Urban landscape as a spatial representation of land rent: A quantitative analysis

Jiayu Wu[a]

Shantong Wang[b]

Yang Zhang[c]

Anqi Zhang[d, *]
anqi.xc@pku.edu.cn

Chang Xia[d]

[a]College of Agriculture and Biotechnology, Zhejiang University, Hangzhou 310058 Zhejiang Province, PR China

[b]Department of Architecture, School of Design and Environment, National University of Singapore, 117566, Singapore

[c]College of Urban Economics and Public Administration, Capital University of Economics and Business, Beijing 100070, China

[d]Department of Urban Planning and Design, The University of Hong Kong, Hong Kong, China

*Corresponding author.

Abstract

Due to the emergence of geographical 'big data,' the field of urban studies is enjoying many new research opportunities. By using several sources of geographical 'big data', an analysis framework was structured to measure the urban landscape based on three aspects: city plan, pattern of building form, and urban land use. An association rule analysis was used to explore the relationship between land rent and the urban landscape, and the results indicate that the urban landscape differs across urban areas. The blocks classified as being located in main centers were associated with more convenient public transportation, denser road networks, more vertical street space, more diverse block patterns, more flexible architecture arrangements, mixed uses, high density, and more services. By contrast, non-center areas usually comprised blocks that were larger, tabular, single-purpose, and more regular. Non-center areas often cannot provide high-quality public goods, and they contain scattered large industrial enterprises. The urban landscapes of sub-center blocks fell in between these two urban areas. To our knowledge, this is the first paper that attempts to explain the relationship between land rent and urban landscapes based on 'big data,' and our study may provide meaningful insights into urban design for government officials and academics.

Keywords: Land rent; Urban landscape; Association rules analysis; Big data; China

1 Introduction

The landscapes of contemporary cities have been regarded as contributors to today''s urban planning challenges ((Alberti, 2000; Jenks, 2000; Rapoport, 2016; Tsai, 2005). The urban landscape directly affects ecosystems (Lee, Ahern, et al., 2015; Wu, 2014), urban sprawl (Tsai, 2005; Ye and He et al., 2015), public health (Frumkin, 2016; Koohsari, Mavoa, et al., 2015), neighborhood vibrancy (Wu, Ta, et al., 2018), and housing price (Wu, Song, et al., 2017). In addition, the urban landscape has effects on travel behavior (Hong, Shen, et al., 2014), which, in turn, influences air quality (Lu & Liu, 2016; McCarty & Kaza, 2015) and global climate (Hamin & Gurran, 2009). The popular concept of "sustainable development" emerged in 2004 and revived discussion about the landscapes of cities (Jabareen, 2004). Undoubtedly, scholars and practitioners in different disciplines have been motivated and encouraged to pursue landscapes that can support high-density settlements. The goal is for these landscapes to meet sustainability requirements and enable urban landscapes to function in a more constructive way than they do at present (Jabareen, 2016).

Not surprisingly, existing literature documents how the vast urban landscapes found in various cities (Song & Knaap, 2004a; Wu, Ta, et al., 2018) are perceived as a contributing factor to both environmental and social problems (Bramley & Power, 2009; Camagni, Gibelli, et al., 2002). However, rarely are urban landscapes understood as the consequences of social development and environmental transitions. In other words, there is limited research on what affects the urban landscape.

As landscape traditions differ across disciplines and places (Hartshorne, 1969), the concept of landscape carries much ambiguity and complexity (Morin, 2009). Landscape may be thought of as the ways in which the component parts of an area have been arranged to produce a particular appearance (Morin, 2009). From this perspective, we can talk about 'Agricultural Landscapes', 'Modern and Postmodern Landscapes', and of course 'Urban Landscapes'. The debate over a landscape focuses not only on the question of what the landscape is but also on how it is produced. Landscapes have physical, material forms, or 'morphologies,' that are produced through productivity and production relations (Mitchell, 1994).

Landscape as a traditional geography term has attracted attention for a long time (Meinig, 1979). The ultimate purpose of most scholars concerned with landscape, such as Hoskins (1970) and Jackson (1984), is to attempt to understand the cultural meaning of these landscapes. However, the cultural sense has been widely observed due to the absence of landscape production. Researchers have criticized that the search for cultural meaning neglects the mechanics of what constitutes a landscape (Mitchell, 1994). Landscape textuality among the growing reorienting landscape conceptions has attracted the most focus (Barnes & Duncan, 2013; Duncan & Duncan, 1988). With their efforts, landscape methodologies had been steered from morphology to a complex textual analysis. Regrettably, the theories on landscape textuality neglect landscape production despite the sophistication in methodology and politics. In Mitchell (1994)'s imperishable studies on landscape morphology and surplus value, landscape is defined as a contentious, compromised product of capital shaped by power and the collective. The landscape we saw was schematically produced by different powers and by the production and reproduction of space for ideological legitimacy.

Recent landscape studies have made an emphatically political statement, as they highlight the social conflicts, especially the unequal power relations based on class, that are involved in the interpretation of landscapes (Mitchell, 2003; Staeheli & Mitchell, 2016). In Marxist theory, the unequal economic relationship among landowners, capitalists and workers is reflected in land rent (Aronowitz, 2016; Jäger, 2003), especially in Differential Rent I, which mirrors the distance from the market. According to Alonso's rent model (Alonso, 1960), land value decreases as the distance from the Central Business District (CBD) of a city increases. Different land uses have different additional values, resulting in different abilities to afford land rent. Therefore, urban centers (particularly employment centers) appear and foster monocentric or polycentric cities. In summary, the land rent, and its spatial representation, has an impact on the urban landscape, which is the physical manifestation of class differentiation.

Extensive research has documented that urban landscapes are the spatial representation of power and capital, such as land rent. Regrettably, most studies are organized by theoretical and qualitative approaches. Thus, in this paper, we focus on this research gap and contribute to the literature in a quantitative way:

First, we use a systematic analysis framework to measure the urban landscape. Previous literature has described the urban landscape at different scales. At the block scale, the single element analysis, represented by Space Syntax (Hillier & Hanson, 1989), Spacematrix (Pont & Haupt, 2010) and MXI (Van Den Hoek, 2008), seeks to quantify mixtures of street networks, building types, development intensities and neighborhood function. At the neighborhood scale, researchers quantitatively analyze building patterns by using the building base area, floor height, building floor area, FAR, and other factors (Salat, Labbé, et al., 2011). Based on these quantitative techniques, we adopted the analysis framework proposed by Conzen (1960) to measure the urban landscape. This theory has been widely generalized and applied around the world (Moudon, 1997; Whitehand, 2017). Three dimensions structure our framework: the city plan, the pattern of building forms, and urban land use. In the following chapters, we will describe this quantitative framework in detail.

