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Investigating the spatiotemporal pattern between the built environment and urban vibrancy using big data in Shenzhen, China

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ABSTRACT

Promoting urban vibrancy is one of the major objectives of urban planners and government officials, and it is linked to various benefits, such as urban prosperity and human well-being. There is ample evidence that built environment characteristics are associated with urban vibrancy; however, the spatiotemporal associations between built environment and urban vibrancy have not been fully investigated owing to the inherent limitations of traditional data. To address this gap, we measured spatiotemporal urban vibrancy in Shenzhen, China, using Tencent location-based big data, which is characterized by fine-grained population-level spatiotemporal granularity. Built environment characteristics were systematically measured using the 5D framework (density, diversity, design, destination accessibility, and distance to transit) with multi-source datasets. We investigated the spatiotemporal non-stationary associations using a geographically and temporally weighted regression (GTWR) model. The results indicated that the GTWR models achieved better goodness-of-fit than linear regression models. Built environment factors such as population density; point of interest (POI) mix; residential, commercial, company, and public service POI; and metro station were significantly associated with urban vibrancy. Time series clustering revealed spatiotemporal clustered patterns of the associations between built environment factors and urban vibrancy. To promote urban vibrancy with urban planning and design strategies, both the spatial and temporal associations between the built environment and urban vibrancy should be considered.

1. Introduction

Urban vibrancy has become increasingly important in urban planning owing to its positive impacts on the economy, livability, and sustainability of cities (Botta & Gutiérrez-Roig, 2021; Chen, Hui, Wu, Lang, & Li, 2019; Huang et al., 2019; Montgomery, 1998; Wu, Ta, Song, Lin, & Chai, 2018). Promoting vibrancy has received substantial attention because of the decline of many large cities worldwide since the 1960s (Li, Li, Jia, Zhou, & Hijazi, 2021; Zhang et al., 2020). The concept of urban vibrancy, also referred to urban vitality, was first proposed by Jane Jacobs in her book "*The Death and Life of Great American Cities*" who argued that urban vibrancy promotes active street activity and human interactions, thereby promoting social life (Jacobs, 1961). Higher vibrancy in urban space can enhance resident's well-being, sense of community, safety, and opportunity (Delclòs-Alió, Gutiérrez, & Miralles-Guasch, 2019; Liu, Huang, Li, & Wang, 2021; Marquet & Miralles-Guasch, 2015). Promoting urban vibrancy may also stimulate knowledge diffusion, economic growth, sustainable mobility, and social interaction in cities (Botta & Gutiérrez-Roig, 2021; Chen, Dong, Pei, & Zhang, 2022; Mouratidis & Poortinga, 2020).

Scholars have pinpointed the role of the built environment in urban design for street activity and urban vibrancy (Ewing & Cervero, 2010; Forsyth, Oakes, Schmitz, & Hearst, 2007; Jacobs, 1961; Saelens & Handy, 2008; Sallis et al., 2016). They argue that urban environment characteristics such as appropriate density, mixed land use, small blocks, and safety should be good features to promote urban vibrancy (Jacobs, 1961; Lynch, 1984). Empirical evidence has confirmed that urban vibrancy is related to built environment factors such as density (e.g., population or building density), diversity (e.g., land use mix, functional mix), and accessibility (e.g., street network, public transport) (Botta & Gutiérrez-Roig, 2021; Delclòs-Alió et al., 2019; Huang et al., 2019; Li, Liu, Lin, Xiao, & Zhou, 2021; Xia, Yeh, & Zhang, 2020). Therefore, investigating the association between built environment characteristics and urban vibrancy is rewarding for urban planning to formulate

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development strategies.

Urban vibrancy is often directly assessed in terms of the intensity of all types of human activities on various times at the population level besides walking behaviors (Botta & Gutiérrez-Roig, 2021; Chen et al., 2019; Wu, Ta, et al., 2018). Human activity intensity is generally measured via two approaches: small data collected by survey or field observation, and location-based big data. Small data can only measure human activity intensity in limited areas, such as residential neighborhoods (Delclòs-Alió et al., 2019; Sung & Lee, 2015), and thus are not suitable for investigating urban vibrancy within a large geographic area with detailed population-level spatial and temporal granularity (Huang et al., 2019; Wu, Ye, Ren, & Du, 2018). Big data are characterized by spatiotemporal details and can thus overcome the shortcomings of small data. However, most studies on vibrancy have ignored the relevant spatiotemporal characteristics. Spatiotemporal dynamics is essential to urban vibrancy because both spatial and temporal uncertainty could exert contextual influences (Kwan, 2012). That is, a spatiotemporal nonstationary association exists between the contextual factors and human activity intensity.

Location-based spatiotemporal big data provide a new lens for urban vibrancy measurement. For instance, the Tencent location big data, officially released in 2015, capture real-time user location information for all major cities in China. The dataset has unprecedented user coverage and fine-grained spatiotemporal granularity. To address the abovementioned research gaps, this study used Tencent location data to measure human activity intensity as a proxy for urban vibrancy. Moreover, the spatiotemporal pattern between built environment characteristics and urban vibrancy was investigated in the context of China's cities.

2. Literature review

2.1. Urban vibrancy and its importance

In recent decades, urbanization has rapidly increased worldwide, and it is projected that over 70% of the population will be living in urban areas by 2050 (United Nations, 2018). However, there are several problems associated with this rapid urbanization, including urban sprawl; the deterioration of living environments; and the prevalence of the physical inactivity of urban residents, all of which hinder the sustainable development goals of cities (Kohl et al., 2012; Zhang et al., 2020; Zumelzu & Barrientos-Trinanes, 2019). Most of China's large cities share some typical characteristics of rapid urbanization, such as high density, economy-oriented lifestyle, low-quality sprawl, job-housing mismatch, and the prevalence of bedroom communities, while urban vitality has not received sufficient attention (Li, Li, et al., 2021; Wu, Lu, Gao, & Wang, 2022; Ye, Li, & Liu, 2018; Yue & Zhu, 2019; Zhang et al., 2020). Urban planners and scholars have emphasized the importance of urban vibrancy to promote human interactions in urban spaces for the social stability and economic prosperity of cities.

Urban vibrancy was first proposed by Jacobs, who claimed that a lively environment boosts active living and street vitality (Jacobs, 1961). Some scholars have characterized urban vibrancy in terms of the presence of people on streets and public spaces, human activities and opportunities, and the diversity of the built environment (e.g., dense urban development, mixed land use, small block, aged building) (Gómez-Varo, Delclòs-Alió, & Miralles-Guasch, 2022; Jacobs, 1961; Lynch, 1984; Wu, Ta, et al., 2018; Zumelzu & Barrientos-Trinanes, 2019). Some scholars have also defined vibrancy from the perspectives of survival (e.g., quality of water, air, and food); security (e.g., against fear, disease, and risk), and adaptability (e.g., human body needs, visual characteristics) of urban spaces that support urban operations, biological conditions, and human abilities (Lynch, 1984; Zarin, Niroomand, & Heidari, 2015). Recent decade, urban vibrancy is often quantified in terms of the presence of desirable and attractive urban spaces that have the capacity to stimulate a variety of location-based human activities (Wu, Ta, et al., 2018; Wu, Ye, et al., 2018). Places with high degrees of urban vibrancy help to foster a strong sense of place reflected in active living, physical activity, human interaction, and place attachment (Jacobs, 1961; Li, Li, et al., 2021; Montgomery, 1998; Mouratidis & Poortinga, 2020; Zumelzu & Barrientos-Trinanes, 2019). Vibrant urban environment is able to accommodate various human behaviors and sufficient urban social and economic activities (Chen et al., 2022; Huang et al., 2019; Jia, Liu, Du, Huang, & Fei, 2021; Jin et al., 2017).

2.2. Urban vibrancy assessment

Despite the different definitions of urban vibrancy, there is a basic consensus that urban vibrancy arises from well-designed urban environments that stimulate human interaction and activity. Hence, urban vibrancy is assessed by either the built environment metrics (Delclòs-Alió & Miralles-Guasch, 2018; He et al., 2018; Yue et al., 2021; Zarin et al., 2015), or human activity intensity (Chen et al., 2019; Kim, 2018; Liu, Zhang, & Long, 2019; Yue et al., 2017), or a combination of both (Jin et al., 2017; Tu et al., 2020).

Some studies have evaluated urban vibrancy via objective or subjective assessment of built environment characteristics. For instance, urban vibrancy was assessed based on Jane Jacobs' ideas considering six conditions that are concentration, functional diversity, contact opportunity, aged buildings, accessibility and border vacuums in Barcelona, Spain (Delclòs-Alió & Miralles-Guasch, 2018; Gómez-Varo et al., 2022). One study in China assessed urban vibrancy in terms of the density of small catering businesses (Ye et al., 2018). Using a questionnaire, another study in Tehran, Iran, assessed urban vibrancy in terms of the self-rated variety of destinations; availability; and the levels of contact, safety, pollution, and aesthetics of the built environment (Zarin et al., 2015). Another study assessed urban vibrancy on the basis of the density of points of interest (POIs) and the functional mix in several Chinese cities (He et al., 2018). However, the approach based on built environment metrics can only evaluate the potential of urban vibrancy rather than the actual human activity intensity.

