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# Measuring urban compactness based on functional characterization and human activity intensity by integrating multiple geospatial data sources

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ABSTRACT

Compact development is one of the most effective solutions for sustainable urbanization under the rapid growth of the urban population. Great efforts have been made to measure urban physical compactness while limited attention has been paid to functional zoning of urban areas. Here, we introduce a novel index, called the functional compactness index (FCI), to quantify urban functional compactness through the integration of geospatial data sources, including Points of Interest (POIs) data, Road Network of OpenStreetMap (RNO) data, and National Polar-orbiting Partnership (NPP) Visible Infrared Imaging Radiometer Suite (VIIRS) nighttime light data. The FCI does not require the analysis of the grid scale and thus, is technically simpler than conventional compactness index (CI). We examined the effectiveness of FCI on estimating urban compactness under four land use scenarios and in four Chinese cities. The results suggest that: (1) the FCI can comprehensively reflect the intensity of human activity, the differentiation between residential zones and other functional zones, and the mixing degree of different functional zones; (2) the FCI is not affected by the service radius of residential zones; (3) the FCI can reflect the overall and local-scale functional compactness of a city; and (4) the FCI can be used to effectively compare spatial characteristics of functional compactness among different cities. In conclusion, the FCI considers the rationality of urban functional layout, which not only is helpful for urban planning, but also enriches the quantitative methods of urban compactness evaluation.

## 1. Introduction

The rapid increase in global urban population and fast urban sprawl in the past decades have caused various social and environmental problems (Bierwagen, 2007; Burchell and Mukherji, 2003; Frumkin, 2002; Gong et al., 2012; Hampton, 2010; Huang et al., 2018, 2007; Lo, 2004; Stone, 2008; Sturm and Cohen, 2004; Tannier et al., 2012; Zhao et al., 2014). In order to solve these problems, researchers, policy makers, urban planners and designers have proposed many ideas and methods, one of which is compact development. Since 1973 when the concept of a “compact city” was first proposed (Dantzig and Saaty, 1973), researchers have focused on the concept, characteristics, functions, and feasibility of compact cities, as well as the relationships between the compact development and sustainable development of cities (Anderson et al., 1996; Artmann et al., 2019a, 2019b; Breheny, 1997; Burton, 2000; Elkin et al., 1991; Ewing, 1997; Jia et al., 2019; Liu et al., 2016; OECD, 2012; Richter and Behnisch, 2019; Wang et al., 2019; Williams et al., 2010; Xia et al., 2020; Zhao et al., 2014). The methodology of measuring urban compactness has long been a challenge and popular topic, especially in the context of increasing the emphasis on landscape complexity in urban geographic analysis (Papadimitriou, 2009, 2012).

Although there is still no single unified definition of a compact city, researchers have reached the consensus that compact cities should at least be compact in both physical and functional terms (Burton, 2002; Dantzig and Saaty, 1973; Dempsey, 2010; Ewing, 1997; Galster et al., 2001; Jabareen, 2006). The physical compactness of urban space has been investigated in a large number of studies. The focuses of those studies can be divided into four categories: (1) the physical characteristics of outer contours of urban built-up areas, including the Gibbs Compactness (Gibbs, 1961), Cole Compactness (Cole, 1964), and Richardson Compactness (Richardson, 1973); (2) the relationships

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between patches of urban built-up area and specific locations, such as the compactness index proposed by Bertaud and Malpezzi (1999); (3) the degree of correlations between patches of urban built-up area, including the Thinh Compactness (Thinh et al., 2002); and (4) the building density (Galster et al., 2001).

Due to the unclearness in the definition of urban functional compactness and the difficulty of data acquisition and accessibility, few studies investigated urban functional compactness. Currently, urban functional compactness is usually measured directly based on the degree of land use mixing or indirectly based on economic indicators. The assumption is that the higher the mixing degree of urban land use, the more compact the urban function. The assessment methods of urban land use mixing can be divided into three types (Ewing and Hamidi, 2014): (1) Balance between jobs and population. Commonly used indicators include the ratio of the total number of jobs to the number of residents in the region, the ratio of service jobs to the number of residents (Angel et al., 2018; Ewing et al., 2002; Song and Knaap, 2004), and the degree of mixing between residential land and non-residential land in the same area (Burton, 2002; Galster et al., 2001); (2) Distances to walkable destinations. Commonly used indicators include the distance from a residential area to the nearest commercial area, the distance from a residential area to the nearest public institution, the distance from a residential area to the nearest industrial site, the distance from a residential area to the nearest park (Song and Knaap, 2004), the proportion of residents with shopping facilities within one km of their place of residence, and the proportion of residents with basic education facilities (e.g., primary schools) within one km of their place of residence (Ewing et al., 2002; Habibi and Zebardast, 2016); (3) Land use diversity. Commonly used indicators are the proportions of different types of land (e.g., commercial, residential, industrial, institutional, and parks) (Burton, 2002; