomeration capacity and mountainous territory affect the population aggregation and further influence the local UVD .

Compared to UVD , the spatial pattern of the coefficient of variation (CV) showed a greater difference between holidays and weekdays (Fig. 4c & d). Specifically, unlike the spatial pattern of UVD , the areas with higher CV distributions were generally located in the periphery of the PRD. The core areas of GFMA and SDHMA had smaller CV s in urban vibrancy than other areas. $CV_{holiday}$ (M = 0.47, SD = 0.15) was significantly higher than $CV_{weekday}$ (M = 0.409, SD = 0.164).

3.3. Disparities of tidal vibrancy

The tidal vibrancy between daytime and nighttime (VT_{dn}) is shown in Fig. 5a & b. The red and yellow colors indicate that the urban vibrancy level was higher during the day than at night, while the blue and green colors denote the reverse. Low-value units of VT_{dn} during the holiday were commonly found in the city center and subcenter (i.e., Futian and

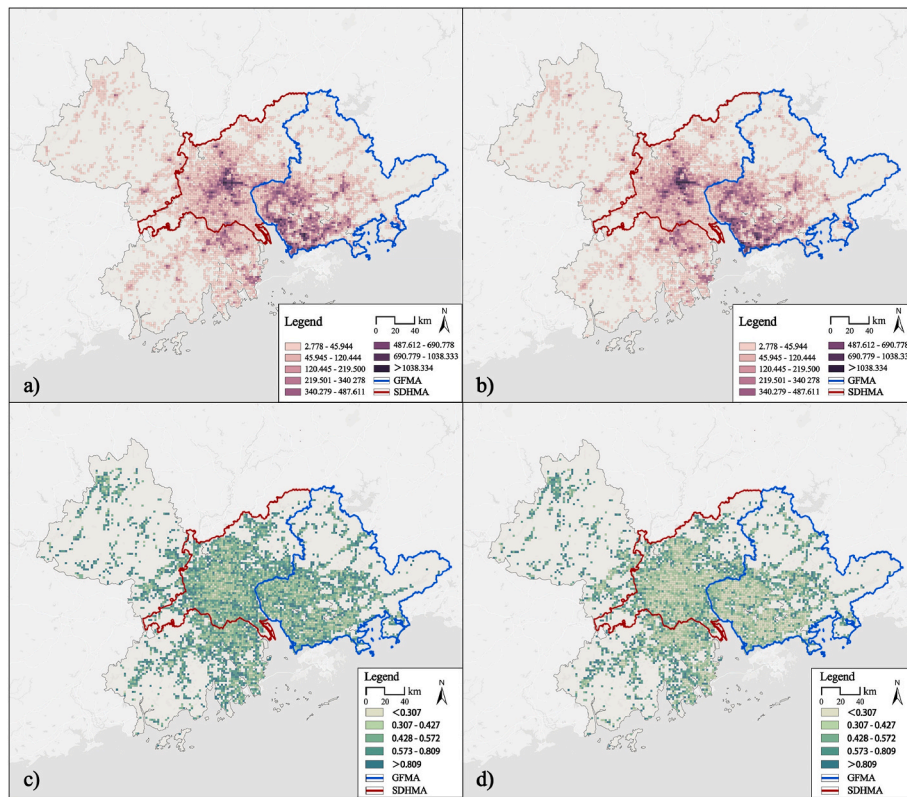


Fig. 4. a) Distribution pattern of urban vibrancy density during holidays ($UVD_{holiday}$). b) Distribution pattern of urban vibrancy density during weekdays ($UVD_{weekday}$). c) Spatial distribution of CV during holidays ($CV_{holiday}$). d) Spatial distribution of CV during weekdays ($CV_{weekday}$). Note: GFMA is the Guangzhou-Foshan Metropolitan Area, and SDHMA is the Shenzhen-Dongguan-Huizhou Metropolitan Area.

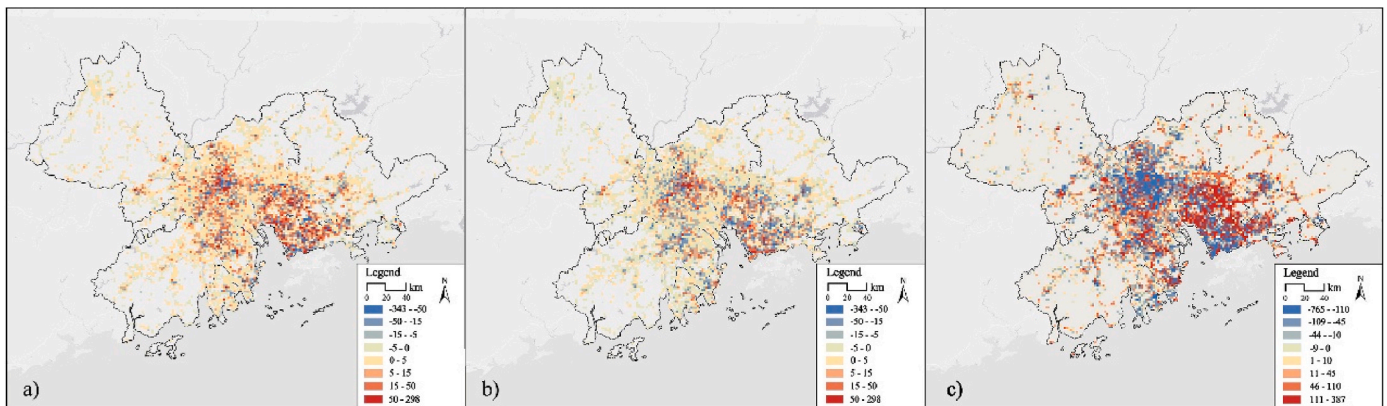


Fig. 5. a) The spatial distribution of tidal vibrancy between daytime and nighttime during holidays ($VT_{dn_holiday}$). b) The spatial distribution of tidal vibrancy between daytime and nighttime during weekdays ($VT_{dn_weekday}$). c) The spatial distribution of tidal vibrancy between holiday and weekday (VT_{hw}).

Nanshan of Shenzhen, Liwan of Guangzhou) of the megacity in the PRD. Peripheral areas of the city center, e.g., Guangming and Longgang of Shenzhen and Huadu of Guangzhou, were dominated by high value units of VT_{dn} . During weekdays, the VT_{dn} in the PRD decreased from 2.36 (SD = 19.83) to -1.06 (SD = 12.65), and high value units appeared in city centers and subcenters. The distribution of $VT_{dn_weekday}$ in the PRD was roughly opposite to that of $VT_{dn_holiday}$. Fig. 5c shows the spatial distribution of urban vibrancy tidal density between holidays and weekdays (VT_{hw}). The low value areas were mainly distributed in the two core cities of the PRD, i.e., Guangzhou and Shenzhen, due to the concentration of employment and cross-boundary commuting on weekdays. High value areas were mainly located in Dongguan and Foshan, where holiday activities are stimulated by the outflow of

population from core cities for home visits.

