Sustainable Cities and Society 88 (2023) 104291

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Using street view images to examine the association between human perceptions of locale and urban vitality in Shenzhen, China

Chao Wu [a,b], Yu Ye [c], Fanzong Gao [a], Xinyue Ye [d,*]

[a] School of Geographic and Biologic Information, Nanjing University of Posts and Telecommunications, Nanjing 210023, China

[b] Smart Health Big Data Analysis and Location Services Engineering Lab of Jiangsu Province, Nanjing University of Posts and Telecommunications, Nanjing 210023, China

[c] College of Architecture and Urban Planning, Tongji University, Shanghai 200000, China

[d] Department of Landscape Architecture & Urban Planning, Texas A&M University, College Station, TX 77843, United States

A R T I C L E I N F O

Keywords:
Human perception
Urban vitality
Random forest
Spatial regression
Spatial-temporal variations

A B S T R A C T

There is a high correlation between the physical environment, human perception, and urban vitality. However, fine-scale variations in urban vitality are complex, and human perceptions of locale are difficult to measure. In this study, EasyGo data provided by Tencent, are used to distinguish differences in daytime and nighttime vitality in Shenzhen, China. Then, a series of subjective and objective variables is calculated to reflect human perceptions of locale based on street view images (SVIs). Finally, random forest and spatial lag regressions are adopted to analyze the driving forces of urban vitality. The results suggest that differences in urban vitality are manifestations of the unbalanced allocation of urban function, accessibility, building form, and human perceptions. The dominant variable category is urban function. There are obvious distinctions between daytime and nighttime vitality, particularly because the human perception category is increasingly important to nighttime vitality. This work sheds light on the relationships between human perceptions and urban vitality, providing suggestions for urban microrenewal and the construction of high-quality streets and liveable communities.

1. Introduction

Urban vitality is an important indicator of city quality (Jacobs, 1961; Lopes & Camanho, 2013; Meng & Xing, 2019). Studies have reported that vitality benefits the daily needs of residents, enables the equitable distribution of facilities, improves people's perceptions, and enhances human interaction and neighbourhood resilience (Lynch, 1984; Sharifi, 2019; Xu et al., 2017). Recently, the construction of public spaces in China has transitioned to an emphasis on quality (Guan et al., 2018). Stimulating urban vitality in the local environment is thus essential to the refinement of urban planning. The intensity of the population at a specific time is often used to quantify the intangible concept of urban vitality (Wu et al., 2018; Yue et al., 2017).

A locale is an outdoor activity space frequently used by residents (Gong et al., 2018). The appearance of a locale can affect human perceptions such as senses of security, beauty and depression (Jia et al., 2022). In turn, human perceptions of a locale can influence residents' preferences for locale selection, leading to spatial differentiation in urban vitality (Kang et al., 2020a; Wu et al., 2022a). However, it is difficult to conduct large-scale and fine measurements of human perceptions of locales due to the limitations of available data and technologies. Recently, artificial intelligence technologies have been combined with street view images (SVIs) to enable the evaluation of human perceptions of locales. This approach quantifies visual elements such as green visibility, sky visibility and pedestrian volume in massive SVI databases through computer image recognition technologies to reflect human perceptions of locales (Chen et al., 2020; Gong et al., 2018; Ye et al., 2019). Previous studies have shown that SVIs can accurately represent residents' experiences and preferences of locales (Amiruzzaman et al., 2021).

Most previous research on the driving forces of urban vitality assumed that there are linear relationships between influencing factors and urban vitality (Wentz et al., 2018). The most commonly used methods, including ordinary linear regression, spatial regression and binomial regression, cannot reveal the nonlinear effects of influencing factors on urban vitality (Huang et al., 2019; Wu et al., 2018; Ye et al., 2018). However, some factors may have a nonlinear effect on urban vitality (Xiao et al., 2021) and ignoring the nonlinear relationships

* Corresponding author.
E-mail address: xinyue.ye@tamu.edu (X. Ye).

https://doi.org/10.1016/j.scs.2022.104291
Received 2 July 2022; Received in revised form 7 October 2022; Accepted 5 November 2022
Available online 7 November 2022
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between them may lead to erroneous conclusions (Wu et al., 2019).

In this study, an analytical framework is designed to overcome the limitations of previous research. Specifically, fine-scale geotagged data, namely, EasyGo data, are adopted to measure urban vitality and distinguish vitality between daytime and nighttime. Then, subjective and objective variables are measured using SVIs to reflect human perceptions of locales, which are used to enrich the influencing factors of urban vitality. Finally, random forest regression (RFR) and spatial lag regression (SLR) are used to identify the driving forces of urban vitality. This work makes the following contributions: (1) it provides an inexpensive and generalized way to measure spatiotemporal variations in urban vitality at fine scales; (2) it promotes the implementation of human-centered urban planning by quantifying human perceptions of locales; and (3) it captures the nonlinear relations between driving forces and urban vitality. This work provides suggestions for urban microrenewal and the construction of high-quality streets and liveable communities.

2. Literature review

2.1. Measurements of urban vitality

Early research focused mainly on the theoretical framework of urban vitality based on information from interviews, surveys, and audits (Azmi & Karim, 2012; Filion & Hammond, 2003; Lynch, 1984; Montgomery, 1998; Zarin et al., 2015). From Gehl (1987) to Lynch (1992) to Montgomery (1998), researchers believed that urban vitality could be defined through diverse human activities and interactions. Therefore, urban vitality was measured by the spatial concentration of human activities. The intensity of the population at a specific time was found to be a basic quantifiable characteristic of urban vitality (Jacobs, 1961). Later scholars focused on the microexpression of urban vitality as reflected mainly in spatial aggregations of human activities (Maas, 1984). Notably, fine-scale temporal dynamics and spatial variations were considered to be important for sensing vitality (Kang et al., 2020a).

Scholars used recently emerging geotagged data, such as social media, Wi-Fi and GPS data, to study various perspectives of urban vitality (De Nadai et al., 2016; Kim, 2018; Wu et al., 2018; Yuan et al., 2018). However, most of these studies failed to consider the dynamics of geotagged data and measured only static urban vitality. Nighttime vitality was often overlooked in previous studies, despite its differences from daytime vitality (Brands et al., 2015; Kim, 2020). Consequently, using reliable and complete data sources to portray the temporal dynamics of urban vitality is necessary.

2.2. Urban vitality and influencing factors

Many scholars explored the influencing factors of urban vitality based on the theories of Jacobs (1961), Katz (1994), Montgomery (1998) and Gehl & Gemzøe (2001). They used diverse variables, including traffic conditions (connectivity and accessibility), facility convenience, point of interest (POI) density and diversity, economic level, location attributes (e.g., distance to the city center), and landscape patterns (Bramley et al., 2009; Sharifi, 2019; Ye & Van Nes, 2014). In response, urban planners gradually adopted strategies for the development of urban forms, including mixed land use, improvement of accessibility and optimization of urban landscape, to stimulate neighbourhood vitality (Chen et al., 2019; Yue et al., 2017). However, an important research gap was that the selected variables ignored the effects of urban design and the physical characteristics of neighbourhoods on resident perception, which could not be directly reflected by objective characteristics (Ewing & Handy, 2009; Ye et al., 2019; Zhou et al., 2019). As Zhang et al., (2018a) noted, locales include not only the physical settings but also the visual appearance of a place; however, visual appearance was rarely included in evaluations of the local environment. Without a sufficient understanding of perceptions of the environment, quantitative variables of urban form could not be effectively used to simulate vitality and design practice (Boeing, 2018; Wentz et al., 2018).

