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Exploring the relationship between landscape characteristics and urban vibrancy: A case study using morphology and review data

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ABSTRACT

Urban vibrancy is a vital component that supports urban form and is dependent on the physical entities in urban landscapes. Thus, the relationship between urban landscapes and urban vibrancy is a major concern for city planners. While existing studies mainly capture mixed land use, density, and accessibility properties of the physical environment, urban characteristics depicted by the city morphologies have seldom been addressed. To fill this gap, a novel framework is proposed in this paper to explore the relationship between landscape characteristics and urban vibrancy. First, research approaches for delineating multi-level urban landscape characteristics – including places, land use, and single and multiple landscape elements – using spatial metrics were analysed. Then, place-based reviews from social media data were applied as proxies to quantitatively measure urban vibrancy. Finally, regression analyses were proposed to assess the relationship between landscape characteristics and urban vibrancy. Satisfactory regression model performances were attained with adjusted R^2 values of 0.65, 0.65, 0.66, and 0.67 at each landscape characteristic level. The results indicate that changes in urban vibrancy are variable and highly dependent on the proposed multi-level characteristics. These findings may provide guidance for city planning and urban landscape design.

1. Introduction

Urban vibrancy is one of the vital elements used in assessing city quality. According to the concept proposed by Jacobs (1961), urban vibrancy is highly affected by a dense concentration of people associated with social and economic activities. Lynch (1984) later considered the influence of the physical properties of a city and suggested that urban morphology – which presents main elements of streets, buildings, and roads and precisely depicts physical forms of cities – is one of the three major components of urban vibrancy, along with urban function and society. Other influential urbanists including Montgomery (1998) and Whyte (1980) have also established new methods of understanding impacts on urban vibrancy. Consequently, from the perspective of social factors, urban vibrancy is regarded as the liveness and variety that are usually variably influenced by social and economic patterns. Meanwhile, from the perspective of physical factors, urban vibrancy is highly affected by the capacity of an area that produces urban space vitality with its physical configurations.

Considering the various social and physical impacts, urban vibrancy analyses are essential for a wide range of applications, such as equalising the spatial arrangement of local facilities (van Lenthe, Brug, & Mackenbach, 2005), improving urban life quality (Jin et al., 2017), and promoting strong connections among social interactions (Krier, 2009). Many studies concerning urban vibrancy research depend mainly on the impacts of social factors. Specifically, such studies have associated urban vibrancy with social life, which is supported by the concentration of size, density and heterogeneity of people (Wirth, 1938). This type of research involves discussions of socioeconomic indicators such as population, employment, and social interactions. For example, Dubin and Sung (1990) determined that the characteristics of neighbours are important determinants of urban vibrancy. Likewise, Montgomery (1995) summarised urban vibrancy as activity, transactions and diversity, which are supported by the city population. Meanwhile, Dougal, Parsons, and Titman (2015) noted the linkage between urban vibrancy and the selection of firm locations. Other factors including pedestrian flow and property yields were also highlighted in the research proposed by Ravenscroft (2000). However, concentration on social factors ignores the influence of the physical landscape characteristics, which support the vital functions of socioeconomics. For city planners, urban landscapes and forms are composed of physical entities that are treated as key factors for urban management and vibrancy promotion. Consequently, to effectively investigate and improve urban vibrancy, a

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deeper understanding of landscape characteristics is required.

From this perspective, urban vibrancy is a term used to assess the physical properties of the cities (He et al., 2018). According to the current research, density, mixed land use, and accessibility are common factors used to analyse urban vibrancy. Based on the accessibility of multiple urban facilities, Smith and Miller (2013) proposed an ecocity model for assessing and improving urban vibrancy. A study proposed by Song, Popkin, and Gordon-Larsen (2013) derived land use diversity as well as street density to quantify urban vibrancy. However, questions regarding how landscape characteristics affect urban vibrancy have not been thoroughly answered because urban vibrancy depends on the physical entities of urban form and landscapes in nature, especially urban morphology, which are substantially associated with social processes (Lefebvre, Kofman, & Lebas, 1996). Thus, the main challenges in urban vibrancy research can be summarised as follows: (1) regardless of the proposed indicators, such as mixed land use and accessibility, there is a lack of a comprehensive delineation of urban landscape and morphology characteristics. (2) Approaches to quantitatively defining urban vibrancy using a proper proxy are necessary. (3) To evaluate the effects of landscape characteristics on urban vibrancy, methodologies aiming to effectively analyse this relationship are required. On this basis, the existing literature corresponding to each challenge is further reviewed and discussed.

For the delineation of urban landscape characteristics, key urban landscape elements, such as streets and buildings, which constitute the physical aspects of the built environment, are considered the basic units for capturing urban morphology. Depicting the morphology of a city has strong effects on analysing social activities (Dempsey, Brown, & Bramley, 2012), urban functions (Xing & Meng, 2018), health care (Frank & Engelke, 2001), and traffic conditions (Zhou & Gao, 2018). These variable applications have established deep linkages between landscape characteristics and the complexity and diversity of dynamic urban processes (Wentz et al., 2018). Therefore, the spatial characteristics of urban landscapes are considered vital elements for promoting urban vibrancy. On this basis, by involving several types of urban elements, Wu, Ta, Song, Lin, and Chai (2018) proposed an urban form index to capture the meaningful characteristics of urban landscapes. Studies have also focused on illustrating how buildings contribute to urban vibrancy: Ye, Li, and Liu (2017) suggested that both topology and density of buildings play significant roles in promoting urban vibrancy; also, the physical and social properties of a building, such as building size and age, must inevitably be addressed to sustain urban vitality (Sung, Lee, & Cheon, 2015). In addition, by integrating multi-sourced geographic data, the dynamic process impact of urban growth patterns on urban vitality has also been investigated (He et al., 2018). However, existing studies focused on only depicting single landscape elements and ignored the interactions of multiple elements. Additionally, the integration of conventional indicators (such as place density and land uses) and characteristics of multiple landscape elements to gain a deeper understanding of urban morphology were not investigated in these studies.

For urban vibrancy quantification, a suitable proxy must be found to accurately measure urban vibrancy. Although traditional data sources, generally derived from surveying and interviewing, can provide detailed information about individuals, this data collection is costly and captures only the static attributes of the population instead of the dynamic patterns. Meanwhile, with the rapid development of communication technology, social media data have provided significant advantages for quantifying urban vitality. This type of data is available and can be obtained in real time, and these data are also capable of capturing dynamic patterns from the individual perspective (Liu et al., 2015). Wu, Ye, Ren, and Du (2018) adopted social media check-ins to identify spatiotemporal patterns of urban vibrancy. Yue et al. (2017) investigated the diversity of points of interest (POIs) and further associated these with urban vibrancy. Studies have also integrated multi-sourced, open big data, and effective measures for vitality quantification were further proposed (Jin et al., 2017; Keler, Li, Mazimpaka, Wang, & Krisp, 2017). Apart from the aforementioned data, place-based reviews, which are generated from the comments of different locations via social media, have great potential to be used to indicate a city's vitality. This type of data solely represents place descriptions related to human activities, and thus, noise data that are contained in other sources of social media data can be avoided. Current applications involving place-based reviews include the detection of tourist attractions (McKenziea and Adamsb, n.d.), geographical boundary delineation of commercial patterns (Rahimi, Mottahedi, & Liu, 2018), and spatial distribution analysis of consumer satisfaction-based commercial facilities (Wang, Wang, Zhao, & Fu, 2018). However, the usability of place-based reviews on urban vibrancy has not been discussed.