Several studies have measured urban vibrancy in terms of human activity intensity using both small and big data (Chen et al., 2019; Huang et al., 2019; Sung & Lee, 2015). Small data used for measuring urban vibrancy are usually obtained through surveys (Marquet & Miralles-Guasch, 2015; Sallis et al., 2016; Sung & Lee, 2015), or field observations (Zumelzu & Barrientos-Trinanes, 2019). However, small data collection through surveys is labor-intensive, and the data are heterogeneous. Big data for measuring urban vibrancy are in the forms of mobile phone data (Botta & Gutiérrez-Roig, 2021; Wu & Niu, 2019), social media data (Chen et al., 2019; Lu, Shi, & Yang, 2019; Wu, Ye, et al., 2018; Yue & Zhu, 2019), heat map (Fan et al., 2021), Wi-Fi access (Kim, 2018), and multi-source big data (Guo, Chen, & Yang, 2021; Huang et al., 2019; Kang, Fan, & Jiao, 2020; Li, Liu, et al., 2021). For instance, Huang et al. (2019) assessed urban vibrancy by social activity intensity, economic activity intensity, and pedestrian density using multi-source big data such as social media check-in and GPS positioning data. The big data of human activities are considered a valid proxy for urban vibrancy (Botta & Gutiérrez-Roig, 2021; Huang et al., 2019; Wu, Ye, et al., 2018).

According to such principles, some studies have measured urban vibrancy by considering both built environment characteristics and human activity. For instance, Jin et al. (2017) evaluated vitality by street intersection density, POI density, and location-based big data. Tu et al. (2020) described the spatial characteristics of urban vibrancy using POI density, social media check-ins, and mobile phone records.

2.3. Built environment and urban vibrancy

Moreover, some scholars have claimed the conceivable linkages between the built environment and urban vibrancy (i.e., human activity intensity). Jacobs (1961) discussed that there are four important factors that boost urban vibrancy including compactness, mixed land use, small street block, and rich historical building. Lynch (1984) considered that a good urban form supports people's lives and needs. Katz, Scully, and Bressi (1994) stated out that compactness, walking scale, mixed land use, and appropriate building density are important factors that impact urban vibrancy. Montgomery (1998) commented that urban vibrancy is more related to the features of public open space such as greenery and water, mixed land use, and pedestrian accessibility.

Strong evidence has confirmed that the built environment considerably influences urban vibrancy (Liu et al., 2021; Meng & Xing, 2019; Saelens & Handy, 2008; Jiang et al., 2021; Sung and Lee, 2015). The built environment is usually assessed using the D variables: density, diversity, design, destination accessibility, and distance to transit; these factors can directly influence vitality. For instance, the density and land use mix of the built environment are strongly associated with vitality (Delclòs-Alió et al., 2019; Huang et al., 2019; Lu et al., 2019; Wu et al., 2022; Yue et al., 2017). Huang et al. (2019) found that building density, density and mixture of urban functions, accessibility, and walkability were associated with urban vibrancy in Shanghai, China. Tu et al. (2020) assessed urban vibrancy using multi-source big data and found that employment density, land use mix, street density, and metro station were associated with urban vitality in Shenzhen, China. Other studies have also found that street accessibility, walkability, and pedestrian-friendly street environment are important factors influencing urban vibrancy (Huang et al., 2019; Lu et al., 2019; Sung & Lee, 2015; Wu, Ye, et al., 2018). The use of public green spaces can also positively influence vitality (Lopes & Camanho, 2013). Some studies have suggested that urban spatial structure and urban form are associated with urban vibrancy (Chen et al., 2019; Meng & Xing, 2019; Xia, Zhang, & Yeh, 2021; Yue et al., 2021; Zumelzu & Barrientos-Trinanes, 2019).

2.4. Research gaps

Despite the numerous studies on urban vibrancy, major research gaps still exist. Findings on the association between the built environment and urban vibrancy are inconclusive. For instance, some studies have found that functional diversity is positively related to urban vibrancy (Wu, Ta, et al., 2018; Yue et al., 2017; Zumelzu & Barrientos-Trinanes, 2019), while such a relationship was not found in others (Nadai et al., 2016; Sallis et al., 2016). Similarly, some studies have found a positive relationship between transportation accessibility and urban vibrancy (Huang et al., 2019; Lu et al., 2019), while others have not (Sallis et al., 2016; Wu, Ta, et al., 2018).

The inconsistency in the findings is largely caused by the differences among the urban vibrancy measurement approaches in different city contexts. As mentioned earlier, both small data and big data can be used to access human activity intensity. The small data approach is labor-intensive and characterized by data heterogeneity (owing to limited samples, a rough spatial scale, and limited cross-sectional data) (Huang et al., 2019; Wu, Ye, et al., 2018). Thus, the small data approach is prone to the uncertain geographic context problem (Kwan, 2012) and the modifiable areal unit problem (Wong, 2004) which might cause bias.

Big data provide a feasible approach to assess human activity using population-level sample size with spatiotemporal information. Hence, big data approaches can partly eliminate the limitations of small data approaches (Botta & Gutiérrez-Roig, 2021; Huang et al., 2019; Wu, Ye, et al., 2018). Although some studies have measured urban vibrancy using big data on a large geographic scale (Huang et al., 2019; Jiang et al., 2021; Liu et al., 2021), they have largely neglected the spatiotemporal dynamics of urban vibrancy (Kang et al., 2020; Kim, 2018). A few studies have investigated the spatial relationship between the built environment and urban vibrancy using location-based big data (Yang, Ma, & Jiao, 2021; Zhang et al., 2020), or have considered temporal characteristics of urban vibrancy (Guo et al., 2021; Li, Liu, et al., 2021; Liu et al., 2021; Wu & Niu, 2019). To the best of our knowledge, only one study has explored the spatiotemporal non-stationary relationship between urban vibrancy and POI data (Wu, Ye, et al., 2018); however, that study used check-in data from a social media platform, which is dominated by young users and hence may not be representative of the whole population. In summary, the relationship between built environment characteristics and urban vibrancy in China's high-density cities has not been comprehensively investigated using location-based spatiotemporal big data.

To address these research gaps, in this study, we measured the spatiotemporal dynamics of urban vibrancy using real-time Tencent location big data in a high-density and economy-oriented city in China. Tencent location big data have a large user coverage with a fine spatiotemporal granularity at a 1 km × 1 km grid level and one-hour time interval. First, we adopted a geographically and temporally weighted regression (GTWR) model to investigate the spatiotemporal association between the built environment characteristics and dynamic urban vibrancy. In addition, we systematically measured the built environment from multi-source datasets using the 5D (density, diversity, design, destination accessibility, and distance to transit) framework. Second, we visualized the spatiotemporal association using a space-time cube, which integrated spatial and temporal patterns. Furthermore, we conducted time series clustering to classify regional clusters with similar spatiotemporal relationships between built environment characteristics and urban vibrancy. Exploring such spatiotemporal association can elucidate the dynamic, rather than static, impact of the built environment on urban vibrancy, and help government officials and urban planners develop evidence-based and targeted interventions to stimulate urban vibrancy.

3. Data and method

3.1. Study area

Shenzhen is one of the largest cities in China with a resident population of 17.56 million in 2020, an area of 1997 km^2, and 10 main administrative districts (Fig.1). It is a fast-growing city and has been a special economic zone since China's economic reform. Its economy-oriented and high-density urban context make it a representative city for our study.

3.2. Dependent variables of urban vibrancy

Tencent location data were obtained from the Tencent location service, which is integrated into various Tencent location-based mobile phone applications such as WeChat, QQ, Meituan, and Didi (Liu et al., 2021). In 2016, Tencent announced that its location service is used an average of 50 billion times daily, covering 680 million users, making it the largest location service provider in China. The Tencent location service captures the real-time density of location-sensing events on the basis of information obtained from Tencent location-based applications. For instance, a person who is walking could be detected by WeChat Movement. The characteristics of fine-grained spatiotemporal granularity and large population coverage make Tencent location data an excellent instrument for revealing the real-time intensity of human activity.

Tencent location data were aggregated at grid-level with 1-km spatial resolution. Grids without Tencent data (i.e., mainly forest, or other preserved natural areas) in our study area (Shenzhen) during the research period were excluded, resulting in 1342 grids. Each grid was regarded as an analysis unit. Tencent location data in the form of the number of Tencent location-sensing events in each grid were used as the proxy for urban vibrancy. The built environment characteristics in each unit were correspondingly measured (Fig.1).