We applied global Moran's I to evaluate the spatial agglomeration of three population tidal indicators. The global Moran's I of $VT_{dn_holiday}$, $VT_{dn_weekday}$ and VT_{hw} was found to be 0.157 ($p < 0.001$), 0.200 ($p < 0.001$), and 0.364 ($p < 0.001$), respectively, denoting significant positive spatial autocorrelations in all three indicators. To further uncover the spatial features of the three kinds of vibrancy tidal indicators, the local Moran's I was calculated. The LISA map of $VT_{dn_holiday}$, $VT_{dn_weekday}$ and VT_{hw} (Fig. 6a, b & 6c) classified the local spatial correlation into four categories, i.e., HH, HL, LH, and LL. In terms of VT_{dn} , during the holiday, the HH category was mainly distributed in peripheral areas of the city center, e.g., Baiyun District (Guangzhou), Dongguan, Longhua District (Shenzhen), spatially interspersed with abundant LH units. The LL

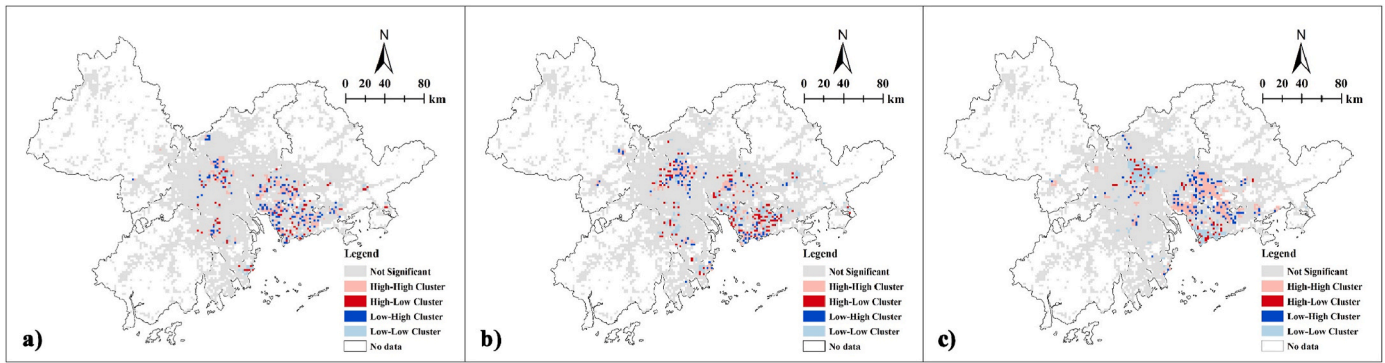


Fig. 6. a) The LISA map of $VT_{dn_holiday}$. b) The LISA map of $VT_{dn_weekday}$. c) The LISA map of VT_{hw} .

category appeared in the core city areas, e.g., Liwan District (Guangzhou), Nanshan District (Shenzhen), and Xiangzhou District (Zhuhai). LL units and HL units developed a fragmentation pattern (Fig. 6a). During the weekday, the HH category was mainly distributed in the core urban areas of Guangzhou, Shenzhen and Dongguan, while LL was mainly concentrated in the residential areas in the periphery areas of cities, such as Baoan District (Shenzhen), Longgang District (Shenzhen) and Xinhui District (Jiangmen). HH and LL units were interspersed with a number of HL and LH units (Fig. 6b). In terms of VT_{hw} , Guangzhou and Shenzhen were dominated by LL units interspersed with some HL units. Dongguan and Huizhou were principally dominated by HH units interspersed with a large number of LH units (Fig. 6c). The LISA maps of vibrancy tidal distribution indicated that the regional vitality pattern was easily influenced.

3.4. The determinants of urban vibrancy aggregation patterns

To obtain a thorough understanding of the driving factors behind urban vibrancy aggregation patterns, four OLS models were applied to assess the simultaneous effect of the extended 5D built environment variables on $UVD_{holiday}$, $UVD_{weekday}$, $CV_{holiday}$ and $CV_{weekday}$. The result is presented in Table 3. The adjusted R-squared values of $UVD_{holiday}$, $UVD_{weekday}$, $CV_{holiday}$, and $CV_{weekday}$ were 0.564, 0.611, 0.276 and 0.398, respectively, suggesting that the two UVD models had relatively higher goodness-of-fit values than the two CV models. Notably, weekday models exhibited stronger associations with built environment factors compared to holiday models, suggesting a more structured interaction between urban form and human activity during workdays.

The coefficient suggested that most built environment variables maintained positive associations with urban vibrancy on holidays and weekdays; specifically, population density, road density, and GDP

density significantly promoted urban vibrancy density in the PRD. The standardized coefficients further revealed that population density and road density exerted the strongest influence on both $UVD_{holiday}$ and $UVD_{weekday}$, underscoring that infrastructure enhancements in densely populated areas tend to amplify vibrancy more effectively. Additionally, we found that the proximity to the railway station had a notable impact on reducing $UVD_{holiday}$ and $UVD_{weekday}$. Residential POI and distance to CBD exerted significant associations only with urban vibrancy on weekdays; specifically, with a one-unit increase in residential POI and distance to CBD, $UVD_{weekday}$ increased by 0.054 units and decreased by 0.024 units, respectively.

In terms of $CV_{holiday}$ and $CV_{weekday}$ models, residential POI, distance to the railway station and NDVI had significantly positive associations with $CV_{holiday}$ and $CV_{weekday}$, while road density and POI mix had significantly negative associations. We found that distance to the CBD had a significant effect on promoting $CV_{weekday}$. Specifically, *ceteris paribus*, if the distance to CBD increased by one unit, $CV_{weekday}$ increased by 0.053 unit. Population density, commercial POI and GDP density were found to have insignificant effects on $CV_{holiday}$ and $CV_{weekday}$. Standardized coefficients indicated that road density had the strongest influence on both $CV_{holiday}$ and $CV_{weekday}$, followed by NDVI. This highlights the dominant role of infrastructure and green environments in shaping the temporal dynamics of urban vibrancy.

Given the spatial heterogeneity of urban vitality across the study area, it is unlikely that built environment variables exert uniform effects in all locations. The OLS model, which assumes spatial stationarity in the relationships between the dependent variables (i.e., UVD and CV) and the explanatory variables, provides a useful global baseline but cannot capture local variations in the strength or direction of these associations. This limitation highlights the need for a more spatially adaptive modeling approach.

Table 3
Results of OLS model regression (global regression model).