For the relationship analysis between landscape characteristics and urban vibrancy, research has been based on qualitative or quantitative approaches. Qualitative methods mainly include field observations and interviews. Filion and Hammond (2003) proposed field surveys for measuring land use with the aim of perceiving the neighbourhood planning evolution. There is also a study in which a series of in-depth interviews were conducted to investigate the visibility of small business communities vital to urban vibrancy (Raco & Tunney, 2010). To assess urban vitality more precisely, much research has been proposed based on quantitative approaches. Linear regression models have been proposed by Yue et al. (2017) to quantitatively establish the linkage between POI-related land use mixtures and urban vitality. To highlight the significance of urban forms, Wu, Ta, et al. (2018) applied multilevel modelling in the comparative studies. Apart from these statistical analyses, typical relationships were also modelled by considering spatial attributes. Wu, Ye, et al. (2018) proposed a geographically and temporally weighted regression to evaluate the linkages between spatiotemporal characteristics and urban vibrancy. Pearson coefficient and bivariate spatial association approaches were also utilised in the quantitative assessment of the relationship between spatiotemporal characteristics and urban vibrancy (Kim, 2018). Although satisfactory results have been obtained, these models are not specifically designed to comprehensively depict landscape characteristics. As a result, only the overall picture of urban landscapes can be modelled in relationship analyses, and detailed characteristics related to landscape elements, which are important to urban planners, cannot be quantitatively measured in nature.

Considering the aforementioned challenges, in this study, a novel framework is proposed to explore the relationship between landscape characteristics and urban vibrancy. The three main contributions of this study are as follows: (1) we comprehensively delineate the multi-level characteristics of urban landscapes by proposing spatial metrics. Four levels of measurements are designed, including places, land use, single landscape elements, and multiple landscape elements. (2) We utilise one type of social media data, namely, place-based reviews, as a proxy and further propose effective measures to quantify urban vibrancy from an individual perspective. (3) Approaches for selecting effective spatial metrics that are capable of representing landscape characteristics are proposed. On this basis, the relationship between multi-level landscape characteristics and urban vibrancy is explored by proposing four linear regression models. The findings of this study have the potential to guide urban planning and urban landscape design.

The remainder of this paper is organised as follows. In Section 2, brief descriptions of the study area and the data sources utilised are provided. In Section 3, the presented methodology used to explore the relationship between landscape characteristics and urban vibrancy is introduced. The results of the experiments are reported in Section 4. In Section 5, the effect of landscape characteristics on urban vibrancy and the limitations of the proposed framework are discussed. Finally, this study is concluded in Section 6.

2. Study area and data sources

As shown in Fig. 1, The study area selected was in the Futian district, Shenzhen, Guangdong Province. This district is considered the political, commercial and cultural centre of Shenzhen, and thus, it could contribute to the city planning to investigate urban vibrancy. Furthermore, the variety of landscape characteristics in Futian provide effective perspectives to depict city morphology.

First, the main roads collected in AutoNavi were utilised to divide the boundaries of parcels, and 411 parcels in total were generated. Second, for characterising city morphologies, we used place related POIs, land use data, and other vector data. In particular, a total of 139,921 POIs containing information about place categories and locations were obtained from AutoNavi via the provided application programming interface (API). After removing non-place related POIs, 139,831 POIs remained. The land use data were provided by the Urban Planning, Land & Resources Commission of Shenzhen Municipality (Municipality Oceanic Administration of Shenzhen). The data were reclassified into four land use classes, including service and public, residential, industrial and commercial land. Other vector data including secondary roads, buildings, green land and water bodies were used. In particular, “other areas” is defined as the remaining regions not covered by buildings, green land and water bodies. Third, for depicting urban vibrancy, a total of 375,518 review data were collected from AutoNavi. In particular, review data refer to the online reviews for many places from social media, such as Yelp and Google Maps. This type of dataset contains the number, position and textual information of reviews of public facilities and thus has potential to reveal urban vibrancy.

3. Methodology

To explore the relationship between landscape characteristics and urban vibrancy, in this study, a novel framework is proposed to measure multi-level landscape characteristics and quantify urban vibrancy using place-based reviews. The overall framework illustrated in Fig. 2 comprises three main components. (1) Delineating multi-level characteristics of urban landscapes. Six data source types, including POIs, land use, secondary roads, buildings, water bodies and green land, are utilised. These data sources are utilised to propose spatial metrics to delineate four levels of urban landscape characteristics, namely, places, land use, single landscape elements and multiple landscape elements (Section 3.1). (2) Defining urban vibrancy. By utilising place-based review data, a density-based measurement is proposed to effectively quantify the vibrancy (Section 3.2). (3) The proposed spatial metrics are evaluated and selected. On this basis, we propose a regression analysis to explore the relationship between landscape characteristics and urban vibrancy (Section 3.3).

3.1. Delineating multi-level urban landscape characteristics with spatial metrics

In this section, we delineate multi-level characteristics of urban landscapes. Generally, four levels are involved, including place, land use, single landscape elements and multiple landscape elements. Based on each level, a variety of spatial metrics are proposed to quantify specific urban landscape characteristics, as reported in Table 1.

3.1.1. Characteristics of places

Because POIs contain information about locations and effective place categories, we utilise place-level spatial metrics based on POIs to especially represent the characteristics of places (Yue et al., 2017). From the perspective of spatial distribution, the density of POIs (DP) in each urban landscape parcel is calculated as one spatial metric. From the perspective of place diversity, the entropy of POIs (EP) is proposed as the second spatial metric. Detailed spatial metric definitions based on the place level are presented in Table 1. In particular, a total of 22 POI categories are effectively reclassified into 17 classes for POI diversity quantification.

3.1.2. Characteristics of land use

Previous studies have conducted a strong linkage between landscape characteristics and land use (Vanderhaegen & Canters, 2017; Xing & Meng, 2018). Thus, land use classes are considered one of the levels of urban landscape characteristics. According to the classification of land use, four spatial metrics are designed, including the percentage of service and public land (PSL), residential land (PRL), industrial land (PIL), and commercial land (PCL) calculated in each urban landscape parcel. These metrics are proposed to capture the spatial arrangement of urban land use, which provides a clue for indicating landscape patterns as well as their mixed uses.

3.1.3. Characteristics of single landscape elements

Urban landscape elements serve as fundamental indicators that constitute the physical configuration of urban forms (Abrantes et al., 2017). Regarding this level, elements are quantified separately using spatial metrics. These elements involving buildings, green land, water bodies, and secondary roads are quantified from the perspective of area, edge, height, and length. On this basis, we use the total area (TAB), number (NB), density (DB), landscape shape index (BLSI) and height of buildings (ABH) for depicting building characteristics (M. Liu, Hu, & Li, 2017). We also propose using the percentage of non-built-up areas (PNA) for characterising green land and water body landscapes and the density of roads (DR) to capture road features. Detailed calculations of these metrics are illustrated in Table 1.

3.1.4. Characteristics of multiple landscape elements

Urban landscape morphologies are significantly influenced by both independent landscape elements and their spatial interactions, which present appropriately relative proportions of each element type in landscape parcels and further show the potential contribution to urban vibrancy. Here, we construct four spatial metrics, including the ratio of POIs and buildings (RPB), the ratio of POIs and other areas (RPO), the ratio of roads and buildings (RRB), and the ratio of roads and other areas (RRO). These metrics are designed to quantify the spatial interactions among POIs, buildings, roads, and other areas, and these metrics provide further clues for city planners to reasonably organise multiple urban landscape elements and contribute to urban vibrancy.