Through the Tencent product application programming interface (https://heat.qq.com), we obtained Tencent location data for three consecutive holidays (May 2–4, 2019) and three weekdays (May 7–9, 2019) in our study area. The number of Tencent location-sensing events

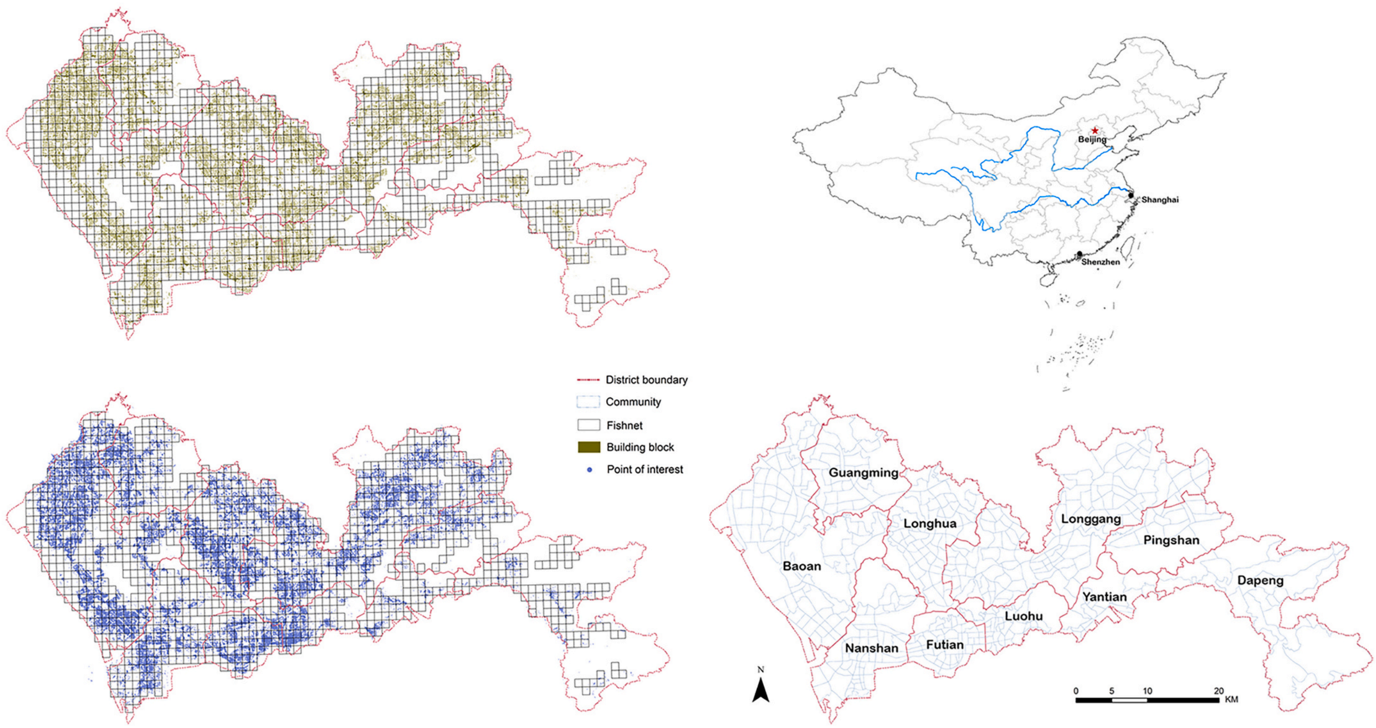

Fig. 1. Study area of Shenzhen.

in each grid was recorded at one- hour interval (i.e., 24 data points for each day) in our retrieved dataset. The raw data contained information about the number of Tencent location-sensing events, timestamps, and the longitude and latitude of each grid (Table 1). To ensure user privacy, the raw data did not contain any personal information about the user.

To explore the differences between weekday and holiday outcomes and mitigate potential bias, the average number of Tencent events at 24 independent timestamps over three days was calculated for weekdays and holidays. Hence, weekday and holiday urban vibrancy levels across Shenzhen were measured with a spatiotemporal resolution of 1 km × 1 km grid level and a time interval of one hour. Overall, we measured the weekday and holiday urban vibrancy in each grid by summing up the average location events at 24-time stamps over three days.

To validate the accuracy of the Tencent location data at the population level, we aggregated the Tencent data into the 10 administrative districts in Shenzhen, and compared them with the 2018 census population data. The Pearson correlation coefficients between weekday and holiday Tencent data and the census population in the 10 districts (observation = 10) were 0.857 ($p < 0.001$) and 0.832 ($p < 0.001$) on weekday and holiday, respectively. Thus, Tencent location data showed high accuracy for measuring the human activity intensity, despite inter-district human mobility.

3.3. Independent variables of the built environment factors

To quantify the built environment characteristics systematically, our study adopted the 5D framework including density, diversity, design, destination accessibility, and distance to transit. The 5D framework is a widely used evaluation framework to measure the built environment characteristics related with travel behaviors and human activities (Cervero & Kockelman, 1997; Ewing & Cervero, 2010; Jiang et al., 2021; Lu, Chen, Yang and Gou, 2018). We summarized the built environment factors considered in our study into the 5D framework.

We measured built environment characteristics using census data and open big data. The geographic census data included population density, building blocks, and the street network of Shenzhen. We also obtained point of interest (POI) data to measure built environment characteristics. POI data are a type of urban big data that can precisely reveal the spatial distribution of entities and functional facilities that accommodate human activities in an urban environment (He et al., 2018; Kang et al., 2020; Wu, Ye, et al., 2018). The POI dataset of 2018 was retrieved from Gaode Map (https://lbs.amap.com/), one of the most popular online map services in China. In addition, we measured urban greenery by Normalized Difference Vegetation Index (NDVI) using remote sensing data.

Density was measured in terms of population density and building density. The population density of each grid was measured using residential population census data. Building density was calculated using the total building coverage area (as known as building coverage ratio), total building floor area (BFA), and functional floor areas of each grid. The floor areas of residential, commercial, office, and industrial buildings were separately calculated according to building usage (Xia et al.,

Table 1
Raw big data of Tencent location for one day.

Grid ID	Number of the Tencent location events for 24 timestamps								Grid coordinates	
	00:00	01:00	02:00	03:00	…	21:00	22:00	23:00	Longitude	Latitude
1	3	0	0	0	…	0	0	0	113.7348207	22.74283378
2	18	5	3	0	…	3	0	0	113.7348274	22.75283075
3	119	102	55	0	…	0	0	0	113.7348193	22.76282763
4	0	166	122	107	…	256	253	243	113.7348187	22.77282441
5	0	197	123	99	…	234	219	0	113.7348187	22.78282111

2020).

Diversity was measured according to building usage mix and POI mix. Building usage mix was calculated based on building floor area. The raw POI dataset retrieved from Gaode Map had multi-layered categories. There is no universal standard to measure urban function by the dataset. We resampled key types and reclassified the POI dataset into five urban functional categories: residential POI, commercial POI (i.e., catering, shopping store), company POI (i.e., company, enterprise, corporation), public service POI (i.e., government, hospital, school), and recreational POI (i.e., park, square, scenic spot). Diversity was measured using the entropy score as follows (Huang et al., 2019; Ye et al., 2018):

$$\text{Diversity} = -\sum_{i=1}^{n}(p_i lnp_i) \tag{1}$$

where n denotes to the total types presented, and p_i denotes the proportion of the i th type. A higher diversity index indicates a higher degree of mixed use.

Design was measured in terms of the street length and street intersection. Street length was measured as the total length of the street network in each grid, while street intersection was the number of street intersections in each grid. In addition, the urban greenery level is an important indicator that can enhance urban vibrancy (Lopes & Camanho, 2013), as areas with greenery allow for social interaction and healthy outdoor activity. The NDVI is commonly used for measuring urban greenery. The NDVI was calculated using Sentinel remote sensing imagery as follows:

$$\text{NDVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}} \tag{2}$$

where *NIR* and *R* denote the reflectance in near-infrared band and red band, corresponding to band 8 and band 4 in the Sentinel satellite, respectively.

Destination accessibility was measured using POI datasets. For each grid, the number of five urban functional types of POI, including residential, commercial, company, public service, and recreational, were calculated as a proxy for accessibility.

Distance to transit was represented by the number of bus stations, and the number of metro stations in each grid. Despite the possible ambiguity in the 5D categorizations (e.g., the number of bus stations was categorized into distance to transit), the 5D framework enabled us to systematically classify built environment characteristics. Finally, 19 independent variables of built environment characteristics were considered.

3.4. Regression analysis

Urban vibrancy levels measured using both weekday and holiday Tencent location data were considered as distinct outcomes in our study. Before implementing regression models, we excluded independent variables that failed the multicollinearity test conducted using variance inflation factors (VIF >4). Hence, of the built environment factors, total building floor area and street length were excluded. All of the variables were standardized in the regression analysis.