Second, we adopt urban structure (main center, subcenter, noncenter area) as the conduction mechanism between land rent and urban landscape. Although it is an indisputable fact in new Marxism that landscape is produced by capital intervention, class conflict and power competition (Aronowitz, 2016), the mechanism is less discussed. As the land rent differs across cities, although urban landscapes are similar to each other, we could conclude that the relationship between land rent and landscape is not linear or does not share the same slope (see Fig. 1). In other words, the mechanisms do not appear to be simple/regular as far as we could tell through two-way plots of landscape indicators. Fig. 1 illustrates that even though the same land rent (B_0) occurs in City m and City n, the urban landscapes are remarkably different (B_1 and B_2). Likewise, when the urban landscape (A_0) in a certain block is the same in these two cities, the land rent may differ sharply (A_1 and A_2). Theoretically and empirically, however, B_1 or B_2 are ranked in a similar order and location in the respective cities. Therefore, we measure the urban center first based on land rent and then explore the association between land rent and the urban landscape.

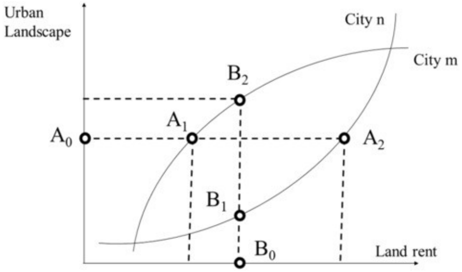

Fig. 1 The indirect relationship between land rent and urban landscape.

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Notably, our analysis differs from those in two earlier studies (Cai, Huang, et al., 2017; Liu & Wang, 2016) in two ways: First, the original academic concept of the urban center referred to an employment center (Giuliano & Small, 1991; Giuliano & Small, 1993) rather than to a residential center or traffic center. As mentioned above, based on Alonso's Rent Model, the employment center is the area where the land rent is the highest. Therefore, we identified the urban polycentric structure according to the distribution of land rent. Second, previous literature on the intracity urban structure is heavily dependent on the availability of data. Available data have been restricted to statistical sources such as population censuses and economic data (Garcia-López, 2010; McMillen, 2001; McMillen, 2003; Riguelle, Thomas, et al., 2007), remote sensing data (Elvidge, Tuttle, et al., 2007; Ma, Zhou, et al., 2012), and social media data (Hawelka, Sitko, et al., 2014; Jiang, Ma, et al., 2016; Stefanidis, Crooks, et al., 2013). Our paper uses a new dataset on rented office space to identify the urban structure, and these data may reflect land rents in a more timely and accurate manner.

In conclusion, our paper explores how the urban landscape is impacted by the land rent in urban areas within certain cities. The paper is organized as follows. The next section introduces and discusses the data resource, the identification of urban centers, and the measurement of an urban landscape and the association rules of the analysis-mining model. Next, polycentric development patterns and the urban landscapes of the main cities in China are presented. The paper concludes with a summary of the major findings as well as several policy suggestions.

2 Study area and data resource

2.1 Study area

The first-tier cities in China were selected as our study areas (Fig. 2). These cities include Beijing, Shanghai, Shenzhen, Guangzhou, Wuhan, Hangzhou, Nanjing, Qingdao, Chengdu, Suzhou, Tianjin, Xi'an, and Chongqing. These cities vary greatly in their geographical characteristics, levels of economic development, urban histories and landscapes. We selected these cities to avoid the problems of ineffectiveness and weak robustness. Only built-up areas that can be interpreted from satellite images from the National Land-Use/Cover Database of China (NLUD-C) (He, Song, et al., 2017) are included in this study; that is, we do not rely on official city boundaries (Arnold Jr & Gibbons, 1996).

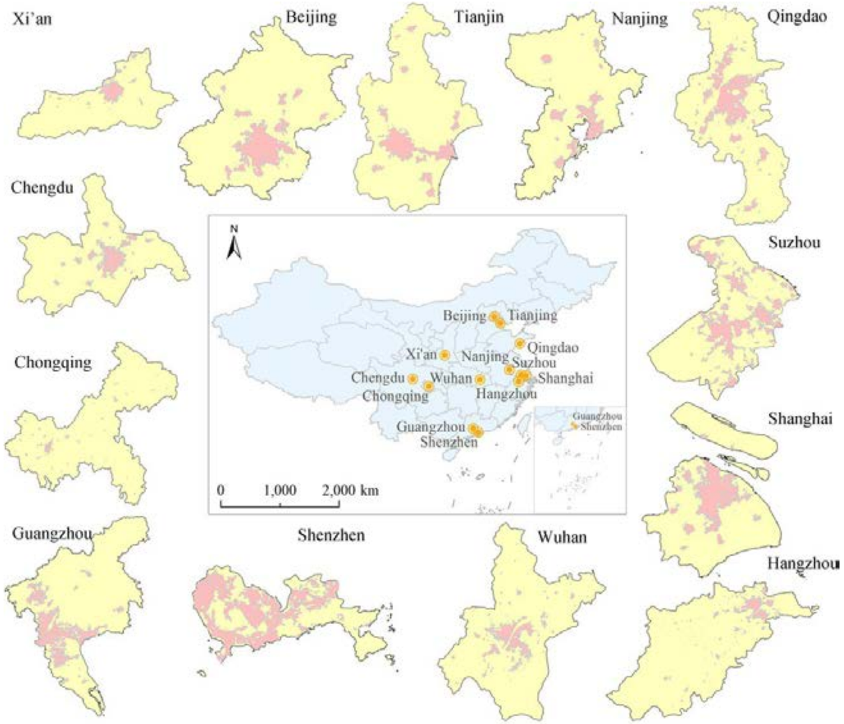

Fig. 2 Study area.

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2.2 Data

As a result of the development of Information and Communications Technology (ICT), Geographical Big Data are now widely used in academic research (Liu, Song, et al., 2015; Long, Zhai, et al., 2018). Data from GPS, smart phones and social media are generated (with the support of ICT technology) using location information and spatiotemporal semantics. POI, location check-in data, mapping data, and other open data are the typical representatives of geographic 'big data'. Geographic 'big data' shows that almost all big data is generated in a certain time and space directly or indirectly related to the location. The essence of geographic 'big data' is the "sum" of the quantity and quality characteristics and data sets changing over time of various elements (phenomenon) in a spatial structure and in relationship to a realistic geographical world. Our data come from four primary sources.

2.2.1 Point of interest (POI) data

POI is point data representing an actual geographic entity, including spatial information such as latitude, longitude, and address and attribute information such as names and categories. The POI data in this article is derived from the open interface technology of Baidu Map (http://map.baidu.com/). They were acquired using JavaScript in January 2016, and they are categorized according to Baidu's internal POI criteria. More than 23 million data items were obtained in 12 categories, including real estate, shopping, transportation facilities, educational facilities, finance, hotels, tourist attractions, lifestyle services, recreation, medical services, food and businesses.

2.2.2 LandScan TM high-resolution global population dataset

LandScan as the population spatial distribution data (http://web.ornl.gov/sci/landscan/) is the community standard for global population distribution data. At a spatial resolution of approximately 1 km (30″ × 30″), it represents the distribution of the environmental population (over 24h on average). The database is updated annually and released to the wider user community around October (http://web.ornl.gov/sci/landscan/). LandScan goes beyond traditional demographic data based on administrative regions and directly demonstrates the spatial distribution of a population (Dobson, Bright, et al., 2000). The data set currently includes global data from 2000 to 2015. This article uses the newly released LandScan data covering the entire mainland China in 2015.

2.2.3 *Building and street data*

Building and street data were obtained from the Gaode Map; these data include the building's location, the area of the building lot, the number of floors, and streets at all levels (levels one to five). The basic unit in our analysis is the block, which is divided by level-five roads. These building data are crucial to measuring the physical urban landscape. There are two reasons why these data are currently rarely used in academic research: First, the Gaode Map (or Baidu map) began to produce building data in 2017, and these data are not widely used in small- and medium-sized cities. Even in the suburbs of large cities, crawling building data are relatively difficult to obtain.

2.2.4 *Office rental data*

Data on office spaces and their attributes were obtained from the SOUFANG website using crawler technology in the year 2015 (for a total of 12,573 office rooms). Crawler technology is an internet bot that systematically browses the web for the purpose of indexing. SOUFANG is a housing service platform that has an approximately 70% market share in China's housing market. Recently, academic studies (Ding & Zhao, 2014; Lee et al., 2015; Wu et al., 2017) have supplemented traditional housing price data sources by exploiting open-access social media data.

3 Methodology

3.1 Identifying the urban centers

To verify our theoretical hypothesis that the land rent and urban landscape are complex and no-linear, we generated a two-way plots scatter diagram (Fig. 3). Apparently, the relationship between land rent and urban landscape could not be captured through a simple statistical analysis. Therefore, we first identified the urban centers.

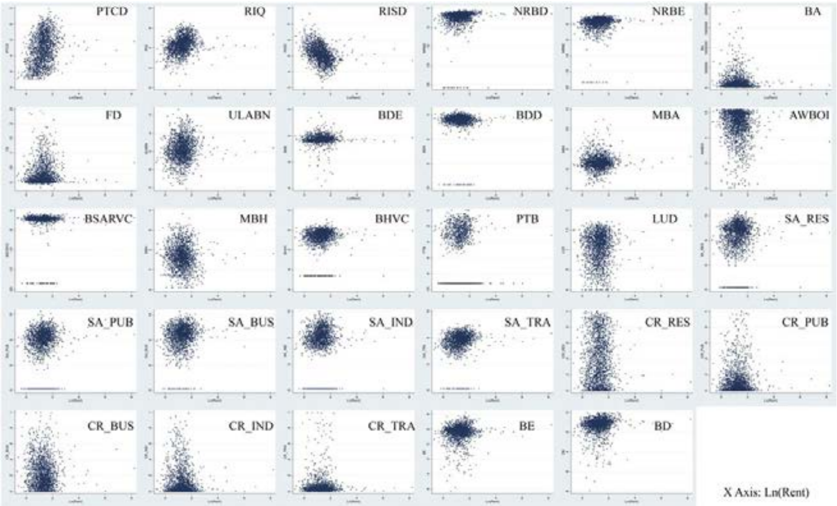

Fig. 3 The two-way plots between land rent and urban landscape.

alt-text: Fig. 3

The main center is that of the spatial cluster blocks, which have affordable but high land rent. Commonly, these blocks also have the highest employment density. Following the example of previous studies (Cai et al., 2017), we adopt Local Moran's I, which was proposed by Anselin (1995), to detect the main center of each city. The Local Moran's I (LMI) for the *i* th office rental sample is given as

$$LMI_i = \frac{x_i - \bar{x}}{S_i^2} \sum_{j=1, j \neq i}^{n} w_{ij} \left(x_j - \bar{x} \right)$$

and S_i^2 is the global sample variance such that

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^{n} \left(x_j - \bar{x} \right)}{n - 1}$$

A positive value for LMI_i indicates that i has neighbors with similar values; therefore, office room i and its part neighbors can form a cluster (Anselin, 1995). To pick up all of the samples with statistically significant positive LMI values, a z-score is introduced (Mitchel, 2005):

$$Z_{LMI_i} = \frac{LMI_i - E\left[LMI_i\right]}{\sqrt{V\left[LMI_i\right]}}$$

where

$$\mathrm{E}\left[LMI_i\right] = -\frac{\sum_{j\neq 1}^{n} w_{ij}}{n-1},$$

and

$$\mathrm{V}\left[LMI_i\right] = E\left[LMI_i^2\right] - E\left[LMI_i\right]^2$$

When a sample is indicated with a high positive z-score (generally larger than 1.96) and the surrounding samples also have high values, we define it as a main center as long as it is statistically significant at $p < .05$.