3.2. Defining urban vibrancy

Because individuals determine city dynamics and further contribute to urban vibrancy, one type of social media data, namely, place-based reviews are selected to measure vibrancy. By utilising this type of data, an approach to quantify urban vibrancy is proposed. Specifically, kernel density estimation (KDE) is first applied, considering both the spatial distribution and density of review data (Wu, Ye, et al., 2018). A search radius of 300 m is empirically determined to ensure the consistency of density patterns where review data are intensively distributed. On this basis, the urban vibrancy can be quantified as follows:

$$UV_i = \frac{\sum_{j=1}^{n} f(k)}{A_i} \quad (1)$$

where UV_i is the quantified urban vibrancy in the ith urban landscape parcel. $f(k)$ represents the kernel density in the jth pixel. n refers to the total number of pixels in the ith urban landscape parcel. A_i indicates the total area of the ith urban landscape parcel. In general, the greater the value of UV_i is, the greater the urban vibrancy.

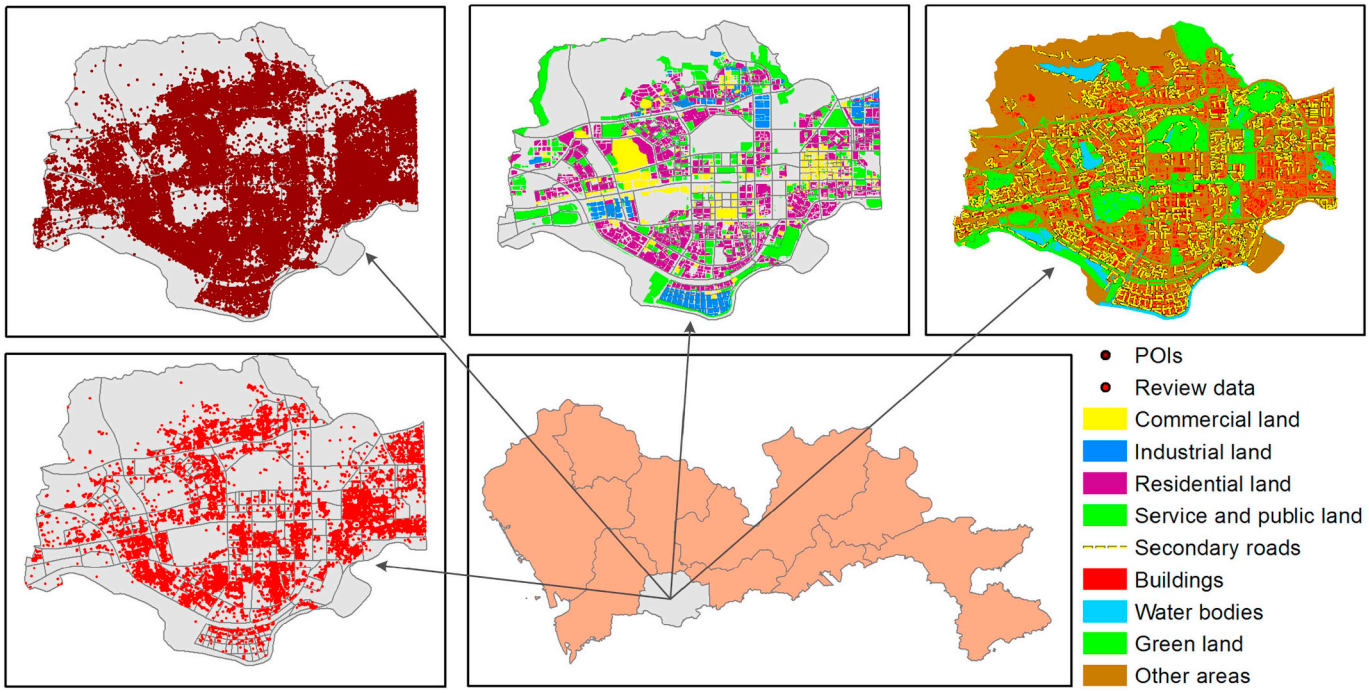


Fig. 1. Study area and data sources.

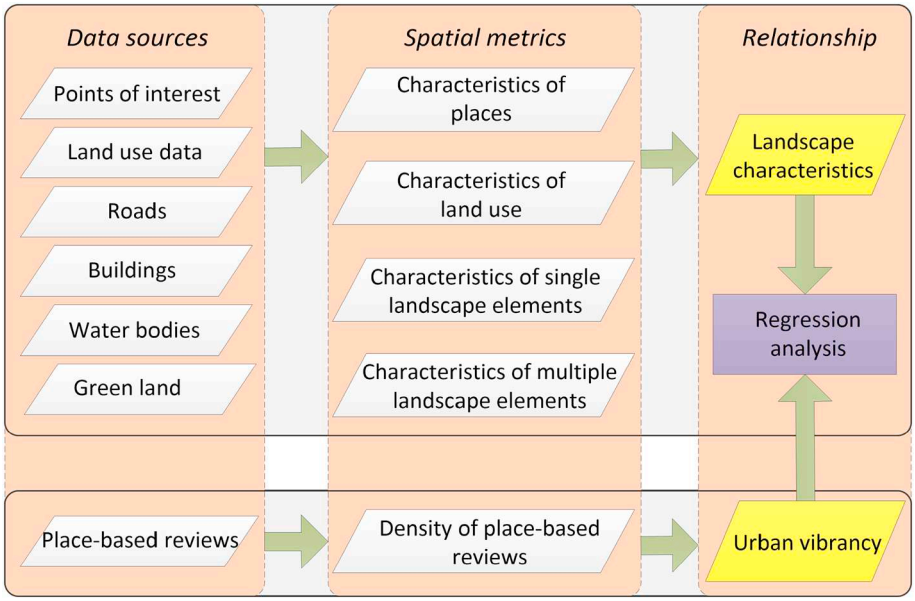


Fig. 2. Framework for examining the relationship between landscape characteristics and urban vibrancy.

3.3. Analysing the relationship between landscape characteristics and urban vibrancy

Linear regression models are proposed to explore the relationship between landscape characteristics and urban vibrancy. In particular, the proposed spatial metrics are considered to be independent variables, whereas the quantified vibrancy is the dependent variable. To analyse the relationship of each urban landscape characteristic level, four models at each level are designed, which are illustrated in Table 2. In particular, spatial metrics that represent only the place level are utilised in model 1. Model 2 involves both place-level and land-use-level spatial metrics. Additional spatial metrics of the single landscape element level are included in model 3. All metrics are considered in model 4.

In addition, to select effective spatial metrics to avoid multicollinearity of the regression models, the tolerance and variance inflation factors (VIFs) of the 17 metrics are calculated, along with the variance proportions within 18 dimensions. Specifically, metrics with tolerance values of < 0.1 and VIF values > 10 should be removed from the independent variables. Moreover, metrics with variance proportions close to 1 are regarded as insufficient variables for regression modelling. As a result, the unqualified spatial metrics will not be considered in the 4 proposed models.

4. Results

4.1. Characteristics of urban landscapes

Four levels of spatial metrics that describe statistical patterns of urban landscape parcels are displayed in Fig. 3. (1) Regarding place-level metrics, the DP statistics indicate a much lower POI density, which is < 0.0002 in approximately 180 out of 411 total parcels, while POIs with higher density cover only a small proportion of parcels. The values of the EP metric vary significantly, with most of the urban landscape parcels contain much larger entropy values, ranging from 2.64 to 3.6. (2) Regarding the urban landscape characteristics of land use, > 200 parcels contain PSL and PRL values < 0.072 and 0.091, respectively. Meanwhile, approximately 380 and 330 parcels are quantified with PIL and PSL values ranging from 0 to 0.057 and from 0 to 0.059, respectively. These statistics reveal that mixed land uses are common in urban landscape patterns. (3) Of the single landscape element descriptors, TAB, NB, and DB, which depict the total area, number, and density of buildings, respectively, exhibit dramatic decreasing trends in parcel number. For BLSI and ABH, there are peak values in the parcel numbers exhibiting increasing and then decreasing tendencies. The two spatial metrics of PNA and DR are designed to depict green land and water bodies as well as roads. More than 250 parcels contain green land and water bodies that are occupied by < 0.071. For road density, the majority of parcels contain DR values within the range of 0–0.025. (4) For multiple landscape elements, RPO values ranging from 0 to 0.006 are obtained in most of the parcels. Parcels with lower values of RPB and RPO contain much higher values of RRB. In addition, compared with other spatial metrics, the final metric, RRO, exhibits a more stable decrease in parcel number in the statistical patterns.