Due to its simplicity and ease of interpretation, the ordinary linear regression model was popular for exploring the relationships between influencing factors and urban vitality (Huang et al., 2019). Ye et al. (2018) revealed urban vitality–form relationships using negative binomial regression. However, these methods failed to reveal nonlinear relationships between factors and urban vitality. Potential interactions and correlations among different variables had nonlinear effects on urban vitality (Xiao et al., 2021). For instance, Yang et al., (2021) reported that the effect of station proximity on vibrancy was nonlinear. To date, nonlinear relationships between factors and vitality have received insufficient attention.

2.3. SVIs for measuring human perceptions

Human perceptions of locales refer to human subjective psychological feelings about and experiences with a place that can be affected by objective scenes (Ordonez & Berg, 2014; Zhang et al., 2018b). Initially, survey methods, including questionnaires and interviews, were primarily used (Quercia et al., 2014), but these approaches could not be applied on a large scale with high efficiency and accuracy. SVI, a new data source, could capture the physical environment of a locale from a three-dimensional perspective, expressing more detailed visual contents at refined scales. Meanwhile, the development of computer vision provided a new method that could rapidly segment images automatically on a large scale. Many studies applied SVIs to quantify human activity, street quality, and environmental comfort (Wu et al., 2020; Ye et al., 2019; Zhang et al., 2018b). The variables retrieved from SVIs were highly correlated with residents' psychology, preferences, and health status (Dai et al., 2021; Kang et al., 2020b; Wang et al., 2019). Furthermore, SVIs could be used to explore human perceptions (such as whether a locale was safe, wealthy or lively) and objective elements (such as housing price appreciation, urban crime and poverty) (Jia et al., 2022; Jiang et al., 2022; Meng et al., 2020; Zhang et al., 2021). Previous studies reported that human perceptions of locales were significantly related to walkability, mobility, and interactions (Ewing & Handy, 2009). However, subjective and objective variables based on SVIs were less likely to be incorporated into analytical frameworks of urban vitality and its influencing factors.

3. Data and methodology

3.1. Analytical framework and study area

To portray the relationships between human perceptions of locale and urban vitality, this study proposes an analytical framework (Fig. 1). Urban vitality is quantified using location-based service (LBS) data. To reflect temporal variations, daytime and nighttime vitality are measured. The influencing factors are classified as accessibility, urban function, building form and human perception (including objective and subjective variables). Finally, RFR and SLR are applied to reveal comprehensive and complex relationships between influencing factors and daytime/nighttime vitality, including the relative importance and quantitative effects of related factors.

Shenzhen, one of the largest megacities in China, is chosen as the study area. There are obvious spatial differences in socioeconomic performance and population distribution in each region of the city. To accurately perceive local variations in vitality, a 500 m grid is used as the analysis unit in this study. For residents engaged in leisure activities, a 500 m distance is walkable via a sidewalk or bike lane (Fan & Khattak, 2008; Yang & Diez Roux, 2012). As this study is based mainly on SVIs to measure human perceptions of the environment, grids without roads and SVIs were removed, resulting in a study area of 4526 grids. The distributions of administrative divisions and grids can be seen in Fig. 2.

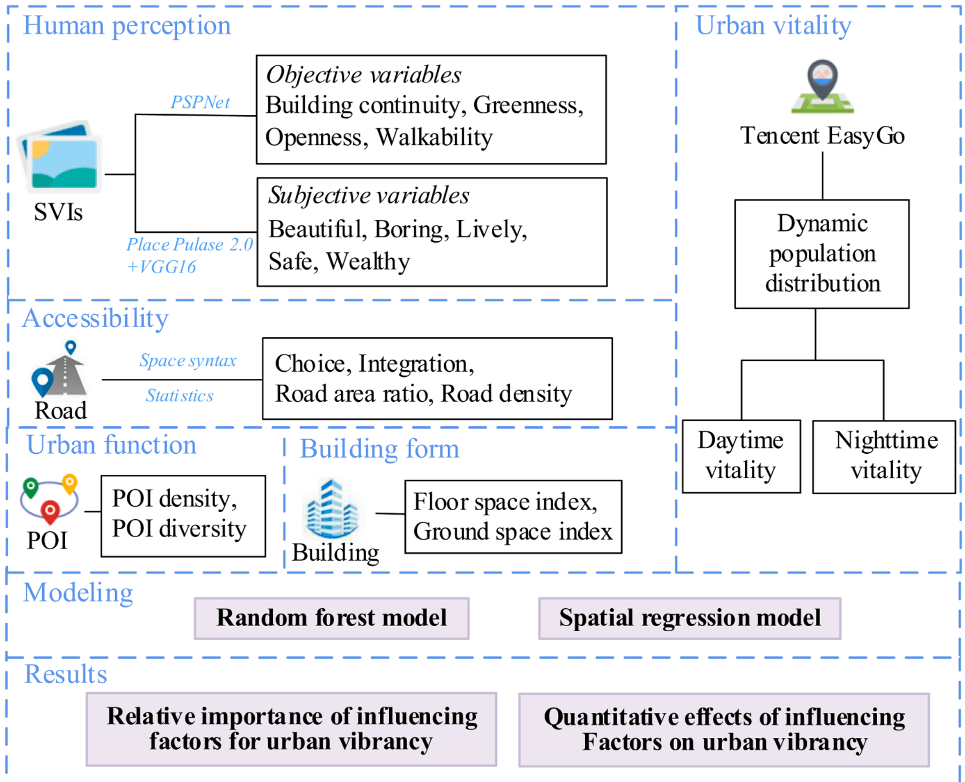

Fig. 1. The analytical framework.

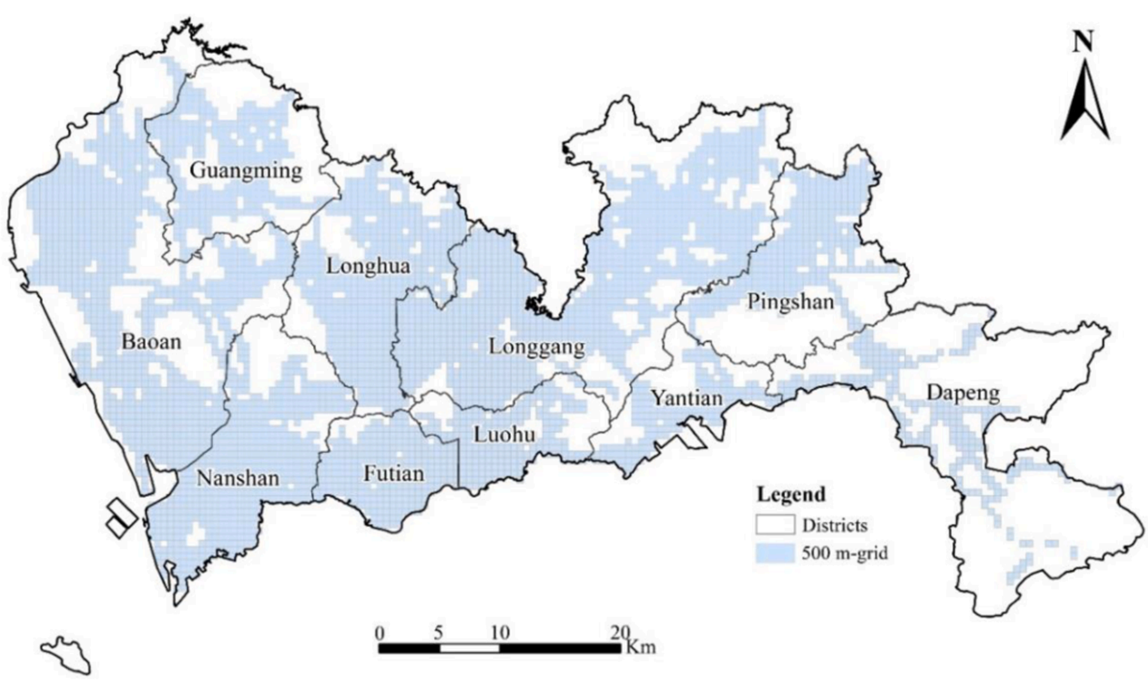

Fig. 2. Shenzhen administrative divisions and 500 m grid.