Variable	$UVD_{holiday}$		$UVD_{weekday}$		$CV_{holiday}$		$CV_{weekday}$		VIF
	Coef. (SE)	p value	Coef. (SE)	p value	Coef. (SE)	p value	Coef. (SE)	p value	
Population density	0.374 (0.014)	0.000***	0.405 (0.013)	0.000***	-0.029 (0.020)	0.135	-0.027 (0.018)	0.137	2.445
Commercial POI	0.019 (0.016)	0.230	-0.003 (0.015)	0.815	-0.001 (0.022)	0.947	-0.015 (0.020)	0.462	2.986
Residential POI	0.011 (0.014)	0.443	0.054 (0.013)	0.000***	0.073 (0.020)	0.000***	0.068 (0.018)	0.000***	2.438
Road density	0.360 (0.016)	0.000***	0.339 (0.016)	0.000***	-0.287 (0.023)	0.000***	-0.252 (0.021)	0.000***	3.253
POI mix	-0.014 (0.012)	0.229	-0.028 (0.011)	0.015	-0.041 (0.017)	0.014	-0.088 (0.015)	0.000***	1.734
Distance to railway station	-0.041 (0.011)	0.000***	-0.030 (0.010)	0.003**	0.100 (0.015)	0.000***	0.148 (0.014)	0.000***	1.413
Distance to CBD	-0.008 (0.012)	0.517	-0.024 (0.011)	0.034*	-0.024 (0.016)	0.139	0.053 (0.015)	0.000***	1.68
NDVI	-0.024 (0.013)	0.060	-0.005 (0.012)	0.700	0.123 (0.017)	0.000***	0.173 (0.016)	0.000***	1.937
GDP density	0.067 (0.011)	0.000***	0.105 (0.010)	0.000***	0.010 (0.015)	0.503	0.015 (0.014)	0.277	1.431
R ²		0.565		0.611		0.278		0.400	
Adjusted R ²		0.564		0.611		0.276		0.398	
AIC		5251.824		4957.360		6916.073		6495.724	
AICc		5252.850		4958.385		6917.098		6496.750	

Note: * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

To address this issue, GWR models were employed to examine the spatially varying relationships between built environment factors and urban vitality across different contexts. Specifically, GWR was applied to analyze the impacts of built environment variables on UVD and CV during both weekdays and holidays.

To evaluate model performance, we compared GWR and OLS results using key fit metrics. As shown in Tables 4 and 5, the GWR models consistently outperformed the OLS models, as indicated by higher adjusted R^2 values (0.698 vs. 0.564, 0.734 vs. 0.611, 0.315 vs. 0.276, 0.446 vs. 0.398) and lower AIC scores (4454.969 vs. 5251.824, 4250.521 vs. 4957.360, 6847.421 vs. 6916.073, 6373.783 vs. 6495.724). These results confirm the presence of spatial non-stationarity and support the use of GWR in capturing localized relationships between the built environment and urban vitality.

One of the strengths of the GWR model is that the coefficients of the GWR model can be used to evaluate the local variation of relationships between outcome and explanatory variables. Tables 4 and 5 present the descriptive statistics of the four GWR models; a greater range of variable coefficients indicates a larger spatial variation in variable influence. A greater standard deviation reflects stronger spatial heterogeneity, suggesting that the variable's impact varies significantly across regions.

For the $UVD_{holiday}$ models, Residential POI exhibited the greatest standard deviation (2.562), highlighting its spatially heterogeneous influence on holiday urban vibrancy due to differences in residential density and activity patterns within PRD. In contrast, POI mix showed the smallest standard deviation (0.189), suggesting a more consistent effect across the study area. Similarly, for the two CV models, GDP density displayed the highest spatial heterogeneity, while POI mix again demonstrated the lowest variation, underscoring its contribution to vibrancy stability throughout PRD.

We also conducted a t -test for four GWR models. The area ratio of significance (90 % level) and directions of the association are presented in Tables 4 and 5, where + indicates a positive effect on the outcome variable and – denotes the opposite. The results revealed that each explanatory variable was associated with the four outcome variables of the urban vibrancy pattern to varying degrees. The majority of explanatory variables were found to bidirectionally (both positively and negatively) affect the four outcome variables. The spatial distributions of coefficients are shown in Appendices 1–4. In terms of the two UVD models, population density had the largest spatial influence areas, with 67.32 % of significant units on holidays and 59.46 % on weekdays, while the POI mix had the smallest significant units. Among the significant units, population density, road density and GDP density were positively associated with $UVD_{holiday}$ and $UVD_{weekday}$, while the majority of commercial POIs, POI mix, distance to the railway station, distance to CBD, and NDVI showed negative associations. There was a general decrease in the significant areas for all variables during weekdays, with population density declining the most, by approximately 10 %.

In terms of the two CV models, road density (80.29 %), NDVI (60.09 %) and distance to railway stations (42.29 %) had the greatest spatial impact during holidays, while commercial POIs maintained the smallest spatial impact of 7.99 %.

All significant units of population density and road density during holidays were negative, indicating that the two factors had significant effects on reducing $CV_{holiday}$. During the weekday, NDVI (77.50 %), road density (67.02 %) and distance to the railway station (66.96 %) became the top three variables with the largest spatial impact units. The proportion of significant areas increased for all variables except for road density and commercial POIs. The largest changes were observed in NDVI and distance to the railway station, which rose by ~17 % and ~14 %, respectively. Greenery usage and regional public traffic positively influenced the internal mechanism of vibrancy-change intensity, with a 100 % positive coefficient value of significant grids during holidays and weekdays. The average coefficient of residential POI increased from 0.052 to 0.101, suggesting an enhancement of its influence on $CV_{weekday}$. Among the variables with a negative correlation, the decreases in

Table 4
Estimated parameters and diagnostic statistics of the population agglomeration density (UVD) GWR model.

Variable	UVD _{holiday}						UVD _{weekday}							
	Mean	Min.	Max.	SD	Area Ratio of Significance (%)	+(%)	-(%)	Mean	Min.	Max.	SD	Area Ratio of Significance (%)	+(%)	-(%)
Population density	0.551	-0.081	2.117	0.355	67.32 %	100.00 %	0.00 %	0.486	-0.130	1.804	0.328	59.46 %	100.00 %	0.00 %
Commercial POI	-0.059	-1.800	1.683	0.273	26.04 %	29.09 %	70.91 %	-0.043	-1.464	1.591	0.257	22.38 %	33.76 %	66.24 %
Residential POI	0.140	-19.486	30.675	2.562	20.01 %	40.15 %	59.85 %	0.068	-17.726	24.951	2.150	18.84 %	41.72 %	58.28 %
Road density	0.205	-0.394	1.053	0.207	42.57 %	100.00 %	0.00 %	0.194	-0.281	1.089	0.201	40.24 %	100.00 %	0.00 %
POI mix	-0.084	-2.005	0.439	0.189	12.70 %	1.05 %	98.95 %	-0.088	-2.329	0.513	0.205	12.49 %	1.38 %	98.62 %
Distance to railway station	-0.097	-2.770	2.894	0.382	20.43 %	17.23 %	82.77 %	-0.085	-3.020	3.193	0.410	19.49 %	22.47 %	77.53 %
Distance to CBD	-0.119	-6.743	4.030	0.930	21.87 %	37.53 %	62.47 %	-0.178	-8.990	4.707	1.092	20.66 %	34.54 %	65.46 %
NDVI	-0.105	-1.417	0.488	0.217	22.21 %	7.49 %	92.51 %	-0.110	-1.687	0.445	0.220	19.59 %	5.66 %	94.34 %
GDP density	0.260	-17.269	14.659	2.049	24.55 %	90.28 %	9.72 %	0.325	-11.664	16.890	1.541	21.63 %	95.84 %	4.16 %
R ²							0.732							0.766
Adjust R ²							0.698							0.734
AIC							4454.969							4250.521
AICc							4626.505							4337.757
RSS							701.276							610.875

Note: The area ratio of significance represents the proportion of significant grids ($p < 0.1$) within all grids.