The spatial distributions of the proposed spatial metrics are shown in Fig. 4. (1) Regarding the place-level metrics, parcels with high values of DP are sparsely distributed across the Futian district. However, these parcels contain much lower values of EP. (2) For land-use-level urban landscapes, parcels with higher PSL values are usually located near the boundary of the Futian district. In contrast, parcels containing higher values of PRL, PIL, and PSL are distributed in the inner district. (3) Regarding single landscape elements of urban landscapes, TAB and NB represent a consistent spatial distribution. In particular, the eastern part of Futian (with high PCL values) contains much lower values of both TAB and NB. Meanwhile, high densities of building (DB) exist only in north central, south central and eastern area of residential land, with high-value parcels being similar to those of PRL. Parcels with high BLSI are located around the Futian area, while high values of ABH are sparsely located in central area. In addition, PNA and DR, representing the spatial arrangement of non-built-up area and roads, are distributed unevenly across the area. (4) For characterising multiple landscape elements, parcels with more POIs and fewer buildings (high values of RPB) are generally located in the central and southern parts of the Futian district, whereas the northern part contains fewer POIs than the building-occupied regions. The spatial distribution patterns of RPO are similar to those of RPB, especially the parcel distribution with lower RPO values. The patterns of RRB are similar to those of TAB, NB and BLSI, while RRO exhibits the opposite patterns.

4.2. Spatial patterns of urban vibrancy

Urban vibrancy was measured through the kernel density of place-based reviews. As shown in Fig. 5(a), dark red colours, representing high values of kernel density, are clustered separately in the centre, southwest, and southeast of Futian district. On the other hand, light red colours, which represent low values of kernel density, are distributed continuously among the “attractive hotspots” (areas in dark red). To capture the variation in kernel density, urban vibrancy is quantified utilising Eq. (1). The spatial distribution of the urban vibrancy is displayed in Fig. 5(b). Finally, based on the quantified spatial metrics and calculated density of place-based reviews, the relationship between the landscape characteristics and urban vibrancy will be analysed in the following section.

4.3. Analysis of the relationship between landscape characteristics and urban vibrancy

To evaluate and select spatial metrics to effectively depict the landscape characteristics, 17 metrics used as independent variables were calculated, along with tolerance and VIF values. While most of the metrics have tolerances > 0.1, DR and RRO have tolerance values of 0.085 and 0.091, respectively. To further assess the usability of DR and RRO, these two metrics were also evaluated using the VIF. The VIF values are > 10 (11.750 and 10.947 for DR and RRO, respectively), indicating DR and RRO do not contribute to the relationship analysis. Thus, both of these metrics were removed from the independent variables and were not considered for depicting landscape characteristics.

Moreover, the variance proportions of the 17 spatial metrics were calculated. In particular, 18 variance proportion dimensions were calculated for each spatial metric. Generally, spatial metrics that contain proportions close to 1 will not be accepted as independent variables. Based on this, three proportion values were chosen, including the EP value of 0.94 in the 18th dimension, the DR value of 0.95 in the 17th dimension, and the RRO value of 0.96 in the 17th dimension. These results reveal that three spatial metrics, i.e. EP, DR, and RRO, do not contribute positively to the regression model. In addition, the evaluation of DR and RRO indicates consistent results among the tolerance and VIF values.

Because EP, DR, and RRO were not considered in the delineation of landscape characteristics, the remaining 14 spatial metrics along with the quantified urban vibrancy were utilised to build linear regression models. The results of four regression models are reported in Table 3. The beta coefficient of each spatial metric was calculated to build the relation between landscape characteristics and urban vibrancy. The performances of the four models were evaluated using five indices: F value, R^2, adjusted R^2, the Akaike information criterion (AIC) and Bayesian information criterion (BIC). In particular, models 1, 2, 3, and 4 have F values of 772.15, 156.33, 74.17, and 59.03, respectively. In addition, with multi-level spatial metrics included in the models, the four models have R^2 values of 0.65, 0.66, 0.67, and 0.68. The adjusted R^2 values are 0.65, 0.65, 0.66, and 0.67. Although the R^2 and adjusted R^2 increase slightly from model 1 to model 4, the relatively high values ensure the performance of the linear regressions. Moreover, the four regression models were assessed using the AIC and BIC, as indicated in the notes to Table 3.

The regression models were further analysed to explore the effects of landscape characteristics on urban vibrancy. From the beta coefficients of model 1, it can be deduced that regardless of the POI diversity, higher POI densities tend to contribute to urban vibrancy. For the land use characteristics in model 2, both PRL and PIL exhibit negative effects on urban vibrancy. In other words, urban landscape parcels containing more areas of residential land and industrial land do not increase urban vibrancy. On the other hand, parcels with a higher percentage of commercial land as well as service and public land (i.e. PCL and PSL) tend to attract more people. Considering the single landscape elements in model 3, the total area and density of buildings (TAB and DB) exhibit positive effects on urban vibrancy, whereas the number, shape, and height of buildings as well as the occupation of green land and water bodies have the opposite impact on urban vibrancy. For the multiple landscape elements in model 4, higher values of both RPB and RPO have the potential to improve urban vibrancy. Meanwhile, high values of RRB tend to decrease the impact of attracting individuals.

It should be noted that by calculating the standardised beta coefficient, spatial metrics including density of POIs (DP) and density of buildings are significant for evaluating urban vibrancy. However, other spatial metrics do not have significant standardised beta coefficients,

Table 1
Definitions of landscape metrics used for analysing urban vibrancy.