3.3. Data and variables calculation

(1)Urban vitality

The urban vitality of Shenzhen is quantified using data from EasyGo, an open-access big data platform provided by Tencent WeChat. EasyGo data can be used to reflect real-time density and crowdedness information that is applicable in describing urban vitality. The original spatial resolution of EasyGo data is 25 m. Based on previous studies (Liu et al., 2020; Yao et al., 2017), data for a two-week span, 4 to 17 May 2019, in Shenzhen are obtained with web crawler technology. The real-time density data are aggregated to a 500 m grid at two-hour intervals to represent urban vitality. To measure temporal variations in vitality and differences in influencing mechanisms, this study uses 8 p.m. as the time node to define daytime and nighttime (Vecchi et al., 2007).

(2)Accessibility

Accessibility is important for residents to reach certain destinations, such as schools, workplaces and leisure and entertainment venues. This study focuses on geometric accessibility related to road network centrality and topological relationships based on space syntax (Morales et al., 2019; Ye et al., 2017). Space syntax reflects the accessibility of streets by considering the actual activities of people in the space and people's feelings about spatial structures. Two commonly used indicators, integration and choice, are used to quantify street accessibility based on spatial design network analysis (sDNA, https://sdna.cardiff.ac.uk/sdna/). In addition, the variables of road area ratio and road network density are used to represent transportation convenience.

(3)Urban function

Urban function refers to the residential, commercial, and public uses of an area, which can be calculated using POI data. POI data are obtained from AMap. The most common POI types within a local neighbourhood can be used to determine the function of the locale and assess the vitality of the neighbourhood Liu & Long, 2016). The densities of six types of POIs, residential type, public administration and services, business services, industry, transportation and green spaces, are determined. Moreover, a variable called POI diversity is added to evaluate the mixed-use urban function based on the concept of Shannon entropy. This variable reflects the amount of order in categories and the number of POIs (Yue et al., 2017). POI diversity can be calculated as shown in Eq. ((1):

$$\text{POI diversity} = \exp\left(-\sum_{i=1}^{k} p_i \ln p_i\right) \tag{1}$$

Here, k is the total number of POI categories and p_i is the proportion of the ith category POI in a 500 m grid, which represents relative abundance.

(4)Building form

This study uses the floor space index and ground space index to describe building form. These two indexes represent the exploitation intensity during urban expansion and are measured using building data from Shenzhen Municipal Bureau of Planning and Natural Resources.

(5)Human perceptions

SVIs data is adopted to measure human perceptions of locales. Objective and subjective variables quantifying human perception can directly reflect urban organization and the order of urban form at a refined scale Long & Ye, 2016). SVIs are extracted from Baidu Maps, and each sample point has four directions of view (0°, 90°, 180°, and 270°). The pyramid scene parsing network (PSPNet) using ADE20K datasets is adopted to classify images into scenes (Zhao et al., 2017). The variables of building continuity, greenness, openness and walkability are used to represent the objective environment of a locale. Previous studies showed that blue and green spaces are of great significance for the mental and physical health of residents and the spatial quality of a community (Wang et al., 2021; Yoo et al., 2022). The variables of greenness and openness are calculated in Eqs. (2) and ((3):

$$\text{greenness} = \frac{Number\ of\ Green\ pixels}{Number\ of\ total\ pixels} * 100\% \tag{2}$$

$$\text{openness} = \frac{Number\ of\ Sky\ pixels}{Number\ of\ total\ pixels} * 100\% \tag{3}$$

Five psychological perceptions, beautiful, boring, lively, safe and wealthy, are measured based on the "Place Pulse 2.0" dataset provided by MIT (Dubey et al., 2016). Senses of security and beauty are two basic needs of human beings (McLeod, 2007). Previous studies showed that socioeconomic context (i.e., wealthy) can be represented by urban vitality (Gong et al., 2018; Wu et al., 2022b). Senses of boring and lively can reflect the degree of attraction of a place to residents (Jia et al., 2022), which is directly related to urban vitality. The detailed calculation processes for subjective variables based on SVIs can be seen in Appendix A.

For all the above influencing variables, descriptions and statistical information, including range, mean, and standard deviation (S.D.), are shown in Table 1. In this study, the dependent variables (daytime/nighttime vitality) are natural log transformed, and all variables are normalized using the Z score method. The variance inflation factor (VIF) values corresponding to all independent variables are lower than 10, indicating that there is no obvious multicollinearity among the independent variables.

3.4. Random forest regression

A newly emerging and highly flexible machine learning algorithm, RFR has been widely used to solve classification and regression problems. RFR integrates the "bootstrap aggregation" concept and a "random subspace" method and involves a classifier containing multiple regression decision trees $\{h(x,\theta_k), t = 1,2,3,\ldots,N\}$. Here, N is the total number of decision trees that are independent of each other, θ_k is an independently distributed random variable and x is an input variable. Each decision tree is classified, and the tree with the most classified results is selected to obtain the final results of RFR. RFR is adopted to identify features with significant impacts. The importance scores of influencing factors are evaluated according to the order of the average size of all contributions. To ensure the stability and robustness of the model results, the method of 10-fold cross-validation (CV) is used. The indicators R^2, root mean square error (*RMSE*) and its percentage (*%RMSE*), mean absolute error (*MAE*) and its percentage (*%MAE*) and accuracy (*P*) are used to evaluate model accuracy.

3.5. Spatial lag regression model

Due to spatial variations in urban vitality, SLR, which is a linear regression approach with a spatial autoregressive disturbance, is introduced. SLR uses a spatial lag term to quantify the spatial autocorrelation of the dependent variable. The semilogarithmic form of SLR is as follows:

$$ln(y_i) = \beta \boldsymbol{x_i} + \rho \boldsymbol{w_{ij}} \ln(y_j) + \varepsilon_i \tag{4}$$

where $ln(y_i)$ and $ln(y_j)$ are the logarithmic values of urban vitality for the ith and jth grids, respectively; $\boldsymbol{x_i}$ is the vector form of the independent variables; β is the vector form of the estimated coefficients; $\boldsymbol{w_{ij}}\ln(y_j)$ is the spatial lag term; $\boldsymbol{w_{ij}}$ is used to reflect the spatial neighbor relationship, called the spatial weight matrix; ρ is the estimated coefficient of the spatial lag term; and ε_i is a random error term.

4. Analytical results and discussion

4.1. Spatiotemporal patterns of urban vitality

The relationships between urban vitality and influencing factors can vary greatly between day and night. The methods of bivariate Moran's I are used to explore spatiotemporal patterns of vitality (Anselin et al., 2010). Urban vitality in daytime is selected as the first variable, with nighttime vitality as the second variable. Thus, the results of bivariate Moran's I identify the spatial autocorrelation of vitality at different times. The value of bivariate global Moran's I is 0.506, implying spatial correlations and significant spatial aggregation characteristics associated with urban vitality in the analysis periods. The results are shown in Fig. 3. The high–high areas are distributed mostly in the center of each district, including the Futian–Luohu center, Qianhai center, Longhua

Table 1
Descriptions and statistical information of influencing variables.