First, we used ordinary least squares (OLS) regression to investigate the relationships between the built environment and spatiotemporal urban vibrancy with 32,208 observations. OLS holds the basic assumption that the residual is random and homoscedastic. The OLS model can be described as follows:

$$y = X\beta + \varepsilon \tag{3}$$

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

Second, we statistically analyzed data with spatial and temporal dimensions. To integrate regression analysis with spatial and temporal effects, we adopted a geographically and temporally weighted regression (GTWR) model to investigate the association between built environment characteristics and urban vibrancy. Compared with other spatiotemporal models (e.g., the generalized additive model and the Bayesian spatiotemporal model), the GTWR model better describes the spatiotemporal non-stationary relationship with weighting functions. As a temporal extension of geographically weighted regression (Brunsdon, Fotheringham, & Charlton, 1996), GTWR introduces a temporal dimension into the regression model to investigate the local spatiotemporal parameters (Fotheringham, Crespo, & Yao, 2015; Huang, Wu, & Barry, 2010). The GTWR model is expressed as follows:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i)X_{ik} + \varepsilon_i \quad i = 1, 2, \ldots\ldots, n \tag{4}$$

where y_i represents the dependent variable for location i; X_{ik} denotes the kth independent variable for location i; (u_i, v_i, t_i) are the space-time coordinates of location i in the spatiotemporal observations; u_i, v_i, t_i denote longitude, latitude, and time, respectively; $\beta_0(u_i, v_i, t_i)$ denotes the intercept value; $\beta_k(u_i, v_i, t_i)$ represents a set of parameter values at location i. $\beta_k(u_i, v_i, t_i)$ varies in the spatiotemporal space, and the GTWR model can simultaneously capture spatiotemporal non-stationarity. Local regression coefficients of the GTWR model are estimated on the basis of locally weighted least squares. The estimated parameter is expressed as follows:

$$\beta(u_i, v_i, t_i) = \left[X^T W(u_i, v_i, t_i)X\right]^{-1} X^T W(u_i, v_i, t_i)Y \tag{5}$$

where the weighting matrix $W(u_i, v_i, t_i)$ is an $n \times n$ diagonal matrix and $W(u_i, v_i, t_i) = diag\ (W_{i1}, W_{i2} \ldots W_{in})$. $W_{ij}(1 \le j \le n)$ is the spatiotemporal distance decay function, which is determined by the spatiotemporal distance d_{st} and bandwidth h. In this study, a Gaussian kernel function was adopted to calculate the spatiotemporal weighting matrix with the greatest efficiency as follows:

$$W_{ij} = exp\left[-\left(d_{ij}^{ST}\right)^2 \Big/ h^2\right] \tag{6}$$

According to (Huang et al., 2010), the spatiotemporal distance is calculated as follows:

$$d^{ST} = \sqrt{\lambda\left[\left(u_i - u_j\right)^2 - \left(v_i - v_j\right)^2\right] + \mu\left(t_i - t_j\right)^2} \tag{7}$$

where h is a nonnegative parameter that produces a decay of influence with the spatiotemporal distance d_{ij}^{ST} between locations i and j. $W(u_i, v_i, t_i)$ depends on the bandwidth h, and the optimal bandwidth is chosen according to the minimum cross-validation value. Finally, we implemented the GTWR model in R, using the GWmodel package to process spatiotemporal big data (Lu, Harris, Charlton, & Brunsdon, 2014).

3.5. Spatiotemporal pattern clustering

Finally, we performed spatiotemporal clustering of local coefficients derived from the GTWR model results, using a time series clustering tool for a space-time cube in ArcGIS Pro. Each grid has time series values with 24 timestamps. We conducted the clustering including two main parts to identify grids with similar time series values. First, dynamic time warping (DTW) distance (Montero & Vilar, 2014) is used to find the mapping r (distance) between the time series that minimizes a specific distance measure between the coupled observations (X_{ai}, Y_{bi}). Let M be the set of all possible sequences of m pairs preserving the observation order in the form. The DTW distance is expressed as:

$$r = ((X_{a1}, Y_{b1}), \ldots, (X_{am}, Y_{bm})) \tag{8}$$

$$d_{DTW}(X_T, Y_T) = \min_{r \in M} \left(\sum_{i=1,\dots,m} | X_{ai} - Y_{bi} | \right) \tag{9}$$

Second, after exploring the similarity and difference between time series, the grids are clustered using the k-means algorithm (Arthur & Vassilvitskii, 2007), expressed as:

$$J = \sum_{j=1}^{K} \sum_{i=1}^{N} \left\| x_i^{(j)} - c_j \right\|^2 \tag{10}$$

$$Pseudo\ F = \frac{(SS_{bg})/(K-1)}{(SS_{wg})/(N-K)} \tag{11}$$

where the objective function J aims to minimize total intra-cluster variance (i.e., squared error) by the distance function; K is the number of clusters; N denotes the number of data points; and c_j represents the centroid of cluster j. Pseudo-F statistic is adopted as the distance function, where SS_{bg} denotes the between-group sum of squares, and SS_{wg} denotes the within group sum of squares.

Spatiotemporal clustering is initially started by randomly selecting locations as representatives of each cluster, and then generated by assigning similar locations to the cluster. The new representative is the average of each timestamp in the cluster. Finally, in our space-time cube, we tentatively set 10 clusters for each built environment factor.

4. Results

Table 2 presents the descriptive statistics of urban vibrancy measured using Tencent location data and the built environment factors in this study. The minimum (Min), maximum (Max), mean, and standard deviation (SD) are reported. For instance, the mean overall urban vibrancy on weekdays and holidays in the 1342 grids are 1966.29 and 1829.30 location events, respectively. The minimum, maximum, and mean population densities are 72.41, 64,764.20, 6135.51 persons per km^2, respectively. The average POI mix value is 0.73. The mean numbers of commercial and company POI are 102.77 and 58.65, respectively. The Maximum numbers of bus and metro station are 27 and 13, respectively.

Table 2
Descriptive statistics of urban vibrancy and built environment factors (N = 1342).

Variables (Unit)	Min	Max	Mean	SD
Dependent variables				
Urban vibrancy on weekday (N)	1.00	18,935.00	1966.29	2372.31
Urban vibrancy on holiday (N)	1.33	19,666.67	1829.30	2187.58
Independent variables				
Population density (N/**km^2**)	72.41	64,764.20	6135.51	7814.96
Building coverage area (**m^2**)	0	502,988.00	133,398.40	118,136.50
Building floor area (**m^2**)	0	4,735,020.40	538,996.70	607,757.40
Residential floor area (**m^2**)	0	2,812,706.20	300,173.60	408,442.10
Commercial floor area (**m^2**)	0	1,609,384.26	34,660.46	95,501.30
Office floor area (**m^2**)	0	1,499,292.83	18,854.24	97,521.88
Industrial floor area (**m^2**)	0	945,502.80	152,336.60	177,041.90
Floor area mix (≥**0**)	0	1.51	0.68	0.36
POI mix (≥**0**)	0	1.57	0.73	0.44
Street length (m)	0	20,104.58	5482.40	3829.47
Number of street intersection (N)	0	115	15.33	16.54
NDVI	−0.33	0.76	0.32	0.18
Residential POI (N)	0	234	12.36	21.04
Commercial POI (N)	0	1411	102.77	134.88
Company POI (N)	0	762	58.65	91.47
Public service POI (N)	0	149	10.24	17.24
Recreational POI (N)	0	68	1.74	3.91
Number of bus station (N)	0	27	4.39	4.27
Number of metro station (N)	0	13	0.26	0.83

Note: Min = Minimum; Max = Maximum; SD = Standard deviation; N = Number.

Ordinary least squares (OLS) regression and geographically and temporally weighted regression (GTWR) models were implemented to investigate the association between the built environment variables and urban vibrancy with 32,208 spatiotemporal observations. Table 3 presents the weekday OLS and GTWR model results. The adjusted R^2 of the OLS and GTWR model are 0.298 and 0.426, respectively, for weekday, which indicates that our data fit the non-stationary GTWR model, rather than the static OLS model. The OLS shows that, population density is positively related to urban vibrancy. The building coverage area, and the building floor areas of residential, commercial, office and industrial are negatively related to urban vibrancy. Floor area mix and POI mix are positively related to urban vibrancy. Residential, commercial, company, and public service POI are positively associated with urban vibrancy. The number of metro station also has a positive association. The number of street intersection and NDVI are negatively associated with urban vibrancy.

The GTWR model reveals varying local associations between the built environment factors and spatiotemporal urban vibrancy. The local coefficients of spatiotemporal observations for population density, POI mix, commercial POI, and company POI are positive. The relationships between spatiotemporal urban vibrancy and building coverage area; floor areas of commercial, office and industrial; floor area mix; street intersection; residential, and public service POI; bus station; and metro station fluctuated between negative and positive. Residential floor area, recreational POI, and NDVI are negatively related to spatiotemporal urban vibrancy.