Level	Landscape metrics (abbreviation)	Definition
Place	Density of POIs (DP)	The number of POIs divided by the area of each urban landscape parcel; the higher the ratio is, the higher the density.
	Entropy of POIs (EP)	The entropy of POIs in an urban landscape parcel $Entropy(L_j) = -\Sigma_{i=1}{}^{c}P_i \ln(P_i)$, where L_j is the jth landscape parcel L, c is the total number of POI categories, and P_i is the proportion of POIs belonging to the ith category.
Land use	Percentage of service and public land (PSL)	The area of service and public land divided by the total area in an urban landscape parcel; the higher the ratio is, the higher the percentage.
	Percentage of residential land (PRL)	The area of residential land divided by the total area in an urban landscape parcel; the higher the ratio is, the higher the percentage.
	Percentage of industrial land (PIL)	The area of industrial land divided by the total area in an urban landscape parcel; the higher the ratio is, the higher the percentage.
	Percentage of commercial land (PCL)	The area of commercial land divided by the total area in an urban landscape parcel; the higher the ratio is, the higher the percentage.
Single landscape elements	Total area of buildings (TAB)	The total area of buildings in an urban landscape parcel.
	Number of buildings (NB)	The total number of buildings in an urban landscape parcel.
	Density of buildings (DB)	The number of building divided by the area of each urban landscape parcel; the higher the ratio is, the higher the density.
	Landscape shape index of building (BLSI)	The landscape shape index of buildings *BLSI* in an urban landscape parcel $BLSI = \frac{\sum_{i=1}^{n} E_i}{2 * \sqrt{\pi \sum_{i=1}^{n} A_i}}$, where n is the total number of buildings and E_i and A_i are the edge and area of the ith building, respectively.
	Average building height (ABH)	The average building height *ABH* in an urban landscape parcel $ABH = \frac{\sum_{i=1}^{n} H_i}{n}$, where n is the total number of buildings and H_i is the height of the ith building.
	Percentage of non-built-up areas (PNA)	The area of non-built-up areas (i.e. green land and water bodies) divided by the total area in an urban landscape parcel; the higher the ratio is, the higher the percentage.
	Density of roads (DR)	The number of secondary roads divided by the area of each urban landscape parcel; the higher the ratio is, the higher the density.
Multiple landscape elements	Ratio of POIs and buildings (RPB)	The total number of POIs divided by the TAB in an urban landscape; the higher the value is, the higher the ratio.
	Ratio of POIs and other areas (RPO)	The total number of POIs divided by the total area of other areas in an urban landscape; the higher the value is, the higher the ratio.
	Ratio of roads and buildings (RRB)	The total number of secondary roads divided by the TAB in an urban landscape; the higher the value is, the higher the ratio.
	Ratio of roads and other areas (RRO)	The total number of secondary roads divided by the total area of other areas in an urban landscape; the higher the value is, the higher the ratio.

Table 2
Variables used in the four models (DR for density of place-based reviews).

Variables	Model 1	Model 2	Model 3	Model 4
Place-level metrics	√	√	√	√
Land-use-level metrics		√	√	√
Single landscape element level metrics			√	√
Multiple landscape element level metrics				√
Urban vibrancy	√	√	√	√

and the insignificant variables do not significantly predict the urban vibrancy. This result may be caused by the spatial heterogeneity of review data. Moreover, as landscape characteristics only partially influence urban vibrancy (socioeconomic factor should also be considered), solely considering urban landscapes can lead to unsatisfactory results. Further discussions are reported in Section 5.2.

5. Discussion

5.1. Effects of landscape characteristics on urban vibrancy

In this study, we have proposed a framework that systematically describes the main features of both urban landscapes and vibrancy. Based on the above experiments, the main findings, referring to the positive relationship between landscape characteristics and urban vibrancy, satisfy the goal of this study and make the following contributions:

(1) Delineated landscape characteristics from multi-level perspectives. In particular, place-level landscapes describe the quantity and diversity of urban facilities. Single-element-level landscapes depict how the main elements, including buildings, roads, green land and water bodies, construct urban landscapes. On this basis, multiple-element-level landscapes reflect how the combination of these elements shape the urban landscapes.
(2) Quantified urban vibrancy from commercial human activities. By utilising place-based review data, we have shown that urban vibrancy can be measured from an available commercial data perspective. In particular, the proposed measures well describe the dense concentration of people and its spatial distinctions. The results indicated that high degree urban vibrancy is related to different urban functions, namely, the central regions of Futian with public functions, eastern part with commercial functions and western areas with residential lands. Since different urban functions reflect various morphologies, it is promising to find that landscapes have significant impacts on urban vibrancy.
(3) Explored the effects of landscape characteristics on urban vibrancy. The findings reveal that place-level landscapes are one of the major factors that increase city attractiveness and urban vibrancy. Land-use-level landscapes indicate that commercial and public lands exhibit positive effects, while residential and industrial lands have negative impacts on urban vibrancy. This result is consistent with the published findings by Yue et al. (2017) that land use mixtures can influence city vitality. The main findings regarding single-element-level landscapes are that a high density of buildings improves urban vibrancy, while a high landscape shape index of buildings or percentage of non-built-up areas decreases urban vibrancy. At the multiple-element level, more urban facilities within less buildings and other areas help attract more people regardless their specific urban functions. In contrast, distributions of more roads among buildings tend to decrease urban vibrancy.
(4) Provided effective guidance for urban landscape designing and city planning. For example, the analysis shows that the density of urban

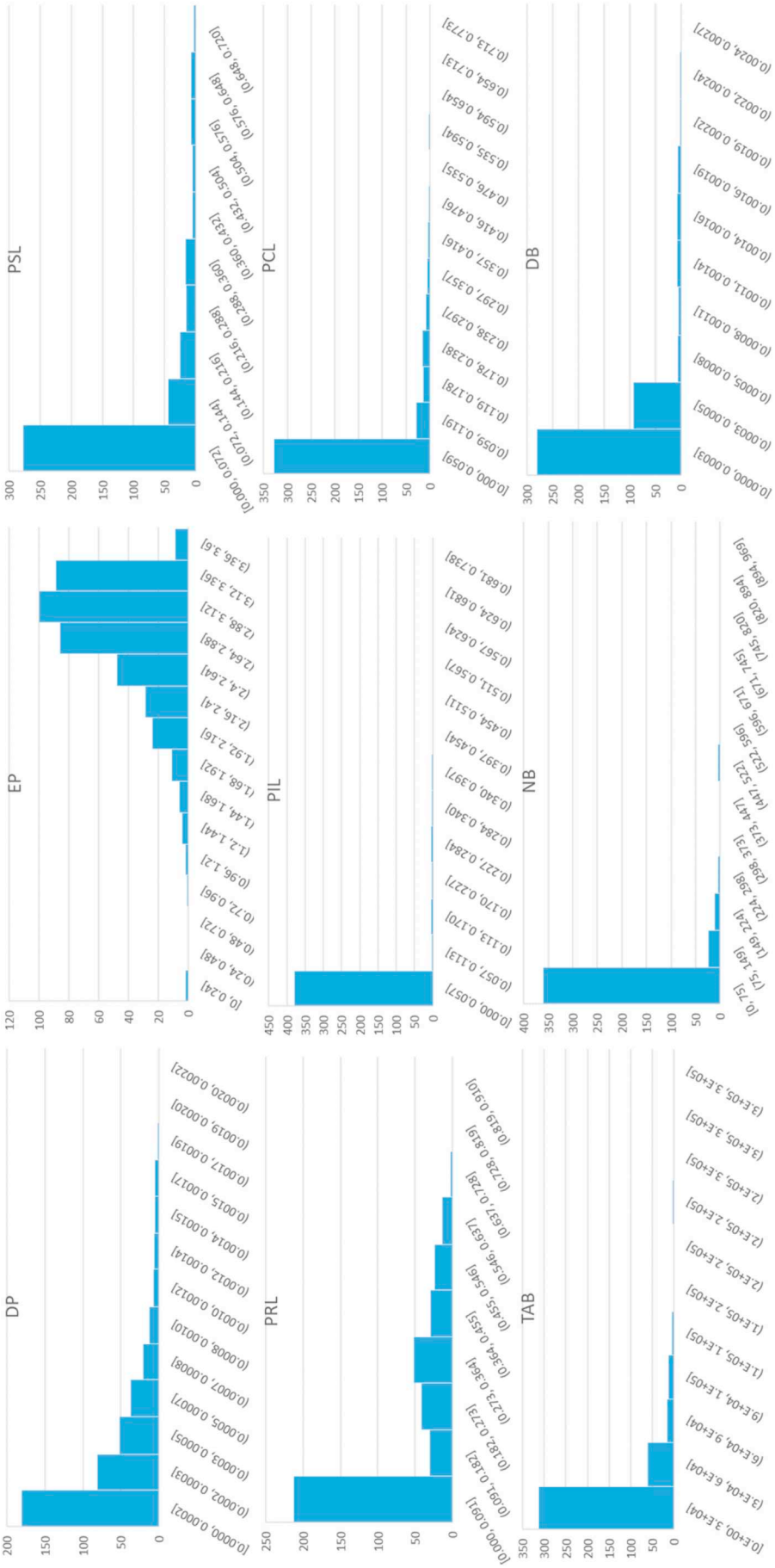


Fig. 3. Statistical patterns of urban landscapes.