Category	Variable	Explanation	Range	Mean	S.D.
Accessibility	Choice	The likelihood of passing through a space.	588,542.252	45,129.042	81,597.061
	Integration	The suitability of a space as a destination to attract arriving traffic, namely, centrality.	87.839	23.905	12.987
	Road area ratio	The proportion of the total area of urban roads to the total area.	97,030.052	18,765.304	14,284.696
	Road density	The ratio of the total distance of the road network to the area.	823.789	204.778	223.512
Urban function	BPOI	The number of business POIs in a 500 m grid.	1233	68	118
	GPOI	The number of green space-related POIs in a 500 m grid.	76	1	2
	IPOI	The number of industrial POIs in a 500 m grid.	512	25	43
	PPOI	The number of public facility-related POIs in a 500 m grid.	358	27	40
	RPOI	The number of residential POIs in a 500 m grid.	115	4	6
	TPOI	The number of traffic POIs in a 500 m grid.	128	9	15
	POI diversity	POI-based mixed use measured by Shannon entropy.	1.696	0.908	0.474
Building form	Floor space index	The proportion of the total floor area characterizing the spatial density of building floors.	14.23	1.06	1.29
	Ground space index	The proportion of the coverage area characterizing the percentage of occupied by buildings.	0.72	0.155	0.12
Human perception	Building continuity	The standard deviation of the proportion of buildings in a grid representing building continuity.	0.375	0.085	0.064
	Greenness	The visibility of greenery based on SVIs.	0.351	0.028	0.020
	Openness	The proportion of visible sky based on SVIs.	0.811	0.428	0.137
	Walkability	The proportion of sidewalk to road.	4.185	0.241	0.206
	Beautiful	Residents' perception of the beauty of a locale.	92.530	30.730	14.595
	Boring	Residents' perception of whether a locale is boring.	84.157	57.421	7.783
	Lively	Residents' perception of whether a locale is lively.	71.609	19.041	7.344
	Safe	Residents' perception of the safety of a locale.	67.543	19.066	10.237
	Wealthy	Residents' perception of the affluence of a locale.	99.043	51.758	13.022

center and Longgang center. Another significant high–high value cluster occurs in the western coastal region. In contrast to the reports in previous studies (Wu et al., 2018), a multicentre spatial cluster structure has gradually formed in Shenzhen.

4.2. Magnitude and relative importance of effects

Moreover, this study uses the RFR method to explore which influencing factors influence urban vitality the most. Table 2 illustrates the performance indicators of RFR results according to the validation dataset. In general, the R^2 values of the two models exceed 0.80, suggesting that the machine learning model based on RFR effectively reflects nonlinear relationships among variables. Fig. 4 shows the order of relative importance of variables. The determinants can be ranked by four categories of influencing factors using average values as follows: urban function (0.059)> building form (0.048)> accessibility (0.045)> human perception (0.035) in daytime and urban function (0.055)> building form (0.050)> accessibility (0.045)> human perception (0.037) in nighttime. Generally, urban function is the major category of factors that influences urban vitality. The urban perception category of factors has increased in importance over time, indicating the need for assessments of locales at the human scale (Zhang et al., 2020). The detailed results of 10-fold CV can be seen in Appendix B.

Specifically, the RFR results reveal different important features during day and night. The first ten factors of relative importance in daytime are IPOI (0.163), BPOI (0.160), integration (0.119), building continuity (0.101), floor space index (0.067), road area ratio (0.049), beautiful (0.046), openness (0.046), POI diversity (0.044), walkability (0.030) and PPOI (0.030). In nighttime, the top ten determinants are BPOI (0.160), IPOI (0.134), integration (0.126), building continuity (0.106), floor space index (0.064), beautiful (0.046), road area ratio (0.043), POI diversity (0.041), wealthy (0.036), ground space index (0.036) and openness (0.033).

A comparison of the two periods indicates that (1) objective variables (0.049 and 0.049) are more important than subjective variables of human perception (0.023 and 0.028). That is, objective variables related to human perceptions overall show stronger explanatory power than the subjective variables of human perception. Objective variables of human perception, including building continuity, greenness and walkability, reflect important perspectives related to urban vitality. SVIs reflect the spatial quality of local places, which is an important factor in promoting population aggregation. (2) The subjective variables of human perception have greater effects on nighttime vitality, which is reflected mainly in the variables of beautiful and wealthy. (3) The most obvious difference between the two time periods is manifested by the largest contributing factors, IPOI and BPOI in daytime and nighttime, respectively. The main purpose of daytime travel is to commute to work, so the most influential variable is IPOI. At night, the impact of BPOI on spatial variations in urban vitality is significantly more important than the effects of other factors, suggesting that during this time, commercial activities have the greatest impact on the lives of residents. (3) The integration level, representing accessibility, displays important effects; notably, the possibility of a local area becoming open is reflected by this variable, and a high degree of freedom can be achieved for both foot and vehicle traffic. (4) GPOI, RPOI and TPOI exhibit less important effects on urban vitality than similar categories, such as greenness and walkability. This result indicates that people's evaluation of the environment is increasingly dependent on human visual perception.

4.3. Relationships between factors and vitality

The ordinary least regression (OLR) and SLR models are calibrated to investigate factors that significantly affect urban vitality. Moran's I values of two dependent variables, vitality in daytime and nighttime, are 0.515 and 0.502, respectively and are statistical significant at 0.01 level. Therefore, it is appropriate to apply the SLR method to explore the influencing mechanisms of urban vitality. The diagnostic information for the regression models, including R^2, RMSE, Akaike information criterion (AIC) and Moran's I values of residuals, is presented in Table 3. The SLR results are characterized by a high R^2, low RMSE and low AIC, which suggests that SLR performs well. The R^2 values in daytime and nighttime are 0.797 and 0.786, indicating that the variables in Table 1 explain 79.7% and 78.6% of variations in urban vitality, respectively. Moreover, the Moran's I test of the SLR residuals indicates that the residuals display a random distribution at the 95% confidence interval. That is, SLR sufficiently explains the relationships between influencing factors and vitality. Fig. 5 shows the predicted values of daytime and nighttime vitality. The distribution trends of daytime vitality and nighttime vitality are consistent, but nighttime vitality is obviously weaker than day time vitality.

Table 4 lists detailed information for the estimated coefficients with corresponding significance levels. Notably, the signs and degrees of the