Table 4 presents the regression results for holiday. The adjusted R^2 of the GTWR model is still greater than that of the OLS model (0.395 vs. 0.283), which indicates that the GTWR model has higher goodness-of-fit than the OLS model. The OLS model results show similar relationships between the built environment and urban vibrancy for holiday with weekday, except for commercial, and office floor areas, and floor area mix. The GTWR model holiday results show similar fluctuation of the local associations with weekday.

According to the model results for weekday and holiday, population density; POI mix; POI of residential, commercial, company, and public service; and metro station demonstrate a significantly positive relationship with dynamic urban vibrancy (see the coefficients of OLS, and the local coefficients of GTWR, especially median local coefficients). However, floor area factors, street intersection, NDVI, recreational POI, and bus station are not good predictors for spatiotemporal urban vibrancy.

Fig. 2 shows the temporal average coefficients of the 1342 grids for the built environment variables for 24 timestamps. Overall, the built environment factors exhibit varying temporal average coefficients at different timestamps. First, the temporal average coefficients of population density are positively associated with urban vibrancy, and are relatively high on weekday and holiday (i.e., non-sleep period during 08:00–24:00). The temporal average coefficients of building coverage area, and building floor area factors are generally negative, except for several periods for some factors (e.g., commercial, and office floor areas). Second, the temporal average coefficients of floor area mix are usually positive on weekday, but negative on holiday. The temporal average coefficients of POI mix are positively associated with urban vibrancy and the coefficients on holiday are higher than those on weekday. The coefficients remain high from 10:00 to 24:00. Third, the temporal average coefficients of the number of street interaction for the 24 hourly periods are negative. NDVI has a negative temporal average relationship with urban vibrancy. Fourth, the temporal average coefficients of commercial, company, and public service POI are positively

Table 3
OLS and GTWR model summary results for weekday (N = 1342 grids × 24 timestamps = 32,208).

	Model OLS		Model GTWR					
	β	p value	Local β					Local T value
			Min.	1st Q	Median	3rd Q	Max.	Median
Population density	0.105	<0.001***	0.035	0.084	0.112	0.127	0.169	7.068
Building coverage area	−0.079	<0.001***	−0.175	−0.108	−0.077	−0.040	0.032	2.642
Residential floor area	−0.080	<0.001***	−0.207	−0.115	−0.086	−0.049	−0.008	3.537
Commercial floor area	−0.019	0.009**	−0.088	−0.031	−0.016	−0.008	0.054	1.006
Office floor area	−0.021	0.003**	−0.116	−0.034	−0.022	−0.006	0.057	1.519
Industrial floor area	−0.061	<0.001***	−0.173	−0.103	−0.068	−0.023	0.030	3.296
Floor area mix	0.016	0.010*	−0.010	0.005	0.013	0.022	0.056	1.160
POI mix	0.111	<0.001***	0.034	0.086	0.125	0.146	0.196	8.720
Number of street intersection	−0.048	<0.001***	−0.139	−0.060	−0.040	−0.028	0.022	2.390
NDVI	−0.109	<0.001***	−0.174	−0.129	−0.116	−0.087	−0.038	8.587
Residential POI	0.038	<0.001***	−0.072	0.013	0.033	0.053	0.165	1.588
Commercial POI	0.235	<0.001***	0.039	0.128	0.258	0.334	0.409	13.357
Company POI	0.141	<0.001***	0.049	0.110	0.134	0.163	0.273	5.843
Public service POI	0.185	<0.001***	−0.009	0.065	0.184	0.315	0.403	6.887
Recreational POI	−0.022	<0.001***	−0.057	−0.030	−0.022	−0.016	−0.003	1.689
Number of bus station	−0.002	0.831	−0.058	−0.015	−0.003	0.008	0.081	0.498
Number of metro station	0.013	0.017*	−0.044	−0.004	0.010	0.024	0.071	1.378
Adjusted $\boldsymbol{R}^2$	0.298	<0.001***	0.426					

Note: ***p < 0.001, ** $p < 0.01$, * $p < 0.05$; In the GTWR model, β indicates regression coefficients, and the T value represents the local regression absolute T value.

Table 4
OLS and GTWR model summary results for holiday (N = 1342 grids × 24 timestamps = 32,208).

	Model OLS		Model GTWR					
	β	p value	Local β					Local T value
			Min.	1st Q	Median	3rd Q	Max.	Median
Population density	0.110	<0.001***	0.056	0.091	0.110	0.124	0.189	6.463
Building coverage area	−0.047	0.001**	−0.171	−0.076	−0.036	−0.002	0.053	1.332
Residential floor area	−0.076	<0.001***	−0.168	−0.096	−0.077	−0.059	0.004	2.925
Commercial floor area	−0.014	0.057	−0.088	−0.037	−0.017	0.001	0.065	1.512
Office floor area	−0.013	0.052	−0.113	−0.031	−0.014	0.005	0.075	1.092
Industrial floor area	−0.061	<0.001***	−0.167	−0.090	−0.069	−0.042	0.021	3.038
Floor area mix	−0.001	0.996	−0.038	−0.009	−0.001	0.005	0.037	0.435
POI mix	0.131	<0.001***	0.048	0.113	0.143	0.166	0.206	9.148
Number of street intersection	−0.093	<0.001***	−0.157	−0.106	−0.089	−0.074	−0.038	4.947
NDVI	−0.128	<0.001***	−0.183	−0.149	−0.131	−0.107	−0.052	8.611
Residential POI	0.035	<0.001***	−0.067	0.014	0.030	0.046	0.169	1.391
Commercial POI	0.196	<0.001***	0.066	0.145	0.199	0.253	0.329	9.579
Company POI	0.189	<0.001***	0.078	0.148	0.199	0.229	0.282	8.002
Public service POI	0.118	<0.001***	−0.015	0.075	0.117	0.164	0.275	4.478
Recreational POI	−0.019	<0.001***	−0.048	−0.027	−0.019	−0.012	0.004	1.438
Number of bus station	0.013	0.090	−0.033	−0.001	0.010	0.021	0.082	0.776
Number of metro station	0.023	<0.001***	−0.020	0.005	0.021	0.034	0.081	1.811
Adjusted $\boldsymbol{R}^2$	0.283	<0.001***	0.395					

Note: ***p < 0.001, ** p < 0.01, * p < 0.05; In the GTWR model, β indicates regression coefficients, and the T value represents the local regression absolute T value.

associated with urban vibrancy both on weekday and holiday, and remain relatively high from 10:00 to 24:00. The coefficients of commercial, and public service POI for weekday are generally greater than those for holiday. However, company POI shows the opposite trend for weekday than holiday. The temporal average coefficients of residential POI are usually positive, but fluctuate. Finally, metro station has a positive temporal relationship with urban vibrancy during rush hours (e.g., 10:00–22:00 on holiday).

Overall, population density; POI mix; POI of residential, commercial, company, and public service; and metro station are strong predictors for spatiotemporal urban vibrancy. Fig. 3 displays the spatiotemporal patterns of local coefficients for population density and POI mix for weekday and holiday (and see Appendix for built environment factors of residential, commercial, company, and public service POI; and metro station). The space-time cubes were created in ArcGIS Pro. As the figure shows, the relationships between each built environment factor and urban vibrancy vary spatially and temporally. Particularly, the coefficients of the built environment factor in a single grid vary across the 24 timestamps. Similarly, the correlation strengths of the built environment factor at a single timestamp vary across the 1342 grids. A higher value of the space-time observation value indicates a higher contribution of the built environment to urban vibrancy.

Fig. 4 illustrates the time series clustering of local coefficients for the built environment factors for weekday and holiday, including population density (and see Appendix for built environment factors of POI mix; residential, commercial, company, and public service POI; and metro station). We classified all grids into 10 clusters. Within each cluster, the temporal trends of the local relationships with urban vibrancy are similar. Different clusters have different average local associations between the built environment factor and urban vibrancy, and different temporal trends. The heatmap for the relationship between the built environment and urban vibrancy illustrates the average local coefficient for each cluster at each hour. A higher value indicates a higher contribution of the built environment to urban vibrancy.