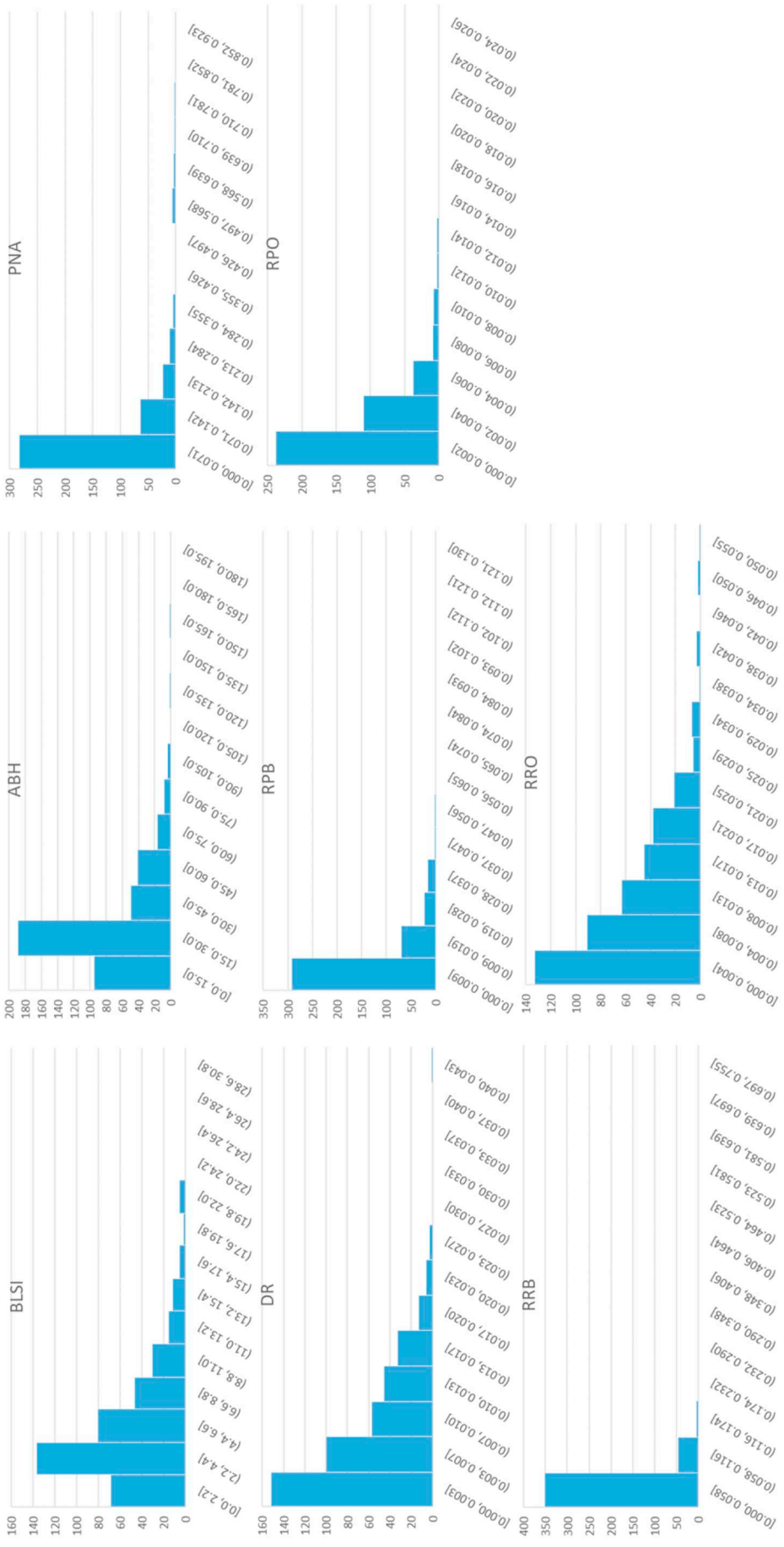


Fig. 3. (*continued*)

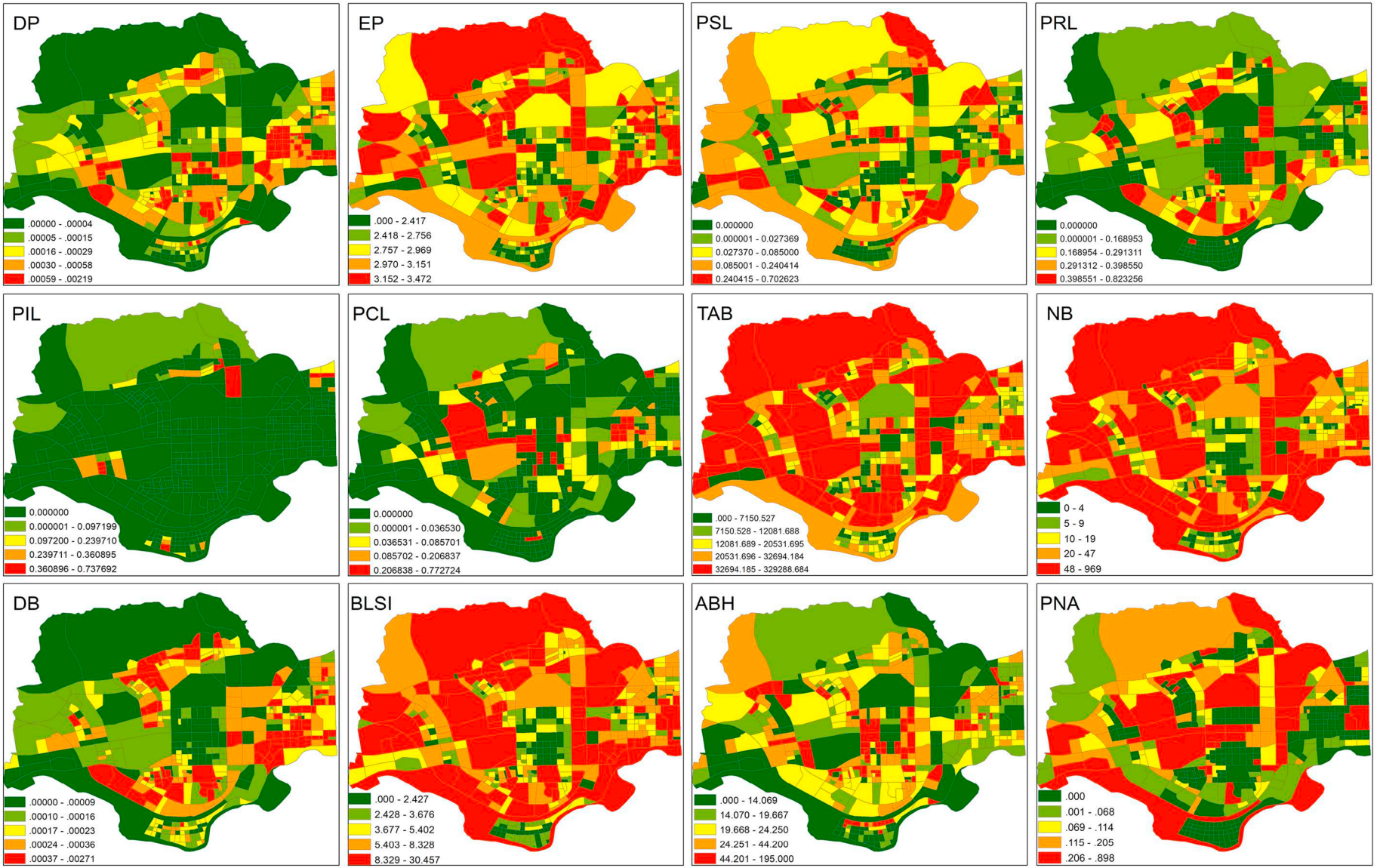


Fig. 4. Spatial distribution of urban landscapes.