We defined the office-rent-weighted centroid of the main center as the center point of the city, and it was used to measure the [Distance] between each sample and the main center of the city. Then, a geographical weighted regression (GWR), which had been proven superior to ordinal logistic regression (OLR) (Cai et al., 2017) due to the strong spatial nonstationary, was used to model the relationship between the [Distance] and the land rent. The GWR formula is given as follows (Fotheringham, Brunsdon, et al., 2003):

$$y_i = \beta_0\left(u_i, v_i\right) + \sum_k \beta_k\left(u_i, v_i\right) d_{ik} + \varepsilon_i$$

where y_i is the office room rent for sample i; u_i and v_i denote the coordinate of latitude and longitude; $\beta_0(u_i, v_i)$ is the intercept, $\beta_k(u_i, v_i)$ is the local estimated coefficient of the k th independent variable for the sample i; and ε_i is the error. The Gaussian kernel is constructed as an adaptive distance, and the cross validation (CV) method is used to select an optimal bandwidth (Fotheringham et al., 2003). The subcenter candidates are blocks that have office rooms with residuals distributed beyond a standard deviation of 1.96, implying that their rent values are significantly higher than average at the local scale. Next, we selected the subcenter candidates with positive residual errors and adopted Jenks's natural breaks classification (Jenks, 1967) to cluster the tracts based on the goodness of variance fit (GVF) value, the threshold of which was set as the GVF value $\geq$0.8.

To evaluate the performance of these methods in detecting the urban polycentric structure, we first evaluate the results by using housing price quantitatively. Previous literature authoritatively states that the urban center is the most influential factor for housing prices. Hence, we collected neighborhood data, including location, average housing price, FAR, green rate and other neighborhood attributes. We estimated two hedonic models, in which the second model contains the distance between a neighborhood and an urban center and the first does not. We then compared the goodness-of-fit of these two models. If the goodness-of-fit in the second model was higher than in the first, the result indicates that our method has good performance in identifying both the main center and the subcenters.

3.2 Measuring the urban landscape

Although the concept of landscape is imbued with great complexity and probably hundreds of nuances in fields as diverse as art and architecture, environmentalism, planning, and the earth sciences, we follow the tradition of landscape research derived from Sauer (1925), Hartshorne (1969), and others. Among the multiple theories in use, Conzen's (1960) contribution to the study of the urban landscape is the most influential worldwide. Hence, we structured our analysis framework based on Conzen's theory of the urban landscape, which includes the city plan, the pattern of building forms, and urban land use (Fig. 4).

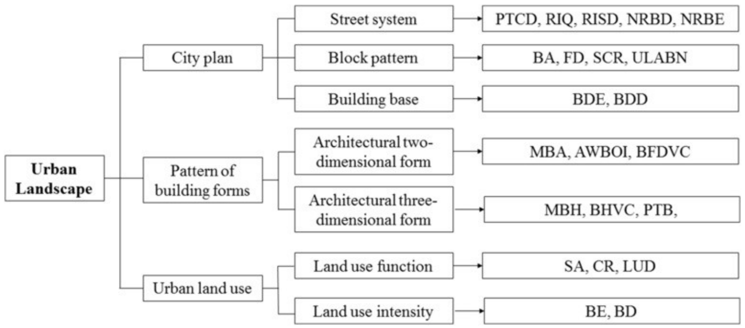

Fig. 4 The analysis framework of the urban landscape.

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The city plan plays an important role in shaping the urban landscape. This plan is defined as the spatial distribution of all artificial features in the urban built-up area, including streets, plots, and block-plans (Conzen, 1960). In addition to the Conzen School in Britain, the Versailles School in France and the Muratori-Caniggia School in Italy are all essentially consistent with the approach to analyzing a city plan by abstracting and analyzing the basic elements such as streets, plots, and block-plans. In summary, this paper quantifies the city plan from three perspectives: street system, block pattern, and building base (Table 1).

Table 1 The indicators of a city plan.

alt-text: Table 1

Code	Indicator	Explanation
Street system		
PTCD	Public Transportation Convenience Degree	The ratio of the number of transportation stop (e.g., bus stops, subway stations, taxi stops) within 500m of the block to the area of the block
RIQ	Road Intersection Quantities	The weighted number of intersections within 500m of the block. $RIQ_{ij} = \sum_{n=1}^{N} \frac{R_n}{\sum_r^{R_n} \frac{Type_{nr}}{R_n}}$ where N is the number of intersections within 500m of block *i* in city *j*. R_n is the number of roads passing the *n*th intersection. $Type_{nr}$ is the level of the *r*th road that passes the *n*th intersection.
RISD	Road Intersection Separation Distance	The average distance between all road junctions within 500m of the block. $RISD_{ij} = \sum_{n=1}^{N} \frac{R_n \cdot \sum_r^{R_n} \frac{Length_{nr}}{R_n}}{\sum_r^{R_n} \frac{Type_{nr}}{R_n}}$ where i, j, N, R_n, and $Type_{nr}$ is the same as above. The $Length_{nr}$ is the length of the *r*th road that passes the *n*th intersection.
NRBD	Near-Road Building Density	The ratio of the building footprint to the land area within 15m from the boundary of the block. $\mathrm{NRBD}_{ij} = \frac{\mathrm{NRBA}_{ij}}{NRA_{ij}}$ where NRBA_{ij} is the building footprint within 15m from the boundary of block *i* in city *j*. NRA_{ij} is the land area within 15m of the boundary of block *i* in city *j*.
NRBE	Near-Road Building Expandability	The ratio of the floor area within 15m of the boundary of the block to the land area of the block. $\mathrm{NRBE}_{ij} = \frac{NRBV_{ij}}{NRA_{ij}}$ where NRBV_{ij} is the floor area within 15m of the boundary of block *i* in city *j*. NRA_{ij} is the same as above.
Block pattern		
BA	Block Area	The area of block
FD	Fractal Dimension	The fractal dimension index of a certain block, for use in quantifying the shape complexity of the block.