5. Discussion

This study extends previous research on urban vibrancy in several

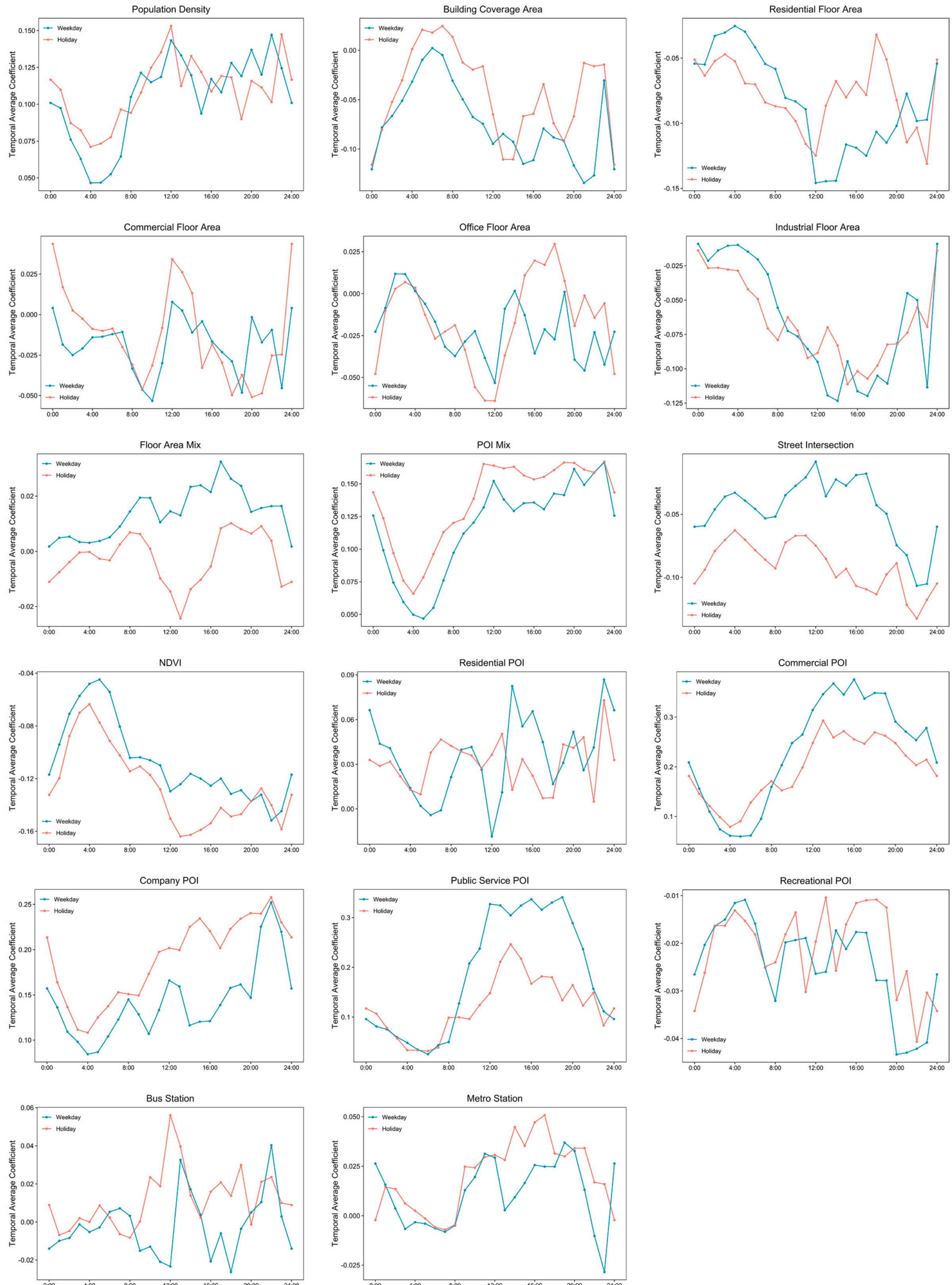

Fig. 2. Temporal average coefficients of the built environment factors.

aspects. First, Tencent location big data, characterized by fine-grained spatiotemporal granularity, was used to portray the real-time human activities at the population level. Second, the spatiotemporal associations between built environment characteristics and urban vibrancy was systematically investigated. The results reveal that the associations between built environment characteristics and urban vibrancy vary both spatially and temporally. Hence, the built environment-urban vibrancy relationship should be treated as dynamic rather than static one.

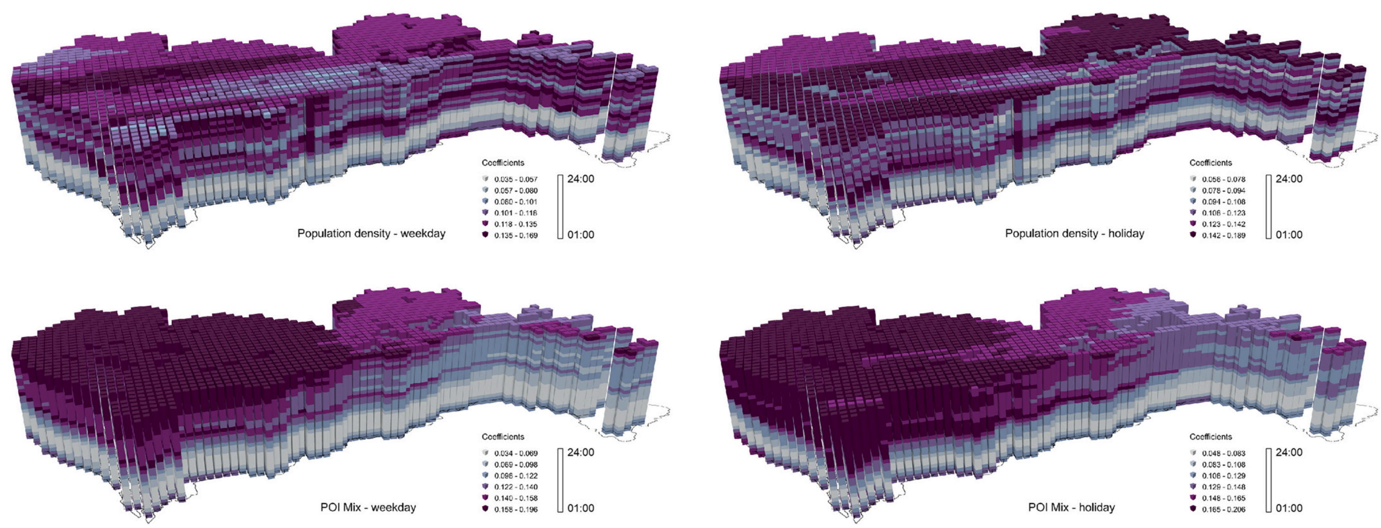

Fig. 3. Space-time cube by local coefficients of the built environment factor (each layer shows data for one timestamp, layers from bottom to top represents hours 1 to 24).

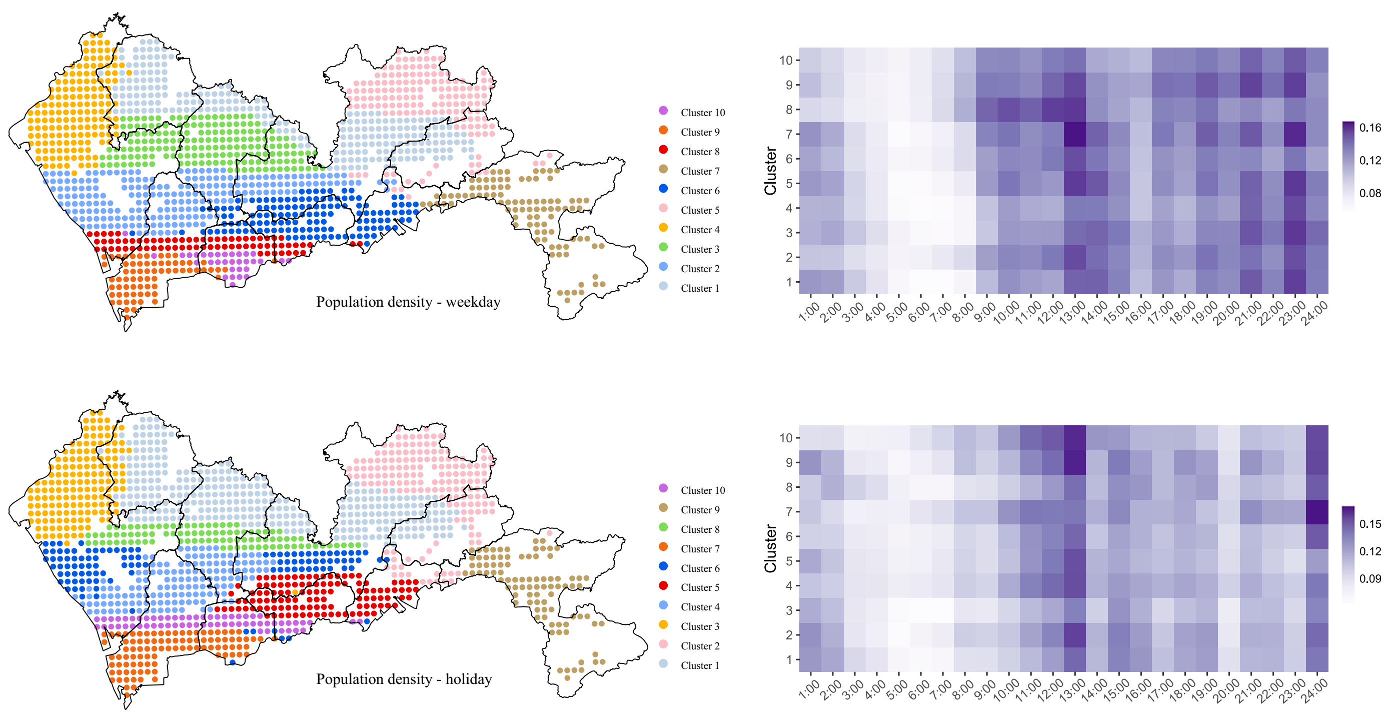

Fig. 4. Time series clustering of local coefficients for built environment factors in the 1342 grids. Areas of the same color in each map represents clustered grids (left figure). Heatmap shows the average local coefficient for each cluster at each timestamp (right figure).