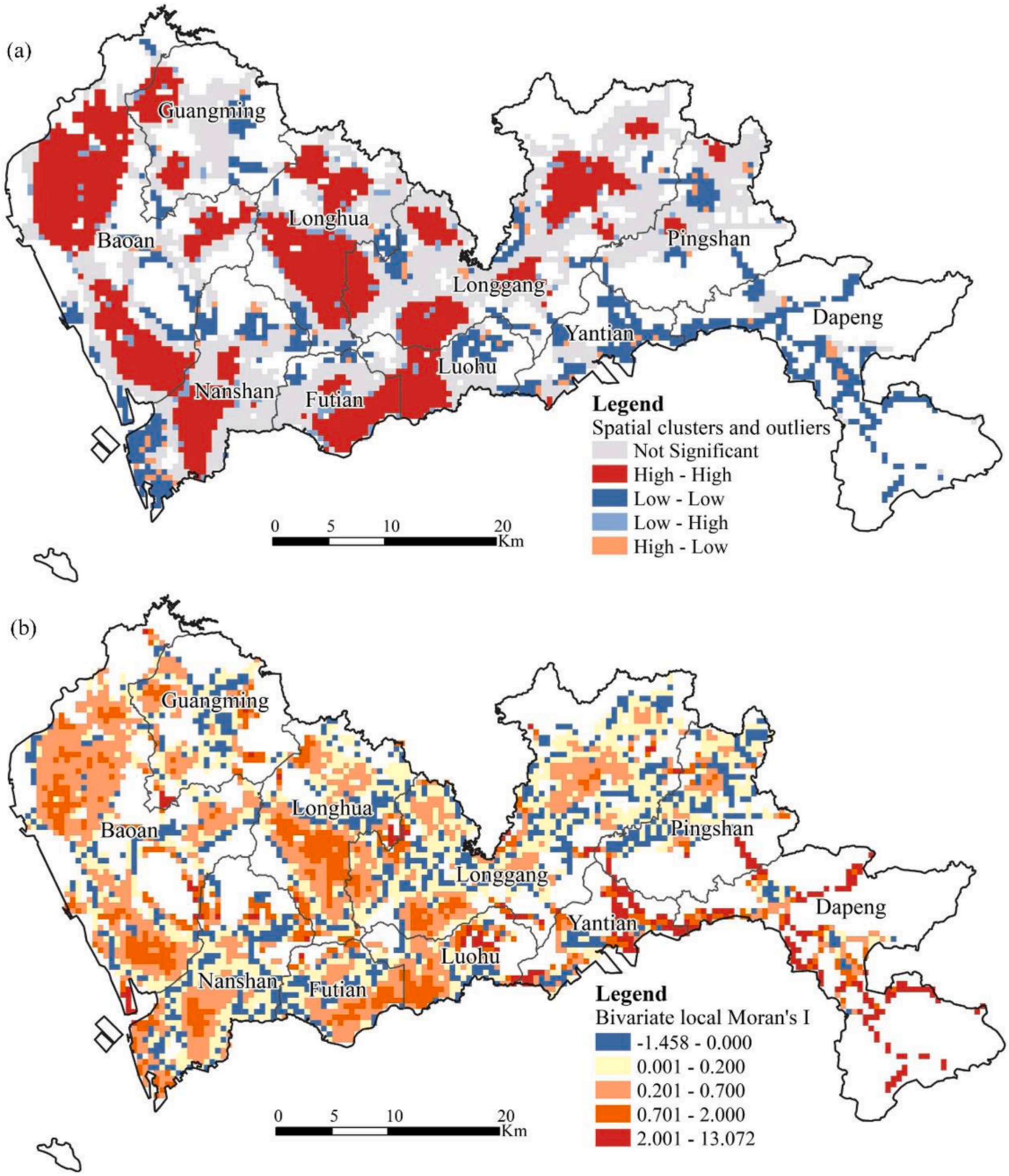

Fig. 3. Results of bivariate local Moran's I.

Table 2
Performance of the random forest regression model in different periods.

	RMSE	%RMSE	MAE	%MAE	*P*	R^2
Daytime	0.288	0.202	0.201	0.131	0.864	0.854
Nighttime	0.332	0.292	0.226	0.123	0.799	0.830

estimated coefficients in daytime and nighttime are similar. The variables choice, lively, GPOI and RPOI are not significant in the daytime activity model. In the nighttime activity model, only the variables choice and lively are not significant. The importance of these variables is also relatively low in the corresponding results of RFR. For the category of accessibility, the variables integration, road area ratio and road density exhibit significant positive effects on improving vitality. Consistent with previous studies, accessibility is a common and important category used to assess local vitality. The more accessible a local place/neighbourhood is, the more likely it is to attract population aggregation. For urban function, (1) the most significant difference is that GPOI and RPOI have no significant effects on urban vitality in the daytime but have significant positive effects on urban vitality at night. (2) The POI diversity variable exhibits the greatest influence among the categories of urban function. Local areas with mixed functions can increase their attractiveness and provide opportunities for people to communicate and interact. (3) BPOI and IPOI also have notable impacts on urban vitality because they can attract residents, enhance the vitality of local places, and improve the development of commerce and industry by concentrating the population. The variables of urban function, especially POI diversity, BPOI, IPOI, can effectively improve the urban vitality.

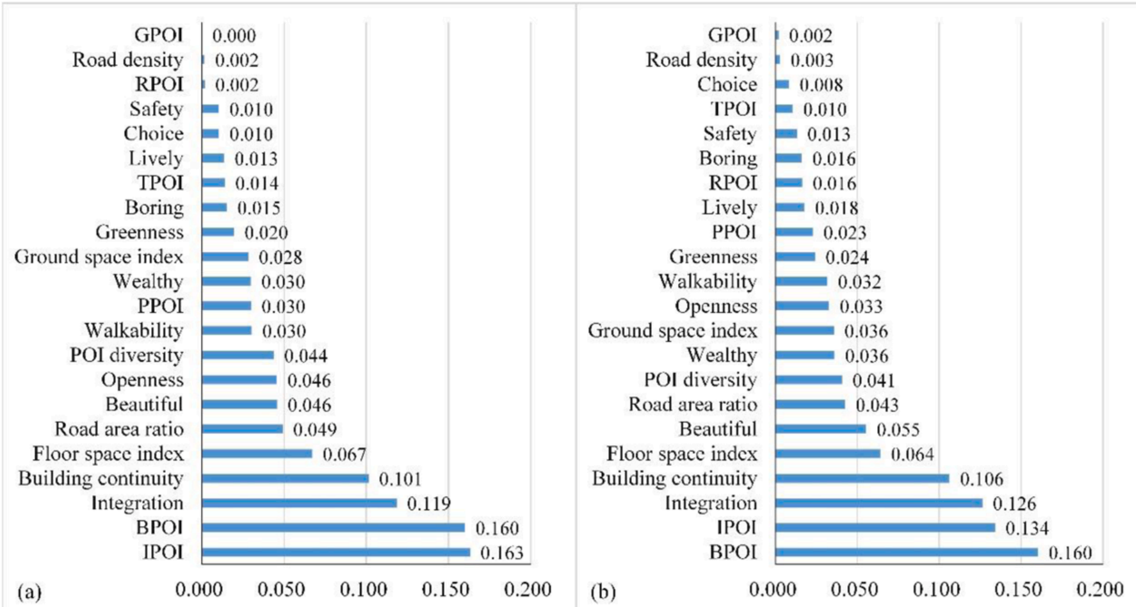

Fig. 4. Relative importance of determinants in daytime (a) and nighttime (b).

Table 3
Diagnostic information for regression models.

	OLR		SLR	
	Daytime	Nighttime	Daytime	Nighttime
R^2	0.739	0.732	0.797	0.786
RMSE	0.391	0.419	0.345	0.375
AIC	4390.77	5016.16	3338.57	4074.3

According to the random forest results, these variables also rank high in importance. For building form, the effects of floor space index and ground space index are statistically significant, while they have a completely opposite relations with urban vitality. The floor space index variable has a negative effect on urban vitality, illustrating that residents tend to travel where the floor area ratio is low. This finding reconfirms that people prefer to live and be active in local environments with low floor space index values because these areas are comfortable and well equipped (Hu et al., 2016). The ground space index variable has a significant positive effect on vitality. That is, the higher the proportion of the ground area of a building is, the lower the vacancy rate and the more ideal the facilities.

For human perception, the objective variables building continuity, greenness, openness and walkability have significant effects on both daytime and nighttime vitality. Notably, greenness, representing space quality, displays a negative effect on vitality. The possible explanations are as follows: (1) residents may not be able to enjoy the greenness of the street (visually or by visiting/using these green spaces during work hours) during the day, and (2) more greenness might be associated with urban peripheral areas or single-functional areas (e.g., parks) that are unsafe at night. A region with high values of building continuity, sky openness and walkability is functional and accessible, which is conducive to boosting urban vitality and improve attractions.

The subjective variables beautiful, boring, safe and wealthy have significant effects on vitality. Beautiful has a negative effect on urban vitality, which is contrary to common sense. The possible explanation is that the urban function of a place perceived as beautiful by residents may be monotonous, which inhibits the occurrence of the street boundary effect and reduces the probability of social interactions. According to Zhang et al. (2018b), the perception of a place as beautiful is related to natural elements rather than objects such as buildings. Especially in the 500 m grid, a beautiful street view indicates a lack of functionality. Our study revealed a significant negative relationship between boring and vitality, which means that residents tend to go to places with a lot of energy. The safe variable shows a positive relation with the vitality, and the effect is greater at night because a safe environment can promote nighttime street vitality. The wealthy variable has a positive effect on urban vitality, which means that increasing the degree of prosperity of locale can be an effective method to improve urban vitality.