Table 5
Estimated parameters and diagnostic statistics of the coefficient of variation (CV) GWR model.

Variable	CV _{holiday}						CV _{weekday}							
	Mean	Min.	Max.	SD	Area Ratio of Significance (%)	+ (%)	-(%)	Mean	Min.	Max.	SD	Area Ratio of Significance (%)	+ (%)	-(%)
Population density	-0.148	-0.659	0.062	0.154	37.19 %	0.00 %	100.00 %	-0.183	-1.058	0.049	0.191	45.54 %	0.00 %	100.00 %
Commercial POI	0.054	-0.263	0.489	0.111	7.99 %	100.00 %	0.00 %	0.021	-0.236	0.446	0.100	3.56 %	88.17 %	11.83 %
Residential POI	0.052	-0.898	0.675	0.188	19.04 %	81.20 %	18.80 %	0.101	-0.396	0.732	0.156	25.54 %	100 %	0.00 %
Road density	-0.267	-0.566	0.070	0.135	80.29 %	0.00 %	100.00 %	-0.195	-0.479	0.026	0.130	67.02 %	0.00 %	100.00 %
POI mix	0.001	-0.321	0.163	0.078	17.14 %	38.62 %	61.38 %	-0.035	-0.264	0.127	0.075	24.03 %	18.71 %	81.29 %
Distance to railway station	0.085	-0.310	0.417	0.122	42.29 %	100.00 %	0.00 %	0.165	-0.193	0.445	0.118	66.96 %	100.00 %	0.00 %
Distance to CBD	0.043	-0.716	0.694	0.221	37.82 %	61.41 %	38.59 %	0.083	-0.544	0.538	0.204	42.24 %	70.61 %	29.39 %
NDVI	0.167	-0.082	0.467	0.121	60.09 %	100.00 %	0.00 %	0.214	-0.243	0.547	0.170	77.50 %	100 %	0.00 %
GDP density	-0.142	-1.385	0.929	0.252	20.66 %	15.46 %	84.54 %	-0.168	-1.901	0.941	0.257	28.75 %	2.53 %	97.47 %
R ²							0.335							0.463
Adjust R ²							0.315							0.446
AIC							6847.421							6373.783
AICc							6850.776							6377.346
RSS							1999.703							1665.723

Note: The area ratio of significance represents the proportion of significant grids ($p < 0.1$) within all grids.

population density (-0.148 to -0.183), POI mix (0.001 to -0.035) and GDP density (-0.142 to -0.168) indicated that their influences were enhanced.

The comparison of *UVD* models for two different periods showed that the mechanisms of urban vibrancy density were similar during the two time periods. The ranges of each influenced variable were slightly smaller on weekdays than on holidays. In addition, population density played the most important role in promoting *UVD*. Regarding *CV*, the correlation and significance of some built environment factors, i.e., road density and commercial POIs, increased during holidays due to the large demand for traveling, returning home and consumer behavior. However, population-level travel behavior was more regular on weekdays, resulting in more significant associations and greater spheres of influence associated with built environment variables. The two major metropolitan areas within the PRD, i.e., GFMA and SDHMA, had some long commuting trips beyond city boundaries, which may be enabled by high-speed intercity rail service.

4. Discussion and conclusion

In this research, we extend the literature on urban vibrancy research into three aspects. First, we move beyond single city boundary to examine urban vibrancy at an urban agglomeration scale. This approach reveals how regional economic and social interactions, driven by increasing cross-city mobility, shape spatial vibrancy patterns. By analyzing nine interconnected cities in the PRD, we provide empirical evidence that enriches core-periphery theory, highlighting how core cities such as Guangzhou and Shenzhen act as social and economic hubs, while peripheral cities like Dongguan and Huizhou play vital supporting roles in sustaining regional vitality. This shift from a single-city to a multi-city regional perspective advances theoretical frameworks for understanding spatial patterns of vitality across administrative boundaries, offering a novel extension to existing urban vibrancy research.

Second, from a methodological perspective, the intensity of vitality variation and two kinds of vibrancy tides, i.e., day-night tides and holiday-weekday tides, are systematically introduced. The findings highlight the spatial mismatches in employment and residential patterns, reflecting a significant jobs-housing imbalance in rapidly urbanizing regions. By introducing vibrancy variation intensity and spatiotemporal tidal phenomena, this study pioneers a dynamic and fine-grained analytical framework that captures short-term vitality fluctuations, an area previously underexplored in vibrancy studies.

Third, we further explore the spatiotemporal correlations between built environment factors, spatial vibrancy and vibrancy-variation intensity. Our findings emphasize the practical implications of integrated land-use and transportation planning, demonstrating its critical role in reducing spatial disparities and promoting sustainable regional development.

4.1. Major findings

Urban vitality is considered a reflection of continuous human activities and interactions (Montgomery, 1998; Ouyang et al., 2022); therefore, it is important to quantify the vibrancy level and the intensity of vitality changes from a dynamic spatiotemporal perspective. This study was conducted in the PRD, one of the most populous and economically vibrant urban agglomerations in China. The results indicate that the spatial vibrancy level displays significant between-city differences and city-integration characteristics at the urban agglomeration scale (Yue et al., 2025). The urban vibrancy of GFMA exhibits a ring-shaped structure, where economic and social activities are concentrated in core hubs like Guangzhou, radiating outward to peripheral areas. In contrast, the contiguous vibrancy in SDHMA reflects principles of polycentric development, with spatially interconnected nodes such as Shenzhen, Dongguan, and Huizhou fostering regional synergies through functional integration.

Urban vibrancy cores tend to be concentrated in the mega-cities of the PRD, consistent with previous studies (Liu & Xiao, 2022; Zhang, Guo, Cheung et al., 2018). Since the Chinese central government announced the New Urbanization Plan in 2014, the population policy has demonstrated a gradual shift from restricting the residence of the floating population to facilitating it (Liu & Wang, 2020). Furthermore, Guangzhou and Shenzhen provide a flexible points-based hukou system, which improves demographic attractiveness, especially for the educated group (Dang et al., 2019; Wang, Zhu, et al., 2021). Hence, the two major metropolitan areas (GFMA and SDHMA) in the PRD demonstrate a high level of urban vibrancy.