5.1. *Major findings*

We found that urban density, diversity, design, destination accessibility, and distance to transit are associated with the spatiotemporal dynamics of urban vibrancy in Shenzhen, China.

Population density is a good predictor of urban vibrancy, consistent with previous findings (Li, Li, et al., 2021; Wu et al., 2022). The availability of people is the key condition for human interactions and human activities, although it is not the only condition. A higher population density corresponds to higher human activity intensity if other conditions are equal. Both on weekday and holiday, except during sleep hours (i.e., 00:00–08:00), population density is positively associated with urban vibrancy. However, the strengths of the association generally tend to be higher for weekday than holiday. For instance, on weekday, population density contributes more to urban vibrancy from 18:00 to 22:00. The densely populated areas of Shenzhen possibly feature more active behaviors on weekday. Overall, urban areas with a high population density may stimulate urban vibrancy.

Buildings are one of the fundamental urban infrastructures, and are expected to be related to urban vibrancy, as they can accommodate various indoor human activities. However, the results show that neither building coverage area nor building floor area factors are significant predictors of urban vibrancy in Shenzhen. Similarly, the spatial and temporal associations between urban vibrancy and the floor areas of residential, commercial, office, and industrial are generally negative in the whole spatiotemporal observations, except for a few areas. This shows that building density cannot reflect the urban vibrancy in a high-density city. This finding is contrary to that of a previous study on core urban areas in Shenzhen; the study suggested that urban areas with more mid- and high-rise building blocks were more conducive to urban vitality (Ye et al., 2018). Another study found that the building density in Shanghai was positively related to urban vibrancy, while no significant associations existed between vibrancy and building height, suggesting that filling horizontal spaces rather than vertical spaces enhances urban vibrancy (Huang et al., 2019). However, our findings suggest that increasing either horizontal (e.g., building coverage area) or vertical (e.g., building floor area) building spaces may not increase urban vibrancy in Shenzhen. Increasing building density may not be an effective method to promote urban vibrancy in high-density urban context. An area with a cluster of skyscrapers or residential buildings could cause psychological strain, which can hinder urban vibrancy.

Diversity, especially POI mix, is positively related to urban vibrancy. Theoretically, functional diversity is regarded as the primary generator of vibrancy (Jacobs, 1961; Montgomery, 1998). Mixed functional use is important to promote human activity intensity for various purposes (Kang et al., 2020; Liu et al., 2019; Yue et al., 2017). Floor use mix is slightly positively related to urban vibrancy in Shenzhen, especially for weekday. Thus, buildings with a mixed floor space use, including residential and commercial uses, commercial and office uses, and more functional uses, are more vibrant on weekday in Shenzhen. POI mix shows a strong positive impact on urban vibrancy both on weekday and holiday. Our findings on POI mix are consistent with those of previous research based on social media check-in data (Wu, Ye, et al., 2018). Compared with social media data, Tencent location data have stronger associations with POI mix. Furthermore, some established urban areas in Shenzhen (e.g., Luohu, Futian, Nanshan, Baoan district) exhibit stronger relationships of POI mix with vibrancy during 10:00–22:00. Areas with mixed destinations can accommodate various human activities such as working, shopping, catering, and social contact (Wu, Ye, et al., 2018; Yue et al., 2017). Hence, the variety of attractive destinations help to promote urban vibrancy and public participation (Jacobs-Crisioni, Rietveld, Koomen, & Tranos, 2014; Lu et al., 2019; Zarin et al., 2015).

Design factors include the number of street intersection and urban greenery, both of which are negatively related to urban vibrancy in Shenzhen. A higher density of street intersection in Shenzhen may not yield higher urban vibrancy. Our findings disagree with those of some studies that reported a higher number of street intersection resulted in higher urban vibrancy (Huang et al., 2019; Tu et al., 2020; Yue & Zhu, 2019). In a city such as Shenzhen, urban areas with a high street intersection density like residence blocks, urban villages, and industrial and technical blocks may not be vibrant during most of the day. The urban areas with more street intersections in Shenzhen may have lower dynamic urban vibrancy. Moreover, urban greenery has a negative association with urban vibrancy. Shenzhen is a garden city famous for its abundant greenery; however, places with abundant greenery are mostly parks, mountains and the greenbelt area. People prefer mixed-use urban spaces such as commercial and leisure public places. In Shenzhen, areas with high human activity intensity usually have less greenery coverage. This shows that green spaces have not effectively attracted public use. Hence, green spaces should be effectively-integrated into areas with high human activity intensity to increase urban residents' exposure to nature at the population level.

Destination accessibility plays a critical role in enhancing urban vibrancy. This study found that in Shenzhen, the accessibilities of commercial, company, and public service POI are significantly associated with weekday and holiday urban vibrancy. First, urban blocks with more commercial destinations will experience more residents' daily activities such as shopping, catering, and social contact. The finding on commercial POI accords with that of a previous study on Shenzhen based on social media check-in data (Wu, Ye, et al., 2018). Urban residents in Shenzhen possibly engage in more commercial and business activities on weekday. Second, a higher number of company destinations results in more working-oriented activities. Places with more companies can accommodate more people for work and other daily activities. However, company POI has a weaker temporal (10:00–22:00) association with vibrancy on weekday. That is reasonable that such areas in Shenzhen are less vibrant on weekday, because most people are busy at work. Third, more destinations of public service POI such as government service centers, schools, and hospitals may also increase urban vibrancy, especially on weekday. Areas providing political, educational, and medical services could experience high human activity intensity (Liu et al., 2019; Tu et al., 2020; Yue et al., 2017). In addition, different POI destinations in Shenzhen might be mixed with each other in Shenzhen. Their contributions to urban vibrancy might complement each other at different times and spaces. Therefore, urban planners should arrange more functional destinations with mixed use to promote urban vibrancy.

As distance to transit, metro station density is able to predict urban vibrancy. Transportation accessibility is closely related to urban vibrancy. Areas with more metro station in Shenzhen experience higher vibrancy, consistent with the findings of previous research (Tu et al., 2020; Yang, Cao, & Zhou, 2021). The metro stations in Shenzhen may be designed to match the urban areas with higher population density. Moreover, metro stations are often designed near residential, commercial, company, and public service facilities, which tend to be higher-vibrancy spaces (e.g., pilot development urban areas such as Luohu, Futian, and Nanshan District). Moreover, station service areas usually serve as important nodes in the city, with more human activities such as traveling and related activities. Metro station generally shows a higher temporal association with vibrancy on holiday and the rush hours (e.g., 9:00–12:00 and 17:00–21:00 on weekday; 15:00–18:00 on holiday). However, bus station density does not show a significant association with urban vibrancy in Shenzhen, probably because bus stations are universally distributed across Shenzhen.

Furthermore, the non-stationary relationships between built environment factors and urban vibrancy vary both spatially and temporally. For a given location, the association strengths vary with time. Likewise for a given time, the association strengths vary with location. Consequently, different built environment factors might have distinct spatio-temporal relationships with human activity intensity. There are distinctive clusters for the spatiotemporal non-stationary relationships between built environment factors and urban vibrancy. Areas in a cluster may exhibit similar spatiotemporal relationships with built environment factors. Urban planning should be cautious about the built environment design in different clusters. From a spatiotemporal perspective, a uniform design strategy for the whole city may be less effective than expected. Design strategies should be tailored to different clusters to effectively improve urban vibrancy.

5.2. Limitations

This study has several limitations. Only the Tencent location data for urban vibrancy measurement were varied temporally, while built environment characteristics remained stationary. Future studies should consider built environment characteristics with temporal details, such as the opening hours of commercial and public service POI. Moreover, we considered limited contextual factors in the measurement of the built environment using the 5D framework. Furthermore, Tencent location data are largely dependent on electronic devices and mobile phone applications. Such data, although with a wide user coverage and a large representative sample size, omit human activities do not require Tencent apps or mobile phones, which can lead to a biased estimation of urban vibrancy. Future studies should quantify human behaviors that do not require mobile phones (such as walking, shopping, and social interaction). In addition, we measured weekday and holiday urban vibrancy levels using only three days for each. Future studies should depict the urban vibrancy over longer time frames and identify any long-term temporal trends.