		$\mathrm{FD}_{ij} = \frac{2\ln\left(\frac{P_{ij}}{4}\right)}{\ln A_{ij}}$ where P_{ij} is the perimeter of block i in city j. A_{ij} is the area of block i in city j. Generally, FD has a value range of [1, 2]. The larger the value, the more complicated the boundary of the block under the same area, and FD = 1 indicates a square block.
ULABN	Adjacent Block Number Per Unit Length	The ratio of the number of adjacent blocks within 100m from the boundary of the block to the perimeter of the block. $\mathrm{ULABN}_{ij} = \frac{\mathrm{Near}_{ij}}{P_{ij}}$ where Near_{ij} is the number of blocks within 100m of the boundary of block i in city j;P_{ij} is the same as above.
Building base		
BDE	Eccentricity Degree of Building Distribution	The distance between the building lot in the block and the center of the block. $\mathrm{BDE}_{ij} = \sqrt{\frac{\pi}{A_{ij}}} \bullet \frac{\mathrm{D}_{ij}}{\bullet B_{ij}} = \sqrt{\frac{\pi}{A_{ij}}} \bullet \frac{\sum_{b=1}^{B_{ij}} \mathrm{D}_b}{\bullet B_{ij}}$ where D_{ij} is the sum of the distances between all building lots and the center of block i in city j. D_b is the distance between building b and the center of the block. B_{ij} is the number of buildings in block i in city j. A_{ij} is the same as above.
BDD	Dispersion Degree of Building Distribution	The coefficient of variation of the distance between the building lot and the center of the block. $\mathrm{BDD}_{ij} = \frac{\sqrt{\frac{1}{B_{ij}}\sum_{b=1}^{B_{ij}}\left(\mathrm{D}_b - \frac{\mathrm{D}_{ij}}{B_{ij}}\right)^2}}{\frac{\mathrm{D}_{ij}}{B_{ij}}}$ where D_{ij}, D_b and B_{ij} is the same as above.

The buildings are the material basis and important components of the urban landscape. Different architectural features form a unique urban landscape. From the perspective of different spatial dimensions, the architectural form consists mainly of two aspects, the architectural two-dimensional form and the architectural three-dimensional form. Therefore, the quantification of patterns of building forms is carried out according to these two aspects (Table 2).

Table 2 The indicators of patterns of building form.

alt-text: Table 2

Code	Indicator	Explanation
Architectural two-dimensional form		
MBA	Mean of Building Area	Mean area of all building lots in the block
AWBOI	Building Area-Weighted Orientation Index	The angle between the longest side of the building lot and the north direction.
BSCRVC	Building Spatial Compact Ratio Variation Coefficient	The coefficient of variation of compactness of all building lots in the block. $\mathrm{BSCRVC}_{ij} = \frac{\sqrt{\frac{1}{B_{ij}}\sum_{b=1}^{B_{ij}}\left(BSCR_b - \mathrm{MBSCR}_{ij}\right)^2}}{\mathrm{MBSCR}_{ij}}$ $\mathrm{MBSCR}_{ij} = \frac{1}{B_{ij}}\sum_{b=1}^{B_{ij}} BSCR_b$ where $MBSCR_{ij}$ is the mean of compactness of all building lots in block i in city j. $BSCR_b$ and B_{ij} are the same as above.
Architectural three-dimensional form		
MBH	Mean of Building Height	Mean height of all buildings in the block.
BHVC	Building Height Variation Coefficient	The diversity of the heights of all buildings in the block. $\mathrm{BHVC}_{ij} = \frac{\sqrt{\frac{1}{B_{ij}}\sum_{b=1}^{B_{ij}}\left(BH_b - \mathrm{MBH}_{ij}\right)^2}}{\mathrm{MBH}_{ij}}$ where MBH_{ij}, BH_b adn B_{ij} are the same as above.

PTB	Proportion of Tower Building	Proportion of buildings with high spatial usage in the block. This study defines a building with BSCR > 0.8 and ≥10 floors as a tower building.

The concepts of land use and landscape are closely linked but also different, as they are distinct aspects of the same thing. Land use function and land use intensity are two important components: the former reflects mixed land use as a result of the heterogeneity of the urban landscape, and the later reflects the degree of land development and utilization as well as land use efficiency. Therefore, this paper quantifies urban land use patterns from two perspectives: Land use function and land use intensity (Table 3).

Table 3 Indicators of urban land use.

alt-text: Table 3

Code	Indicator	Explanation
Land use function		
SA	Service Ability	The ratio of the standardized number of POI points to the size of the block.
CR	Category Ratio	The ratio of the standardized number of certain POI points to the total number of POI points.
LUD	Land Use Diversity	The diversity of land use type, using entropy calculation.
Land use intensity		
BE	Building Expandability	The floor area ratio.
DB	Density Of Building	The density of buildings.

Blocks are a basic unit of urban planning; they are the spaces surrounded by urban roads, and they form the structure of the urban landscape (Perry, 1929). A block is a morphological unit formed by the division of streets; it contains neighborhoods that are adjacent to each other and are filled with buildings. A single block is independent and performs rich urban functions. Thus, the mosaic of combinations and interactions of blocks shapes the spatial pattern of the urban landscape. The block is also an important urban research unit because it is an object of urban planning, design, construction, government, and management. The block has an important impact on urban landscape patterns and urban development patterns. Therefore, the block is adopted as the basic analysis unit of this study.

3.3 Association rules analysis

Association rules analysis is a data mining technique for identifying potential associations between different data fields and exploring dependencies among multiple fields to determine which dependencies satisfy a given support and confidence threshold (Witten, Frank, et al., 2016). In market analysis, the classic application of relevance modeling is applied to identify customer buying habits. The researchers suggest that businesses develop sales strategies for purchases that are usually made together. Association modeling explores the links between items in the basket within the confidence intervals based on transactions or item sets; this approach finds items of high importance, and then finds one or more other items in the frequently supported item sets (He, He, et al., 2018).

The Apriori algorithm is one of the common association rules used to calculate the probability that an item occurs simultaneously with minimal support in the item set or to a large extent with other items (Van der Aalst, 2016). The Apriori algorithm also determines the frequency of the item set to highlight the general trend in the database. In our thesis, the Apriori algorithm was used to explore the relationship between urban land rent and the urban landscape.

Because of the boundedness of the association rules mining model (which can only be used for classified data), the urban landscape indicators were transformed into classified data to be inserted into the formulas presented in the previous section. In our paper, we calculated the value of each city's landscape index in each city block. These values ranged from small to large, and they fell into seven categories: lowest, very low, low, medium, high, very high, and highest; we used the principle of equal distribution to avoid too many or too-small patches in a particular category.