Regarding the intensity of vibrancy changes, weekdays and holidays exhibited distinctive spatial and temporal features (Niu et al., 2022; Zhang, Li, Ma, & Guo, 2021). The vibrancy stability for holidays was generally higher, reflecting more consistent leisure and social activities, whereas weekdays revealed pronounced urban–rural disparities. Urban areas displayed minimal vibrancy variation due to stable employment-driven activities, while distant suburbs and rural areas experienced significant fluctuations linked to resident's motivation to balance wage gains, commuting times, and housing costs (Zhao & Cao, 2020; Zhao, Liu, Yu, & Hu, 2020). In these peripheral regions, large industrial districts and residential zones dominate, and their single-function nature amplifies mobility demands, reinforcing the spatial manifestation of jobs-housing imbalances (Song & Zhang, 2019; Zhao, 2013; Zhao & Cao, 2020). Our findings underscore how employment-focused activities in core cities and leisure-driven interactions in peripheral areas collectively shape vibrancy patterns.

The tidal vibrancy further highlights spatial disparities in land use, urban density, and job opportunities. Previous studies have emphasized long-term intercity mobility patterns but often overlooked the nuanced weekly and daily behaviors that drive vibrancy dynamics (Zeng et al., 2021). This study fills this gap by analyzing the contrasting characteristics of day-night tides ($VT_{dn,holiday}$ and $VT_{dn,weekday}$) and holiday-weekday tides (VT_{hw}). Spatial units with HH-LH patterns reveal clustering of daytime vitality and scattering at night, predominantly occurring in peripheral areas such as Nanhai of Foshan, Longgang of Shenzhen, and Dongguan during holidays, while weekdays see these patterns concentrated in core urban districts like Liwan of Guangzhou, and Nanshan and Futian of Shenzhen. Such spatial features not only indicate that urban development and population mobility are increasingly breaking the traditional administrative boundaries but also reveal a distinct jobs-housing imbalance in the PRD (Wong et al., 2020; Zhang et al., 2020). The adjacent areas of HL-LL units highlight the importance of community-centered and short-distance commuting patterns, where mixed-use developments and localized accessibility, such as 15-min neighborhoods, are crucial in supporting balanced spatiotemporal vibrancy distribution (Allam, Nieuwenhuijsen, Chabaud et al., 2022; Weng et al., 2019).

The holiday-weekday tidal diagram illustrates the difference in vibrancy patterns between the two time periods. During weekdays, Shenzhen and Guangzhou-Foshan demonstrate higher vibrancy levels, while Dongguan and Huizhou exhibit relatively lower vibrancy. The result reflects the spatial imbalance between employment opportunities and residential functions in the PRD, highlighting a significant jobs-housing mismatch (Wong et al., 2020). Core cities such as Guangzhou and Shenzhen maintain high vibrancy levels due to their economic advantages, while peripheral cities primarily serve residential functions. This pattern suggests that weekday vibrancy distribution is strongly influenced by regional economic activities and commuting patterns, further emphasizing the functional division between core and peripheral cities. Some residents may prefer to live in the periphery of metropolitan areas or across cities for different reasons, such as larger and affordable homes and proximity to nature (Zhao, Liu, Yu, & Hu, 2020). This result is consistent with previous studies (Chen & Yeh, 2022; Niu et al., 2022). Dongguan and Huizhou remain the major labor supply areas within the PRD (Hui et al., 2020; Zhang et al., 2020).

Furthermore, we identified major built environment factors linked to urban vibrancy at the urban agglomeration scale, which complements previous evidence at the city scale (Chen, Zhao, et al., 2022; Liu et al., 2021; Wang, Zhang, Yu et al., 2022). The results of OLS models provide evidence that population density, road density, and GDP density are the key parameters facilitating urban vitality on a regional scale, while the distance to railway stations is found to have a significant impact on reducing urban vitality. The results are in line with previous studies (Guirao et al., 2017; Lan, Gong, Da, & Wen, 2020; Niu et al., 2022).

Railway stations, as critical public transit hubs, play a pivotal role in shaping urban mobility and vitality. Proximity to railway stations or enhanced public transit accessibility typically results in higher connectivity, drawing greater human flow and economic activities that collectively boost regional vitality. These areas benefit from improved travel efficiency, which facilitates more frequent movements and interactions among residents, contributing to stable vibrancy levels across both weekdays and holidays.

The land-use patterns around railway stations are often highly diverse, featuring a mix of commercial, office, residential, and public service functions (Xu & Yang, 2019). This functional diversity attracts human flows and economic activities, which further strengthens urban vitality. In contrast, areas farther from public transit hubs (e.g., suburban or semi-urban regions) tend to be characterized by single-use land patterns (e.g., exclusively residential or industrial zones) (Yang, Chau, Szeto et al., 2020). In these areas, limited transport options pose a significant challenge, constraining human mobility and economic activity, and ultimately hindering urban vibrancy.

Residential POI, distance to railway stations, and NDVI are considered the dominant variables to promote the intensity of vibrancy variation, and road density was found to have a significant impact in reducing the intensity of vibrancy variation. These results underscore the importance of public transportation accessibility for urban vibrancy. On weekdays, mobility patterns are predominantly driven by commuting activities, leading to higher vibrancy in central business districts (CBDs) and transport hubs, while suburban areas exhibit lower vibrancy. During holidays, the mobility pattern shifts, with increased leisure and social activities boosting vibrancy in parks, commercial districts, and cultural venues. Areas with better public transit connectivity typically demonstrate more stable vibrancy levels, as residents can more efficiently access diverse urban functions. Conversely, regions with limited transit access often experience greater fluctuations in vibrancy or lower overall vitality. Distance to CBD and residential POI are significantly correlated with urban vibrancy only on weekdays. These findings are not unique. A previous study also found that residential areas and CBDs had a more vital impact on commuting activities on weekdays (Zhang, Liu, Tang et al., 2019).

Unexpectedly, we note that road density and distance to railway stations are significantly associated with both vibrancy levels (UVD) and the intensity of vibrancy variation (CV). The other built environment variables are significantly associated with a maximum of one of the vitality indicators. In addition, the built environment variables have stronger effects on vibrancy levels and vibrancy stability on weekdays than on holidays, which may be related to a more regular daily activity pattern (e.g., commuting, on-shift) during weekdays (Su et al., 2021; Zhang et al., 2019).

In the research, we applied GWR models to estimate the local variations in statistical correlations at the urban agglomeration scale, which provides a refined understanding compared with previous spatiotemporal vibrancy studies (Chen, Zhao, et al., 2022; Wang et al., 2022; Wu, Ye, Ren, & Du, 2018). Specifically, the results from the GWR models indicate that each built environment factor exerts varying influences on vibrancy levels and vibrancy stability across different grids. Except for population density (UVD model), road density (UVD model), population density (CV model), road density (CV model), distance to railway stations (CV model) and NDVI (CV model), the remaining factors present bidirectional impacts. These findings differ from previous related

studies, which overlooked the spatial effect of built environment factors within spatial units (Chen, Lu, et al., 2022; Huang et al., 2019; Niu et al., 2022). By considering spatial heterogeneity, this study clearly reflects regional differences in driving factors on urban vibrancy. It also provides a novel perspective for studying the relationship between urban vibrancy and the built environment at the urban agglomeration scale.

4.2. Planning implications

The findings of this research carry several important planning implications for the PRD region and other urban agglomerations. Firstly, our analysis shows that urban vitality in the PRD has already transcended administrative boundaries, exhibiting cross-jurisdictional flows and diffusion. However, current policy frameworks and public service provision are still constrained by administrative divisions, creating institutional barriers that hinder the coordinated development of regional vitality. To address this mismatch, it is essential to establish multilateral coordination mechanisms, promote the joint development of infrastructure, public services, and ecological spaces, and enhance the integration and continuity of spatial vitality across boundary areas.

Building on this foundation, improvements to the spatial structure and transportation accessibility are crucial for supporting the expansion of vitality. The findings indicate that road density and proximity to rail transit significantly influence both the level and fluctuation of urban vitality. Within the PRD, two typical commuting patterns can be observed: “center–center” long-distance commuting between core cities (e.g., Guangzhou and Foshan) and “border–border” short-distance commuting along administrative boundaries (e.g., Shenzhen–Dongguan, Shenzhen–Huizhou). To accommodate these diverse commuting needs, improvements should be made to the intercity rail network and station integration for long-distance flows, while local transport systems should be strengthened to support short-distance commuting, thereby promoting broader vitality diffusion.

To complement spatial interventions, industrial planning should emphasize functional differentiation and specialization across cities. Core cities should continue to strengthen their leadership in high-end services and innovation-driven industries, while peripheral cities should leverage their resource advantages to develop advanced manufacturing, green industries, and the digital economy. A coordinated industrial division of labor can alleviate the pressure on core cities, stimulate endogenous vitality in peripheral areas, and foster a more balanced regional structure.

Addressing suburban challenges is also essential for revitalizing underperforming spaces. Many suburban areas in the PRD face issues such as outdated industrial land, inefficient land use, and insufficient public facilities. Priority should be given to small-scale, incremental regeneration that enhances public services and open spaces, while promoting the transformation of aging industrial zones toward mixed-use, industry-city integrated developments. Introducing innovative industries, cultural amenities, and community-based commercial spaces can foster jobs-housing balance, stimulate localized vitality, and strengthen the competitiveness of suburban regions in alignment with regional transportation and industrial strategies.

Finally, to support the everyday vitality of peripheral and edge regions, policies should focus on improving housing affordability and service provision. Efforts should be made to expand the supply of rental

housing in transit-accessible locations and optimize the spatial structure of jobs and housing. At the same time, promoting 15-min community developments and enhancing public services such as education, healthcare, culture, and recreation can significantly boost the residential appeal and daily activity levels of peripheral areas, contributing to a more balanced distribution of urban vitality across the PRD.

4.3. Limitations

We acknowledge several limitations that should be addressed in future research. First, Urban vitality assessment at the regional scale is a complicated task. Accurate built environment data (e.g., building floor area and street view imagery) are not always available on this scale. Data derived from satellite imagery can be considered in future work to improve research quality. Besides, we recognize that the calculation method for destination accessibility used in this study is relatively simplified. Future research could consider incorporating temporal or spatial thresholds to improve accuracy.

Second, although the Tencent location data offers the advantage of high accuracy and broad user coverage, the data acquisition relies on smartphones and Tencent's mobile applications and omits groups without smartphones, such as elderly people and children, which may lead to biased estimates of urban vitality. Future studies should integrate other data sources, e.g., travel survey data and nighttime lighting data.

Third, the modifiable areal unit problem (MAUP) is considered a key issue in geography research (Fotheringham & Wong, 1991). Due to the scale-dependent characteristic of urban vitality, the built environment-urban vitality correlation is sensitive to the observation grain. We employed a grid size of 2×2 km considering the spatial resolution of the Tencent location data to ensure unit-scale consistency. Future studies on different spatial and/or temporal units could be considered. Expanding the temporal scope can enrich our data with additional holidays and weekdays, as well as data with different seasons and years. Such improvement could further enhance the validity of the findings and provide a more comprehensive understanding of urban vitality dynamics.

CRediT authorship contribution statement

Yuxiao Jiang: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Zongyao Sun:** Validation, Methodology, Data curation. **Di Wei:** Writing – original draft, Visualization, Data curation. **Pengjun Zhao:** Writing – review & editing. **Linchuan Yang:** Writing – review & editing. **Yi Lu:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