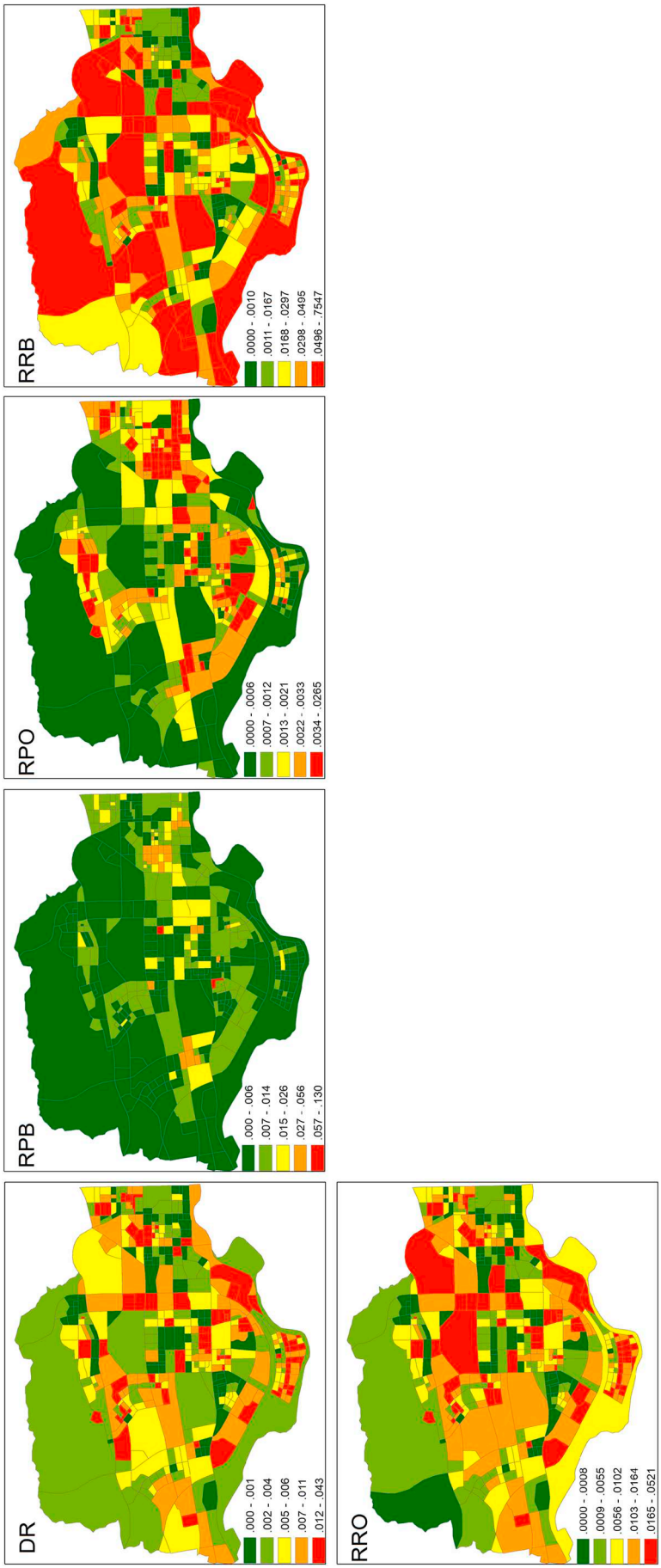


Fig. 4. (*continued*)

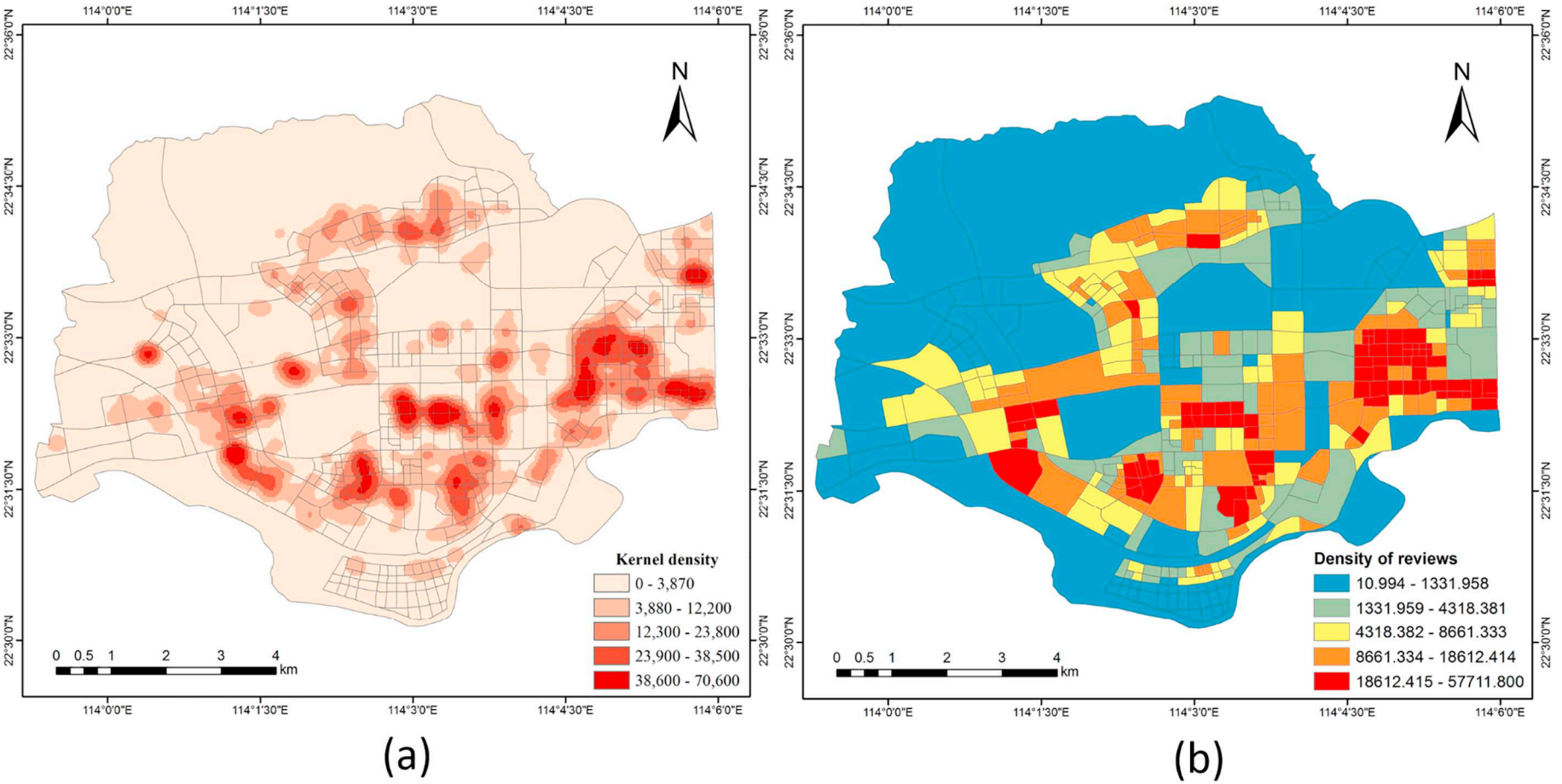


Fig. 5. Density of place-based reviews. (a) Kernel density of place-based reviews with the 300-metre search radius. (b) Density of place-based reviews within urban landscape parcels.