4 Results and discussion

4.1 Main center and submain center

As discussed in the Methodology section, the identification of the main center and the subcenters of these cities is presented in Fig. 5. Beijing is the city with the largest main center (116.6 km^2), followed by Shanghai. There are four other cities with a large main center (above the average area of 50.1 km^2): Hangzhou, Chongqing, Wuhan, and Guangzhou. Qingdao and Chengdu are ranked lowest, with main center areas of 4.99 km^2 and 11.02 km^2, respectively. It is interesting to note that the main center of Wuhan is divided into two parcels, located on the east and west banks of the Yangtze River.

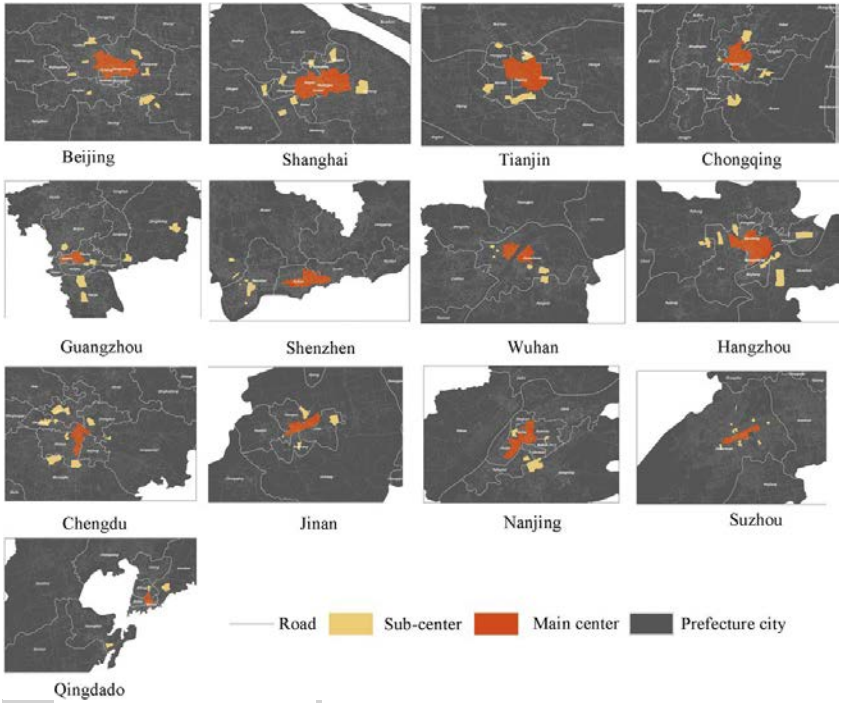

Fig. 5 The identification results of cities' main centers and subcenters.

alt-text: Fig. 5

The results of our analysis of subcenters are beyond our expectations (see Appendix). The subcenter area of Guangzhou is ranked highest (98.98 km^2), and it is twice as large as the subcenter of Beijing. The subcenter areas of Chongqing, Hangzhou, and Shanghai are all nearly the same, at approximately 60 km^2. Shenzhen and Qingdao have the smallest subcenter areas, both of which are approximately 8 km^2. Aside from their areas, the number of subcenters is also surprising. Suzhou turned out to be the city with the most subcenters. Beijing and Shanghai have eight and seven subcenters, respectively, similar to the last edition of the city master plan. Jinan, Tianjin, and Qingdao each have only two subcenters.

4.2 Urban landscape

Values for the urban landscape in each block were calculated with the series of indicators mentioned above, and the urban landscapes for all blocks, divided into seven levels, were ranked in descending order. Figs. 6–8 show examples of several cities as divided into landscape categories and values.

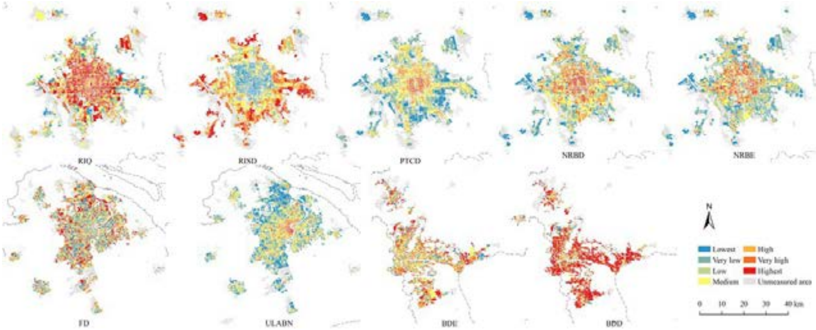

Fig. 6 Measurement of city plans: Beijing, Shanghai, and Guangzhou.

alt-text: Fig. 6

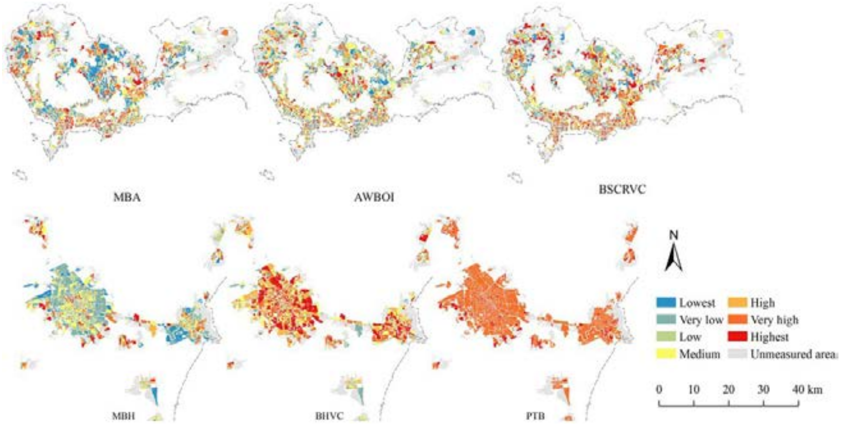

Fig. 7 Measurement of patterns of building form: Shenzhen and Tianjin.