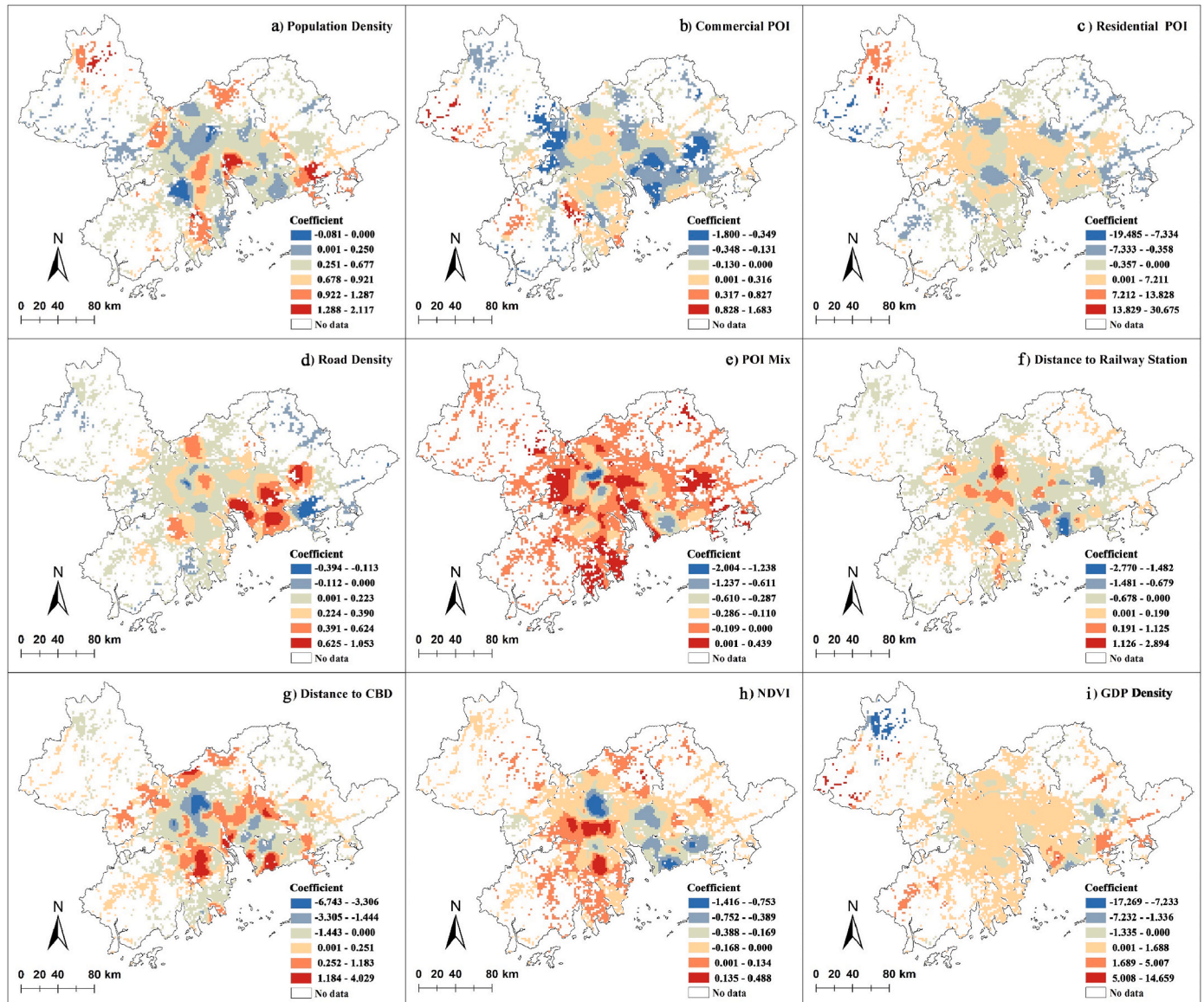
Funding

The work described in this paper was fully supported by the Research Grants Council of the Hong Kong SAR (Project No. CityU11207520).

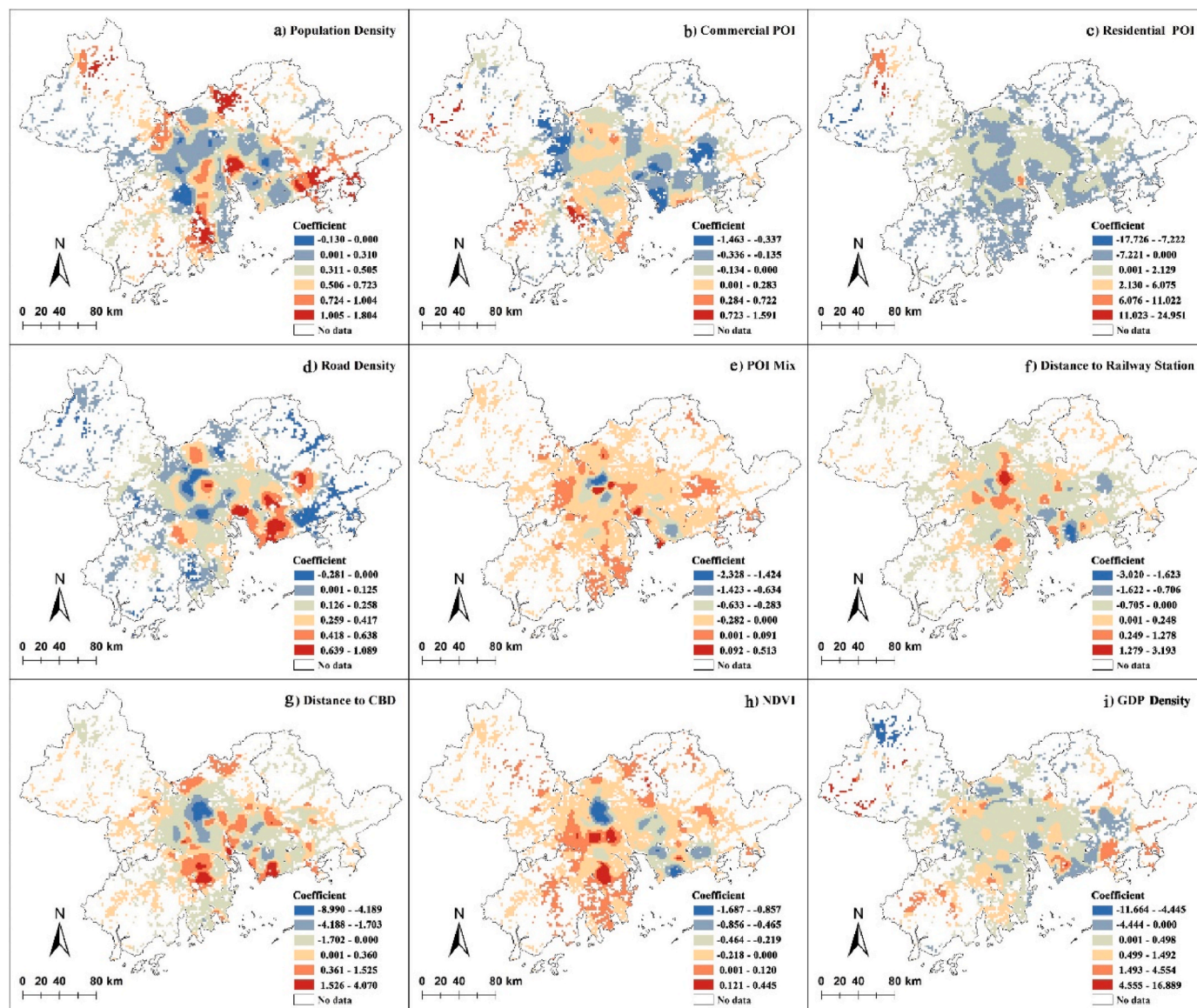
Declaration of interest statement

To the best of the authors' knowledge, no conflict of interest is found and declared.