5. Summary and policy implications

Human perceptions of locales can affect residents' behaviours and choices. Our research aims to determine the effects of human perception on urban vitality. Taking Shenzhen as an example, we use EasyGo data to systematically measure urban vitality at a fine spatiotemporal scale. SVI are used to measure human perceptions of locales, including objective and subjective variables. The models of RFR and SLR are applied to explore urban vitality at different times as well as the influential mechanisms. The quantitative evaluation of human perceptions of locales and their relationships with urban vitality provides important information on residents' daily lives and can inform government policy making related to liveable communities. The conclusions and policy implications are as follows:

(1) This study considers the temporal characteristics of geotagged data to study differences in daytime and nighttime activity. LBS data based on mobile terminals can accurately perceive the spatial-temporal information when residents interact with the environment. The measurement of urban vitality at night is often neglected in the literature but is important for supporting the development of the nighttime economy and promoting continuous innovation for relevant business strategies.

(2) This study provides a human-centered perspective for measuring how residents percept the local environment. A comprehensive and refined measurement of the local environment based on SVIs can be helpful for human-scale planning practices such as street construction and microrenewal. Human perception should not be ignored when studying urban vitality. Greenness will undoubtedly support a better experience and sense of beauty among pedestrians, but a locale should provide diverse interface elements while ensuring a green view, novel visual experiences and diversified functional experiences for residents. It

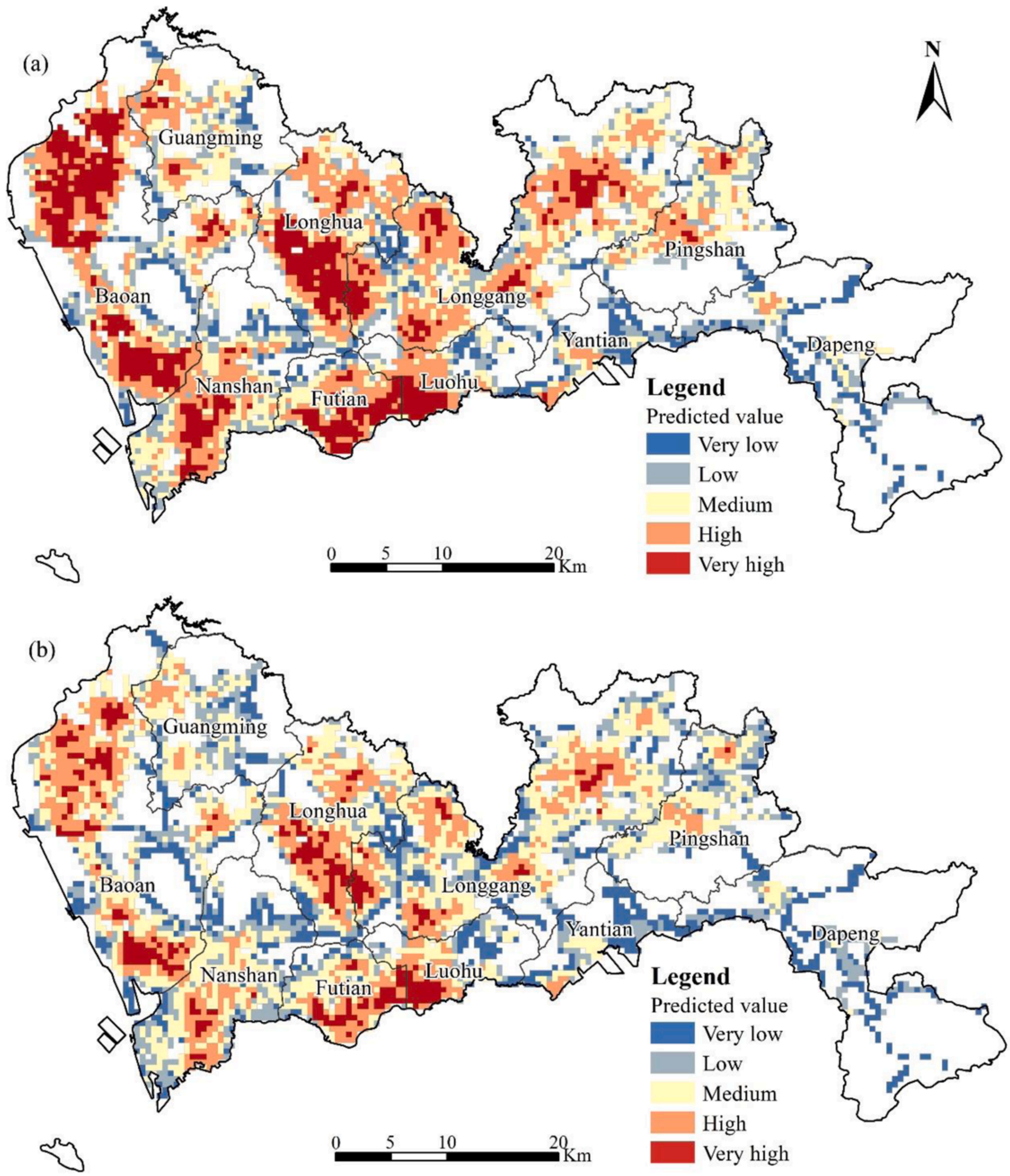

Fig. 5. Predicted values of daytime vitality (a) and nighttime vitality (b).

is necessary to build complete and continuous sidewalks to improve walkability. Improving pedestrian-related attributes of locales may significantly promote walkability and increase urban vitality. At night, residents rely more on their perceptions of the surrounding environment and accessibility. Street safety facilities such as fences and streetlamps, have an extremely important impact on the psychological security of pedestrians. The improvement of safety and accessibility in green public spaces is of great importance for promoting nighttime vitality.

(3) The results of RFR can reveal the relative importance of related factors for urban vitality; however, this topic has rarely been studied. Further research can provide an improved understanding of the building environment and human perceptions of locales and their relationships with vitality. Our findings indicate that objective variables of perceptions have a greater influence on urban vitality than subjective variables. On the one hand, urban planning and design investment in streetscape construction has direct and practical importance for improving urban vitality. On the other hand, subjective perceptions are related to visual scenes but incorporate more sensory information than a single element. Considering that urban function is the most important category, the optimization of urban functions is important for promoting urban vitality. Government departments and planners can cultivate new urban functions through urban renewal so that these functional areas can have a composite effect, and people's diverse demands for physical spaces can then be met.

6. Conclusion

To increase the overall understanding of urban vitality and the influential factors affecting human perception, this study combines machine learning with a spatial regression model to provide a new

Table 4
Estimated coefficients of spatial lag regression in daytime and nighttime.

Category	Variable	Daytime Coefficient	Std. Error	Nighttime Coefficient	Std. Error
	Lag term	0.480***	0.013	0.468***	0.014
	CONSTANT	0.702***	0.020	0.562***	0.017
Accessibility	Choice	−0.001	0.005	−0.002	0.006
	Integration	0.078***	0.008	0.082***	0.009
	Road area ratio	0.042***	0.007	0.032***	0.008
	Road density	0.021***	0.006	0.025***	0.006
Urban function	BPOI	0.075***	0.011	0.084***	0.012
	GPOI	0.001	0.005	−0.013**	0.006
	IPOI	0.073***	0.006	0.042***	0.007
	PPOI	0.037***	0.014	0.057***	0.015
	RPOI	0.001	0.007	0.020***	0.008
	TPOI	−0.071***	0.010	−0.100**	0.011
	POI diversity	0.251***	0.007	0.262***	0.008
Building form	Floor space index	−0.031***	0.007	−0.033***	0.008
	Ground space index	0.043***	0.007	0.050***	0.008
Human perception	Greenness	−0.016***	0.006	−0.013**	0.006
	Building continuity	0.102***	0.007	0.122***	0.008
	Openness	0.054***	0.011	0.061***	0.012
	Walkability	0.056***	0.007	0.063***	0.007
	Beautiful	−0.112***	0.011	−0.116***	0.011
	Boring	−0.017**	0.008	−0.025***	0.008
	Lively	−0.009	0.006	−0.008	0.007
	Safe	0.100***	0.011	0.112***	0.012
	Wealthy	0.020***	0.007	0.024***	0.007

perspective on how human perception affects urban vitality. This work makes three contributions. First, an inexpensive and generalized way to measure temporal variations in urban vitality at fine scales is provided. Second, human perception-related variables, including objective and subjective variables, are incorporated into the study of the influencing mechanisms of urban vitality, which was seldom considered in previous studies. Third, both RFR and SLR are adopted to explore the complex and dynamic relationships between the influential factors and vitality. The findings provide decision-making support for comprehensive evaluations of locales and improvements in urban vitality and thus promote the implementation of human-centered urban planning and management.