alt-text: Fig. 7

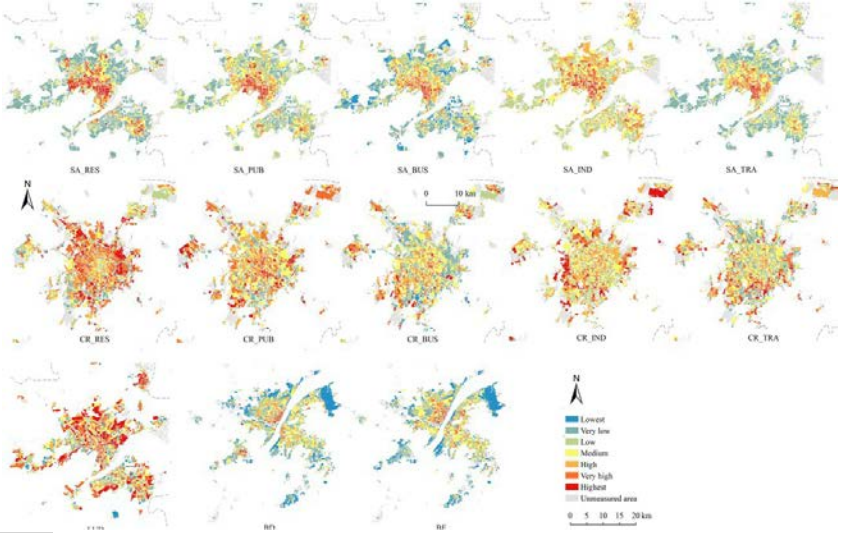

Fig. 8 Measurement of urban land use: Hangzhou, Chengdu, and Wuhan.

alt-text: Fig. 8

To perform the association rules analysis on the data, information about the urban center for each block of cities was combined with urban landscape indicators to create a database of item sets. Each item set contained the following information:

I = (Urban center; {City plan}; {Pattern of building form}; {Urban land use}).

The key link of the association rules analysis is to confirm the support and confidence values. Any given block had a 14.28% (1/7) possibility of having one of the landscape indicators. In addition, main centers account for 19.45% of urban areas, subcenters account for 5.33%, and other areas account for 75.22%. Therefore, the probability of a certain block occurring simultaneously with any urban landscape value is between 0. 76% (5.33%*14.28%) and 10.74% (75.22%*14.28%). Based on the above considerations, the support threshold was set as 0.05 (the approximate average of the 0. 76% and maximum 10.74% probabilities). The probability of a single landscape value occurring for a block is between 0.01% (1.87%/46.7%) and 55.21% (6.67%/13.1%); as such, the confidence threshold was set as 0.27, or approximately the average of 0.01% and 10.74%.

Table 4 shows the result of data mining with association rules. Clearly, the impacts of land rent on urban landscape are mainly embodied in the city plan and in urban land use, while the pattern of building form shows little difference among blocks.

Table 4 Breakdown of the contributors to each urban landscape value.

alt-text: Table 4

Indicators	Lowest	Very low	Low	Medium	Very high	Highest
City plan						
PTCD	O	O	O		M	M
RIQ	O	O	O		M	M
RISD	M	M		O	O	O
NRBD	O	O	S			M
NRBE	O	O	O			M
BA		M		S	O	O

FD						
ULABN	O	O	O		M	M
BDE						
BDD		M			O	O
Pattern of building form						
MBA						
AWBOI						
BFDVC						
MBH						
BHVC		O				
PTB					M	
Urban land use						
LUD		O	O		M	M
BE	O	O				M
BD	O	O	S		M	M
SA_RES						
SA_PUB		O	O	S		M
SA_BUS	O	O	O			M
SA_IND			O	S		M
SA_TRA		O	O	O	M	M
CR_RES						
CR_PUB						
CR_BUS						
CR_IND			S			O
CR_TRA						

Notes: M refers to main center, S refers to subcenter, and O refers to other areas.

4.2.1 *Impact on city plan*

There were 34 associated pairs in the catalogues of city plans, occupying 48.5% (34/70) of all possible associations. In particular, the main centers and other areas depict a distinctive urban landscape.

Among the street system indicators, {M} -> {PTCD_Highest, PTCD_Very high} and {O} -> {PTCD_lowest, PTCD_Very low, PTCD_Low} indicates a clear association between land rent and convenience of public transportation. The rules show that the main centers, compared with other areas, have a remarkable advantage with regard to daily travel. By contrast, the result of RIQ and RISD indicates that the road net in the main center is denser. In the course of urban development, the main centers generally evolve from the historic city, which retains a street system with dense and narrow roads. The NRBD and NRBE are a pair of relevant indicators. {M} is associated with both {Highest} and {Very high} of NRBD and NRBE, while {O} is associated with both {Lowest} and {Very low}. The only difference between the two indicators is that {S} -> {NRBD_Low} and {O} -> {NRBE_Low}. The series of associations reveals that the feeling of street space in the main center is more vertical, as the buildings press relatively close to the block boundaries. There are also potential explanations for these different urban landscapes among blocks. As mentioned above, our paper identifies urban structure based on land rent, which has shaped the urban landscape. The land rent in a city's main center is higher than in other areas; thus, the buildings are high and close to the block boundary.

Among block pattern indicators, the results, {M} -> {BA_Very low}, {S} -> {BA_Medium}, {O} -> {BA_Very high, Highest}, are an objective way to describe the change in block areas as we move from the urban center to other areas. It is a universal phenomenon that blocks are smaller in urban centers and subcenters than in other areas (Long et al., 2018). In additional of area, the layout of blocks in the urban center becomes more compact, which is reflected in the results {O} -> {ULABN_lowest, Very low, Low} and {M} -> {ULABN_Very high, Highest}. Defying our expectation, the indicator FD has no confident association with urban areas. According to our hypothesis, the boundaries of blocks in urban centers are usually more complex than the boundaries of other blocks; the former boundaries are suited to the block's historical surroundings. In contrast, other recently developed areas, created under modern planning technology, are more regular. This result indicates that our hypothesis does not hold true.

Among building base indicators, the result is interesting. When we compare urban centers with other areas, there is no difference in the distance between the building lot in the block and the center of the block. However, the variable coefficients of the distance differ across urban areas. We infer that due to property rights being especially complicated in main urban centers, construction and development is more fragmentary and flexible. Therefore, the building base is randomly assigned to the blocks of main urban centers.