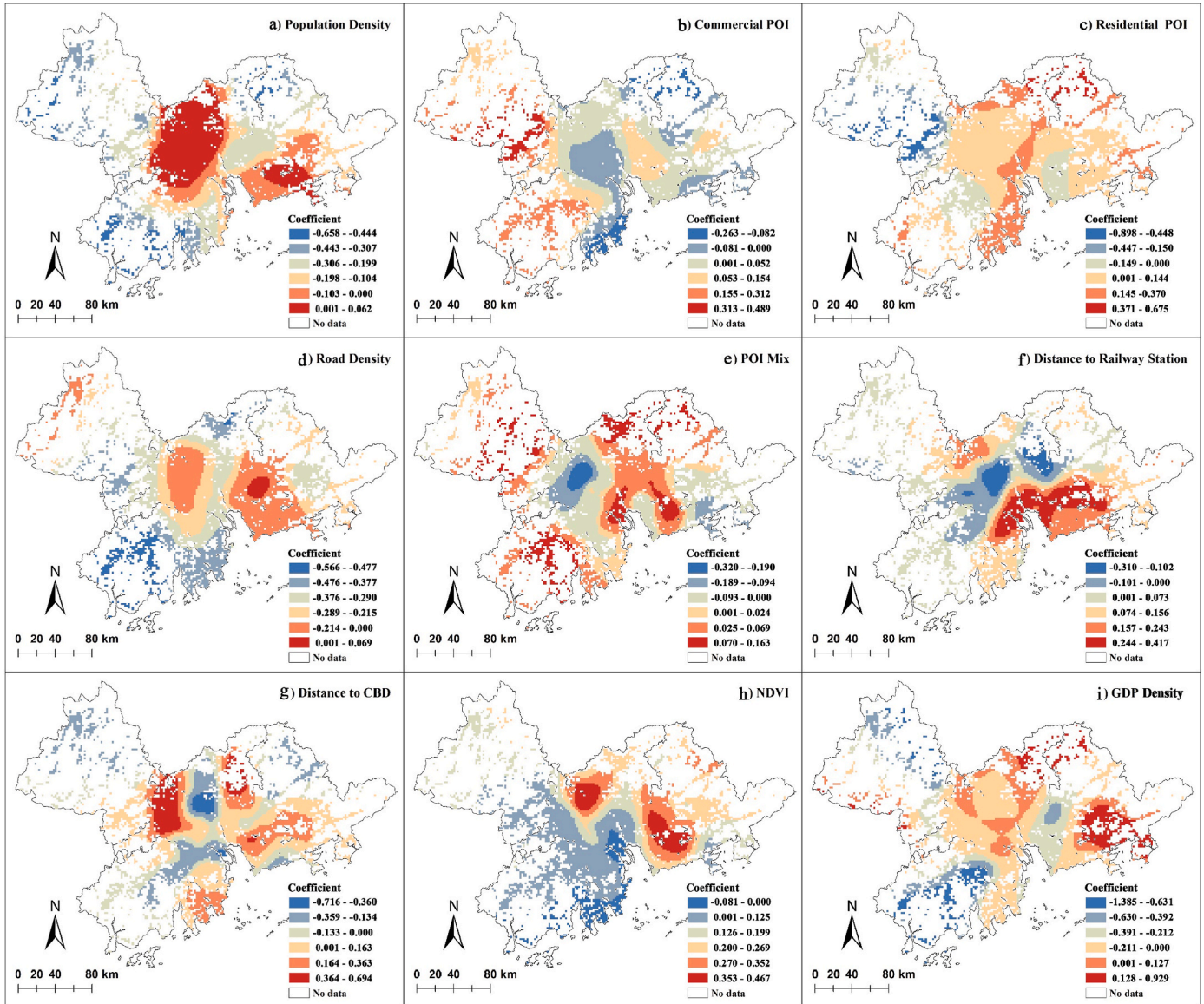
Appendix 1. Spatial pattern of coefficients in $UVD_{holiday}$ GWR model. a) Population density. b) Commercial POI. c) Residential POI. d) Road density. e) POI mix. f) Distance to railway station. g) Distance to CBD. h) NDVI. i) GDP density



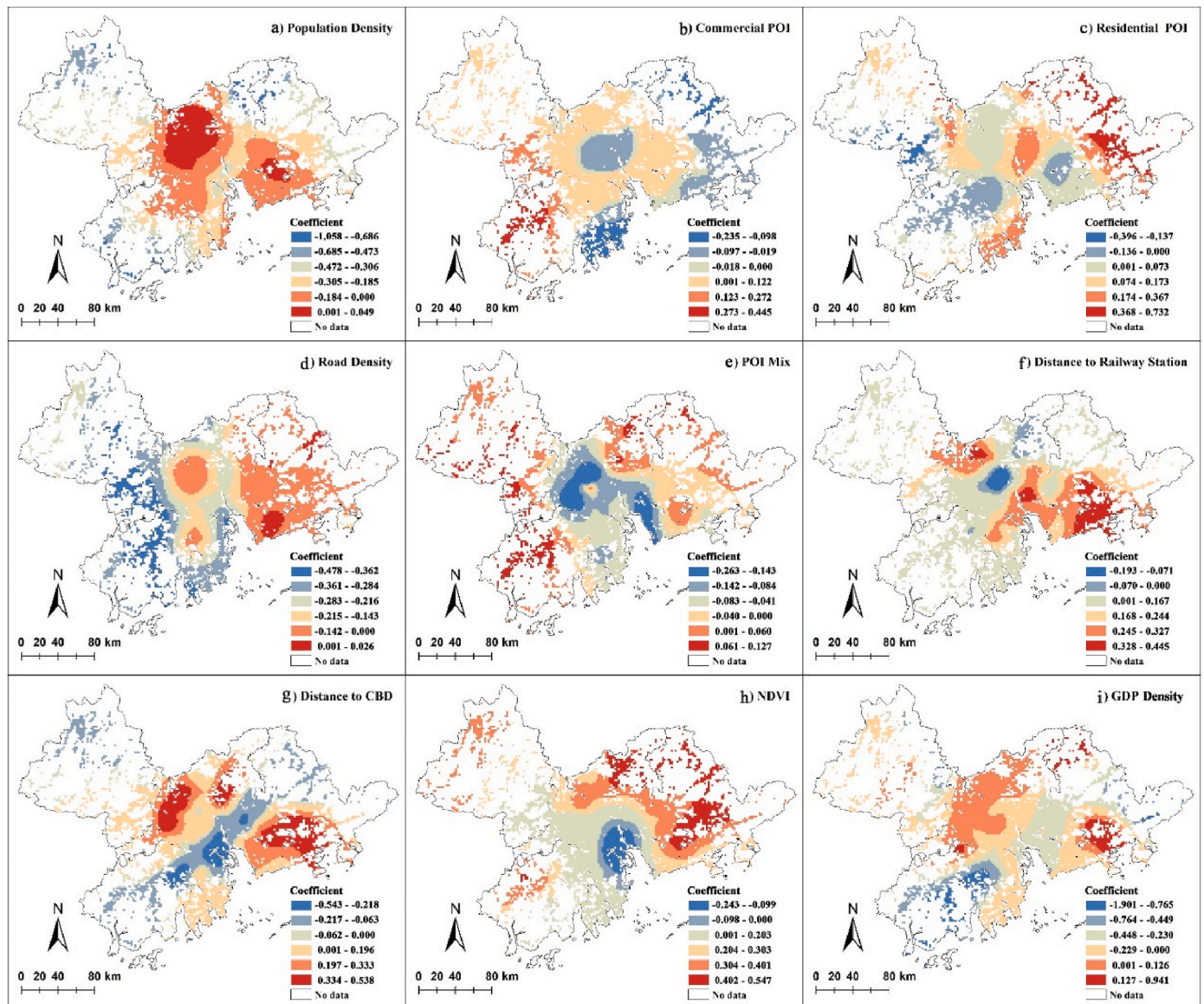
Appendix 2. Spatial pattern of coefficients in $UVD_{weekday}$ GWR model. a) Population density. b) Commercial POI. c) Residential POI. d) Road density. e) POI mix. f) Distance to railway station. g) Distance to CBD. h) NDVI. i) GDP density



Appendix 3. Spatial pattern of coefficients in CV_{holiday} GWR model. a) Population density. b) Commercial POI. c) Residential POI. d) Road density. e) POI mix. f) Distance to railway station. g) Distance to CBD. h) NDVI. i) GDP density



Appendix 4. Spatial pattern of coefficients in $CV_{weekday}$ GWR model. a) Population density. b) Commercial POIs. c) Residential POI. d) Road density. e) POI mix. f) Distance to railway station. g) Distance to CBD. h) NDVI. i) GDP density



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