This study draws the following main conclusions: The main factors that influence daytime and nighttime vitality exhibit obvious differences. Urban function affects daytime and nighttime vitality more than other factors. Additionally, comprehensive factors are integrated to assess the environment of locales and explore the corresponding effects on urban vitality, leading to novel conclusions that were not discussed in previous studies. To promote urban vitality and optimize urban areas, policymakers and planners should perform research at the human scale and at fine spatiotemporal scales based on geotagged data from multiple sources.

Our study has some limitations. First, to aggregate multisource geotagged data to a unified spatial scale, a 500 m grid is used as the basic analysis unit. There is a certain deviation between this unit and actual morphological feature units. Comparisons of the impacts of different research units would be useful for urban design and planning. In addition, the results may differ for weekdays and weekends, which needs to be studied. Second, this study adopts only population distribution to assess urban vitality; consequently, only a single perspective on urban vitality is considered. Social media data, such as Dianping and Meituan data, and remote sensing data can be used to reflect other perspectives on urban vitality. Finally, in the process of calculating subjective perception scores, a public scoring dataset (Place Pulse 2.0) is used as the training set without considering the cultural background of the volunteers. In the future, volunteers in the city will be organized to evaluate perception scores based on SVIs. The volunteers can depend on their experiences to lead to different results of daytime and nighttime perception according to SVIs.

Conflict of interest and authorship conformation form

Please check the following as appropriate:

X All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.

X This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

Acknowledgments

This work is supported by the National Natural Science Foundation of China (41901326, 52078343), the Natural Science Foundation of Jiangsu Province (BK20190742), Social Science Foundation of Jiangsu Province (21SHC005) and the Scientific Research foundation of Nanjing University of Posts and Telecommunications (NY219036).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2022.104291.

References

Amiruzzaman, M., Curtis, A., Zhao, Y., Jamonnak, S., & Ye, X. (2021). Classifying crime places by neighborhood visual appearance and police geonarratives: A machine learning approach. *Journal of computational social science, 4*(2), 813–837.

Anselin, L., Syabri, I., & Kho, Y. (2010). *GeoDa: An introduction to spatial data analysis handbook of applied spatial analysis* (pp. 73–89). Springer.

Azmi, D. I., & Karim, H. A. (2012). Implications of walkability towards promoting sustainable urban neighbourhood. *Procedia-Social and Behavioral Sciences, 50*, 204–213.

Boeing, G. (2018). Measuring the complexity of urban form and design. *Urban Design International, 23*(4), 281–292.

Bramley, G., Dempsey, N., Power, S., et al. (2009). Social sustainability and urban form: Evidence from five British cities. *Environment and Planning A, 41*(9), 2125–2142.

Brands, J., Van Aalst, I., & Schwanen, T. (2015). Safety, surveillance and policing in the night-time economy:(Re) turning to numbers. *Geoforum; Journal of Physical, Human, and Regional Geosciences, 62*, 24–37.

Chen, L., Lu, Y., Sheng, Q., et al. (2020). Estimating pedestrian volume using street view images: A large-scale validation test. *Computers, Environment and Urban Systems, 81*, Article 101481.

Chen, T., Hui, E. C., Wu, J., et al. (2019). Identifying urban spatial structure and urban vibrancy in highly dense cities using georeferenced social media data. *Habitat International, 89*, Article 102005.

Dai, L., Zheng, C., Dong, Z., et al. (2021). Analyzing the correlation between visual space and residents' psychology in Wuhan, China using street-view images and deep-learning technique. *City and Environment Interactions, 11*, Article 100069.

De Nadai, M., Staiano, J., Larcher, R., et al. (2016). The death and life of great Italian cities: A mobile phone data perspective. In *Proceedings of the 25th international conference on world wide web*.

Dubey, A., Naik, N., & Parikh, D. et al.D(2016).eep learning the city: Quantifying urban perception at a global scale. Paper presented at the European conference on computer vision.

Ewing, R., & Handy, S. (2009). Measuring the unmeasurable: Urban design qualities related to walkability. *Journal of Urban Design, 14*(1), 65–84.

Fan, Y., & Khattak, A. J. (2008). Urban form, individual spatial footprints, and travel: Examination of space-use behavior. *Transportation Research Record, 2082*(1), 98–106.

Filion, P., & Hammond, K. (2003). Neighbourhood land use and performance: The evolution of neighbourhood morphology over the 20th century. *Environment and Planning B: Planning and Design, 30*(2), 271–296.

Gehl, J. (1987). *Life between buildings, 23*. New York: Van Nostrand Reinhold.

Gehl, J., & Gemzøe, L. (2001). New city spaces.

Gong, F., Zeng, Z., Zhang, F., et al. (2018). Mapping sky, tree, and building view factors of street canyons in a high-density urban environment. *Building and Environment, 134*, 155–167.

Guan, X., Wei, H., Lu, S., et al. (2018). Assessment on the urbanization strategy in China: Achievements, challenges and reflections. *Habitat International, 71*, 97–109.

Hu, S., Yang, S., Li, W., et al. (2016). Spatially non-stationary relationships between urban residential land price and impact factors in Wuhan city, China. *Applied Geography, 68*, 48–56.

Huang, B., Zhou, Y., Li, Z., et al. (2019). Evaluating and characterizing urban vibrancy using spatial big data: Shanghai as a case study. *Environment and Planning B: Urban Analytics and City Science*, Article 2399808319828730.

Jacobs, J. (1961). *The life and death of great american cities*. New York: Vintage Books.

Jia, J., Zhang, X., Huang, C., et al. (2022). Multiscale analysis of human social sensing of urban appearance and its effects on house price appreciation in Wuhan, China. *Sustainable Cities and Society*, Article 103844.

Jiang, Y., Han, Y., Liu, M., et al. (2022). Street vitality and built environment features: A data-informed approach from fourteen Chinese cities. *Sustainable Cities and Society, 79*, Article 103724.

Kang, C., Fan, D., & Jiao, H. (2020a). Validating activity, time, and space diversity as essential components of urban vitality. *Environment and Planning B: Urban Analytics and City Science*, Article 2399808320919771.

Kang, Y., Zhang, F., Peng, W., et al. (2020b). Understanding house price appreciation using multi-source big geo-data and machine learning. *Land Use Policy*, Article 104919.

Katz, P. (1994). The New Urbanism. Toward an architecture of community.

Kim, Y. L. (2020). Data-driven approach to characterize urban vitality: How spatiotemporal context dynamically defines Seoul's nighttime. *International Journal of Geographical Information Science, 34*(6), 1235–1256.

Kim, Y. L. (2018). Seoul's Wi-Fi hotspots: Wi-Fi access points as an indicator of urban vitality. *Computers, Environment and Urban Systems, 72*, 13–24.

Liu, W., Wu, W., Thakuriah, P., et al. (2020). The geography of human activity and land use: A big data approach. *Cities (London, England), 97*, Article 102523.

Liu, X., & Long, Y. (2016). Automated identification and characterization of parcels with OpenStreetMap and points of interest. *Environment and Planning B: Planning and Design, 43*(2), 341–360.