6. Conclusion

This study investigated the spatiotemporal patterns between built environment factors and urban vibrancy in Shenzhen using Tencent location-based urban big data. Built environment characteristics were systematically measured using the 5D framework. The spatiotemporal associations were investigated using GTWR models, and spatiotemporal clustering patterns were analyzed through local coefficient time series clustering. The findings revealed that population density, POI factors, and metro station are significantly associated with dynamic urban vibrancy in Shenzhen, while building density, street intersection, and urban greenery are not. The results also showed that POI mix, rather building density, may stimulate urban vibrancy. Moreover, we observed considerable spatiotemporal non-stationary associations between the built environment factors and urban vibrancy. To effectively promote urban vibrancy, urban planners and policy makers should pay more attention to the spatiotemporal effects of built environment characteristics on urban vibrancy, and customized design interventions should be developed for different areas.

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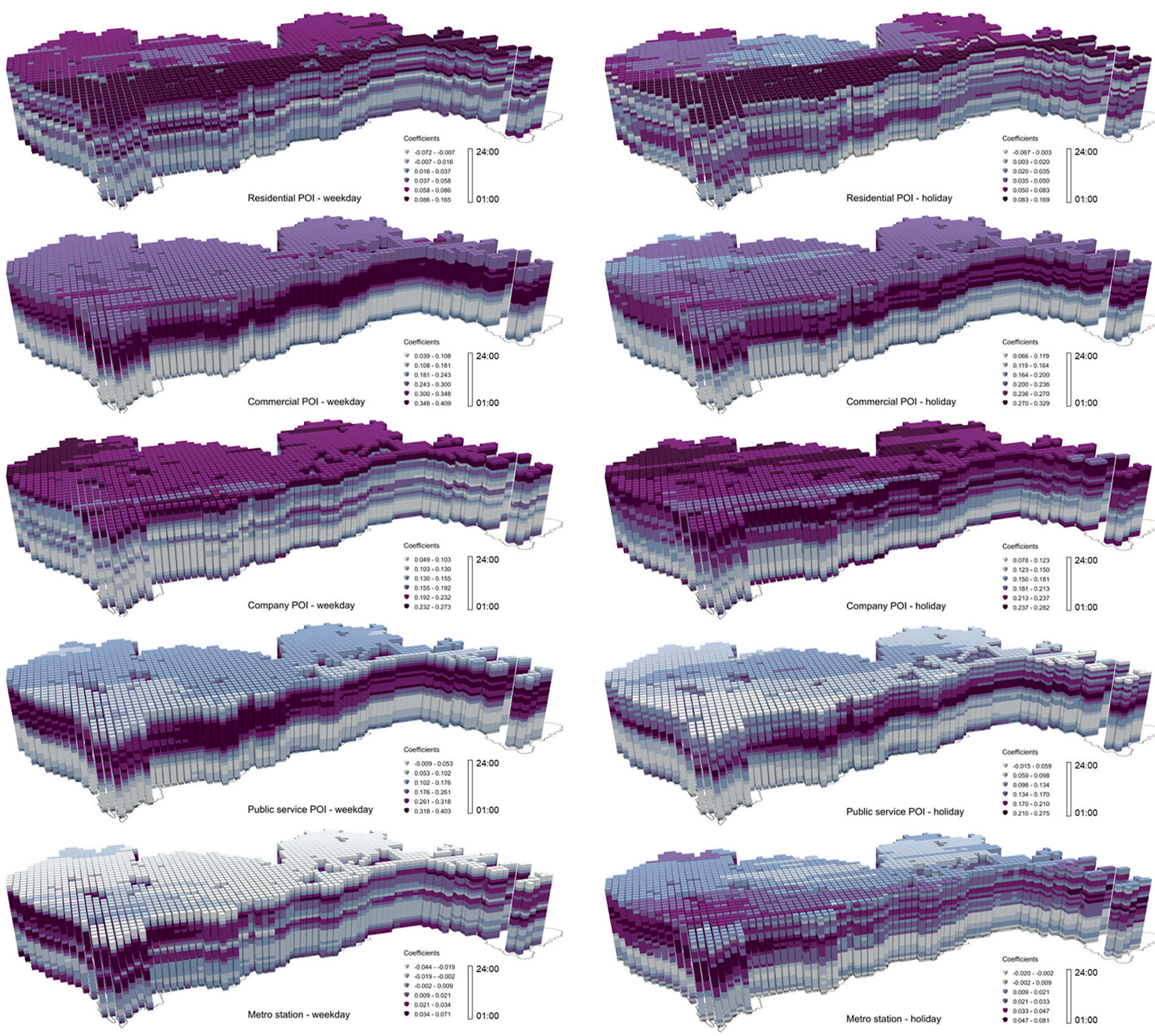
CRediT authorship contribution statement

Long Chen: Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft. **Lingyu Zhao:** Conceptualization, Formal analysis, Writing – original draft. **Yang Xiao:** Writing – review & editing. **Yi Lu:** Conceptualization, Writing – review & editing.

Declaration of Competing Interest

None.

Appendix



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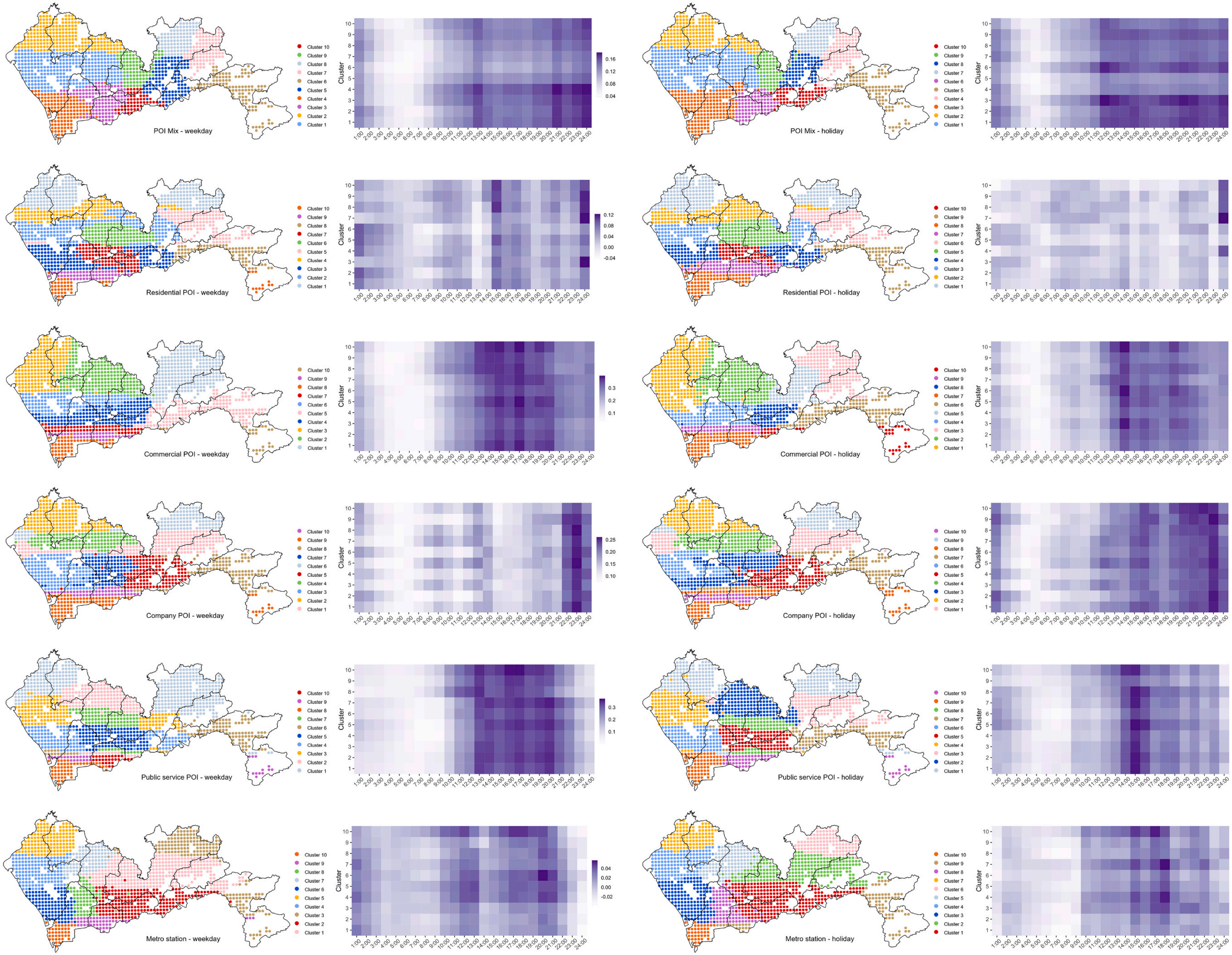

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