Table 3
Results of the regression model (B denotes the unstandardised beta coefficient).

	Variables	B	Std. Error	β
Model 1	(Constant)	1968.43		
	Density of POIs (DP)	26,570,477.36	956,199.49	0.81***
	Entropy of POIs (EP)	–	–	
Model 2	(Constant)	2591.99	731.15	
	Density of POIs (DP)	26,321,582.50	1,003,058.95	0.80***
	Entropy of POIs (EP)	–	–	
	Percentage of service and public land (PSL)	409.58	2437.68	0.01
	Percentage of residential land (PRL)	−3656.50	1938.16	−0.06
	Percentage of industrial land (PIL)	−4099.07	3969.25	−0.03
	Percentage of commercial land (PCL)	2689.61	3707.15	0.02
Model 3	(Constant)	3655.11	1070.78	
	Density of POIs (DP)	25,056,599.44	1,103,206.46	0.76***
	Entropy of POIs (EP)	–	–	
	Percentage of service and public land (PSL)	795.29	2447.42	0.01
	Percentage of residential land (PRL)	−2943.54	2219.34	−0.05
	Percentage of industrial land (PIL)	−4306.28	4055.12	−0.03
	Percentage of commercial land (PCL)	5488.15	3892.27	0.05
	Total area of buildings (TAB)	0.01	0.02	0.02
	Number of buildings (NB)	−4.49	8.32	−0.04
	Density of buildings (DB)	4,333,178.69	1,522,132.87	0.14**
	Landscape shape index of building (BLSI)	−276.31	189.45	−0.10
	Average building height (ABH)	−16.80	15.91	−0.03
	Percentage of non-built-up areas (PNA)	−1676.49	2530.53	−0.02
	Density of roads (DR)	–	–	
Model 4	(Constant)	3670.17	1110.91	
	Density of POIs (DP)	23,380,819.71	1,455,712.19	0.71***
	Entropy of POIs (EP)	–	–	
	Percentage of service and public land (PSL)	993.06	2446.41	0.01
	Percentage of residential land (PRL)	−2729.47	2223.04	−0.04
	Percentage of industrial land (PIL)	−5097.81	4063.96	−0.04
	Percentage of commercial land (PCL)	3741.77	3953.59	0.03
	Total area of buildings (TAB)	0.01	0.02	0.02
	Number of buildings (NB)	−4.05	8.33	−0.03
	Density of buildings (DB)	4,094,527.37	1,533,373.16	0.13**
	Landscape shape index of building (BLSI)	−280.65	189.19	−0.11
	Average building height (ABH)	−22.60	16.06	−0.05
	Percentage of non-built-up areas (PNA)	−1381.47	2559.64	−0.02
	Density of roads (DR)	–	–	
	Ratio of POIs and buildings (RPB)	63,739.54	37,009.16	0.06
	Ratio of POIs and other areas (RPO)	173,076.70	204,903.48	0.04
	Ratio of roads and buildings (RRB)	−3960.82	5415.52	−0.02
	Ratio of roads and other areas (RRO)	–	–	

Note. $F = 772.15$, $R^2 = 0.65$, Adjusted $R^2 = 0.65$, $AIC = 7297.08$, $BIC = 7305.12$ for Model 1; $F = 156.33$, $R^2 = 0.66$, Adjusted $R^2 = 0.65$, $AIC = 7299.14$, $BIC = 7299.18$ for Model 2; $F = 74.17$, $R^2 = 0.67$, Adjusted $R^2 = 0.66$, $AIC = 7295.36$, $BIC = 7283.40$ for Model 3; $F = 59.03$, $R^2 = 0.68$, Adjusted $R^2 = 0.67$, $AIC = 7295.67$, $BIC = 7277.71$ for Model 4; $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

facilities and buildings has a significant impact on improving urban vibrancy. On the contrary, the diversity of urban facilities, total area of buildings and the density of roads have limited effects on urban vibrancy. The findings may have implications regarding developing towards spatial compactness of urban facilities and buildings. Moreover, it would be possible to quantitatively assess urban landscapes and vibrancy in time for guiding city planning.

5.2. Towards building a landscape characteristics approach for measuring urban vibrancy

This study reveals the necessity of incorporating landscape characteristics into urban vibrancy. On this basis, several concerns regarding building a general approach to measure urban vibrancy still exist. The first issue is that only the morphologies of urban landscapes, physical properties, were analysed, and the socioeconomic features highly related to human activities remain undiscussed in nature. Questions about how these human dynamic-driven features influence urban vibrancy and approaches to integrating both urban landscapes and socioeconomic features to improve urban vibrancy will be further investigated in future studies. Second, only the spatial distributions of review data were considered in the quantification of urban vibrancy. However, the temporal patterns of social media data, which can reflect valuable information about the dynamics of cities (García-Palomares, Salas-Olmedo, Moya-Gómez, Condeço-Melhorado, & Gutiérrez, 2018; Xing, Meng, & Shi, 2018), were not considered in this study. Third, place-based reviews cannot comprehensively represent urban vibrancy in one region because young people, instead of individuals of all ages, tend to post reviews on the Internet. As a result, biases in quantifying the degree of the vibrancy within urban landscape parcels exist. To better quantitatively define urban vibrancy, future research will involve both spatial and temporal information using multi-sourced social media data. Fourth, the analysis of the relationship between landscape characteristics and urban vibrancy solely focused on a single study area, namely the Futian district in Shenzhen. Despite that the proposed framework can be utilised beyond the study area, different cities may exhibit distinct landscape characteristics due to their different development conditions (Zhang et al., 2019). This observation further leads to the question of whether various multi-level landscape characteristics among cities have different impacts on urban vibrancy. On this basis, we can conclude that the proposed framework can be fitted among cities, but different findings about how landscape characteristics specifically influence urban vibrancy may be obtained. We will further explore this issue in a larger study area, such as China, in future studies.

6. Conclusions

As a vital component of city planning, the morphology and arrangement of landscape characteristics can potentially profoundly affect the degree of urban vibrancy. Meanwhile, the wide availability of review data offers opportunities to quantify urban vibrancy from the individual perspective. In this study, a novel framework to explore the relationship between landscape characteristics and urban vibrancy is proposed. First, to effectively depict urban landscapes, multi-level characteristics were quantified using 17 spatial metrics. Second, we applied place-based reviews from social media data and proposed effective measures to quantitatively define urban vibrancy. Then, to select reliable spatial metrics and avoid multicollinearity problems, 17 metrics were evaluated using the tolerance, VIF, and variance proportions. As a result, EP, DR, and RRO were excluded from the study. Finally, considering the multi-level landscape characteristics, four linear regression models were proposed to explore the relationship between landscape characteristics and urban vibrancy. The results show that the adjusted R^2 values are 0.65, 0.65, 0.66, and 0.67, indicating satisfactory performance and reliability of the proposed models. In summary, the exploratory regression analysis provides insights into the relationship between landscape characteristics and urban vibrancy. As urban landscape morphologies based on different characteristic levels exhibit variable effects on urban vibrancy, the findings of this study provide guidance for city planning and urban landscape design, which could potentially improve urban vibrancy.

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Declaration of Competing Interest

The authors declare no conflict of interest.

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