Long, Y., & Ye, Y. (2016). Human-scale urban form: Measurements, performances, and urban planning & design interventions. *South Architecture, 36*(5), 39–45.

Lopes, M. N., & Camanho, A. S. (2013). Public green space use and consequences on urban vitality: An assessment of European cities. *Social indicators research, 113*(3), 751–767.

Lynch, K. (1984). *Good city form*. MIT press.

Lynch, K. (1992). *The image of the city, 11*. MIT press.

Maas, P. R. (1984). Towards a theory of urban vitality. *University of British Columbia*.

McLeod, S. (2007). Maslow's hierarchy of needs. *Simply Psychology, 1*, 1–18.

Meng, Y., & Xing, H. (2019). Exploring the relationship between landscape characteristics and urban vibrancy: A case study using morphology and review data. *Cities (London, England), 95*, Article 102389.

Meng, Y., Xing, H., Yuan, Y., et al. (2020). Sensing urban poverty: From the perspective of human perception-based greenery and open-space landscapes. *Computers, Environment and Urban Systems, 84*, Article 101544.

Montgomery, J. (1998). Making a city: Urbanity, vitality and urban design. *Journal of Urban Design, 3*(1), 93–116.

Morales, J., Flacke, J., Morales, J., et al. (2019). Mapping urban accessibility in data scarce contexts using Space Syntax and location-based methods. *Applied Spatial Analysis and Policy, 12*(2), 205–228.

Ordonez, V., & Berg, T. L. (2014). Learning high-level judgments of urban perception. In *Proceedings of the European conference on computer vision*.

Quercia, D., O'Hare, N. K., & Cramer, H. (2014). Aesthetic capital: What makes London look beautiful, quiet, and happy?. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*.

Sharifi, A. (2019). Resilient urban forms: A review of literature on streets and street networks. *Building and Environment, 147*, 171–187.

Vecchi, R., Marcazzan, G., & Valli, G. (2007). A study on nighttime–daytime PM10 concentration and elemental composition in relation to atmospheric dispersion in the urban area of Milan (Italy). *Atmospheric Environment, 41*(10), 2136–2144.

Wang, R., Feng, Z., Pearce, J., et al. (2021). The distribution of greenspace quantity and quality and their association with neighbourhood socioeconomic conditions in Guangzhou, China: A new approach using deep learning method and street view images. *Sustainable Cities and Society, 66*, Article 102664.

Wang, R., Liu, Y., Lu, Y., et al. (2019). Perceptions of built environment and health outcomes for older Chinese in Beijing: A big data approach with street view images and deep learning technique. *Computers, Environment and Urban Systems, 78*, Article 101386.

Wentz, E. A., York, A. M., Alberti, M., et al. (2018). Six fundamental aspects for conceptualizing multidimensional urban form: A spatial mapping perspective. *Landscape and Urban Planning, 179*, 55–62.

Wu, C., Du, Y., Li, S., et al. (2022a). Does visual contact with green space impact housing prices? An integrated approach of machine learning and hedonic modeling based on the perception of green space. *Land Use Policy, 115*, Article 106048.

Wu, C., Peng, N., Ma, X., et al. (2020). Assessing multiscale visual appearance characteristics of neighbourhoods using geographically weighted principal component analysis in Shenzhen, China. *Computers, Environment and Urban Systems, 84*, Article 101547.

Wu, C., Ye, X., Ren, F., et al. (2018). Check-in behaviour and spatio-temporal vibrancy: An exploratory analysis in Shenzhen, China. *Cities (London, England), 77*, 104–116.

Wu, C., Zhao, M., & Ye, Y. (2022b). Measuring urban nighttime vitality and its relationship with urban spatial structure: A data-driven approach. *Environment and Planning B: Urban Analytics and City Science*, Article 23998083221108191.

Wu, X., Tao, T., Cao, J., et al. (2019). Examining threshold effects of built environment elements on travel-related carbon-dioxide emissions. *Transportation Research Part D: Transport and Environment, 75*, 1–12.

Xiao, L., Lo, S., Liu, J., et al. (2021). Nonlinear and synergistic effects of TOD on urban vibrancy: Applying local explanations for gradient boosting decision tree. *Sustainable Cities and Society*, Article 103063.

Xu, Y., Belyi, A., Bojic, I., et al. (2017). How friends share urban space: An exploratory spatiotemporal analysis using mobile phone data. *Transactions in GIS, 21*(3), 468–487.

Yang, J., Cao, J., & Zhou, Y. (2021). Elaborating non-linear associations and synergies of subway access and land uses with urban vitality in Shenzhen. *Transportation Research Part A: Policy and Practice, 144*, 74–88.

Yang, Y., & Diez Roux, A. V. (2012). Walking distance by trip purpose and population subgroups. *American Journal of Preventive Medicine, 43*(1), 11–19.

Yao, Y., Liu, X., Li, X., et al. (2017). Mapping fine-scale population distributions at the building level by integrating multisource geospatial big data. *International Journal of Geographical Information Science, 31*(6), 1220–1244.

Ye, Y., Li, D., & Liu, X. (2018). How block density and typology affect urban vitality: An exploratory analysis in Shenzhen, China. *Urban Geography, 39*(4), 631–652.

Ye, Y., Richards, D., Lu, Y., et al. (2019). Measuring daily accessed street greenery: A human-scale approach for informing better urban planning practices. *Landscape and Urban Planning, 191*, Article 103434.

Ye, Y., & Van Nes, A. (2014). Quantitative tools in urban morphology: Combining space syntax, spacematrix and mixed-use index in a GIS framework. *Urban Morphology, 18*(2), 97–118.

Ye, Y., Yeh, A., Zhuang, Y., et al. (2017). Form Syntax" as a contribution to geodesign: A morphological tool for urbanity-making in urban design. *Urban Design International, 22*(1), 73–90.

Yoo, E.-. H., Roberts, J. E., Eum, Y., et al. (2022). Exposure to urban green space may both promote and harm mental health in socially vulnerable neighborhoods: A neighborhood-scale analysis in New York City. *Environmental Research, 204*, Article 112292.

Yuan, F., Wu, J., Wei, Y. D., et al. (2018). Policy change, amenity, and spatiotemporal dynamics of housing prices in Nanjing, China. *Land Use Policy, 75*, 225–236.

Yue, Y., Zhuang, Y., Yeh, A. G., et al. (2017). Measurements of POI-based mixed use and their relationships with neighbourhood vibrancy. *International Journal of Geographical Information Science, 31*(4), 658–675.

Zarin, S. Z., Niroomand, M., & Heidari, A. A. (2015). Physical and social aspects of vitality case study: Traditional street and modern street in Tehran. *Procedia-Social and Behavioral Sciences, 170*, 659–668.

Zhang, F., Fan, Z., Kang, Y., et al. (2021). Perception bias: Deciphering a mismatch between urban crime and perception of safety. *Landscape and Urban Planning, 207*, Article 104003.

Zhang, F., Zhang, D., Liu, Y., et al. (2018a). Representing place locales using scene elements. *Computers, Environment and Urban Systems, 71*, 153–164.

Zhang, F., Zhou, B., Liu, L., et al. (2018b). Measuring human perceptions of a large-scale urban region using machine learning. *Landscape and Urban Planning, 180*, 148–160.

Zhang, F., Zu, J., Hu, M., et al. (2020). Uncovering inconspicuous places using social media check-ins and street view images. *Computers, Environment and Urban Systems, 81*, Article 101478.

Zhao, H., Shi, J., Qi, X., et al. (2017). Pyramid scene parsing network. In *Proceedings of the IEEE conference on computer vision and pattern recognition*.

Zhou, H., He, S., Cai, Y., et al. (2019). Social inequalities in neighborhood visual walkability: Using Street View imagery and deep learning technologies to facilitate healthy city planning. *Sustainable Cities and Society, 50*, Article 101605.