4.2.2 *Impact on pattern of building form*

The results for patterns of building form are neither noteworthy nor unusual. Only two indicators (BHVC and PTB) had supportable and confident associations with land rent. Nevertheless, the results of the data mining do reflect the urban landscape to a certain extent.

The {O} -> {BHVC_ Very low} mirrors the landscape of a new town, where building height is monotonous. Although we did not reach the conclusion that buildings in main centers are strewn at random, the primeness of buildings in other areas is intuitive. The similarities in the development and construction processes lead to our cities losing their features. The {M} -> {BHVC_ Very high} illustrates that the buildings in main areas are quite varied. On the one hand, the results show that spatial usage is more efficient in main areas. On the other hand, the vertical sense of space is stronger in the main center.

Notably, all indicators in the categories of architectural two-dimensional form were sector-related. This result may be a case in point that in the past one hundred years, there has been no significant change in the plane modality of the buildings.

4.2.3 *Impact on urban land use*

The results of the data mining analysis indicate that land rent conspicuously influences urban land use. As shown in previous literature (Wu, Ta, et al., 2018), the diversity of urban land use increases from the urban main center to the urban fringe based on the results of {O} -> {LUD_Very low, Low}, {M} -> {LUD_Very high, Highest}. Mixed land use and land rent interact as both cause and effect. Mixing land uses could stimulate an increase in the housing price (Wu et al., 2017) and indirectly foster high land rent, while increasing land rent develops diversity in spatial usage efficiency and shapes the landscape of mixed land use (Song & Knaap, 2004b). The results of BE and BD are similar, demonstrating a universal rule that the intensity of development in urban centers is remarkably higher than it is in other areas (He et al., 2017; Long et al., 2018).

The indicator groups of SA and CR reveal a wealth of information. First, most SAs, with the exception of SA_RES, have an association with land rent, whereas most CRs have no association with land rent, with the exception of CR_IND. By making a general survey of SAs, the service ability of main areas is shown to be superior to that of subcenters and much better than in other areas. Second, it is interesting that the SA_IND and CR_IND show contrasting results. {M} -> {SA_IND _Highest}, {S} -> {SA_IND _Medium}, and {M} -> {SA_IND _Low} imply that the density of industrial POI is higher in main areas. However, {O} -> {CR_IND _Highest} and {S} -> {CR_IND _Low} show that the proportion of industrial POI is higher in other areas. This result implies a difference in industrial companies. Most industrial enterprises are located in noncentral areas, but they generally occupy more land. By contrast, industrial companies located in main centers usually occupy less land or concentrate in high- rise office buildings.

Conclusion

Given the rapid changes in technology today, city managers and researchers can monitor, analyze, and understand cities by using unprecedented information and communication technologies as well as geographical 'big data' (He et al., 2018; Liu, Derudder, et al., 2016). These resources have the potential to compensate for the deficiencies of traditional data resources. Our paper adopts geographical open data to explore the relationship between land rent and urban landscapes at the block scale, thus going beyond the restrictions of traditional data collection methods.

By using Local Moran's I and Geographical Weighted Regression, we identified urban main centers and subcenters with ≥400,000 office-rental samples in thirteen large cities in China. We also use hedonic models to detect the accuracy of our identification. In addition, we structure an analysis framework to measure the urban landscape based on three aspects: city plan, pattern of building form, and urban land use. Several sources of geographical 'big data' were adopted to detect the association between the landscapes in each block of these metropolitan areas. The landscape indicators of each block were divided into seven values: lowest, very low, low, medium, high, very high, and highest. In total, 66 rules were explored by using an association rules analysis. We found that the three areas (main center, subcenter, others) affect urban landscapes in different ways.

The blocks classified as being located in main centers are associated with more convenient public transportation, denser road networks, more vertical street space, more diverse block patterns, and more flexible architecture arrangements. With regard to patterns of building form, there are more tower buildings in main centers than in other areas. In addition, the blocks in main centers are more mixed, have higher density, and afford more services than blocks in subcenters. In contrast to this finding, noncenter areas are usually composed of blocks that are larger, tabular, single-purpose, and more regular. These blocks often cannot provide high-quality public goods, and they contain scattered larger industrial enterprises. The urban landscapes of subcenter blocks fall in between the aforementioned two urban areas.

In our paper, an association rules analysis was applied to explore the relationship between urban land rent and the urban landscape. The results of this modeling suggest that main center, subcenter, and other areas have different effects on the urban landscape; our results thus provide useful insights for urban planning. Much of the news and academic literature (He et al., 2017; Jun, 2010) criticizes the urban landscape for having lost its traditional context, as seen in street pattern changes, single land uses and so on. However, few studies explain why urban landscapes differ across the internal structures of cities. Our paper offers a new perspective on urban land rent. The results prove that associations do exist. Although this paper provides explanations for how land rent and the urban landscape affect each other, it does not provide guidance on how urban planners should renew urban landscape. Future research could address this subject.

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Uncited references

Satter, 2007

Ye et al., 2015

Appendix A. Appendix

The detection accuracy evaluates the performance of our method in detecting the urban polycentric structure. For this purpose, we collected the cities' neighborhood data (from the SOUFANG website) and compared the results of the two hedonic models (Wu, He, et al., 2018). Clearly, the goodness-of-fit is significantly enhanced when the distance variable is introduced into the equation (Table 5). Overall, our method has good performance in identifying the main center and the subcenters.

Table 5 Detection accuracy of the urban structure.

alt-text: Table 5

City	R^2 in first model	R^2 in second model
Beijing	0.621	0.785
Shanghai	0.572	0.707
Tianjin	0.649	0.738
Chongqing	0.220	0.357
Guangzhou	0.454	0.541
Shenzhen	0.410	0.570
Wuhan	0.346	0.428
Hangzhou	0.526	0.613
Chengdu	0.328	0.493
Jinan	0.386	0.476
Nanjing	0.436	0.451

Suzhou	0.381	0.528
Qingdao	0.434	0.525

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Highlights

- Urban landscape are verified as spatial representation of land rent by a quantitative approach.
- We structure an analysis framework to measure the urban landscape based on three aspects.
- Association rule analysis is used to explore the relationship between land rent and the urban landscape the results indicate that the urban landscape differs across urban areas.

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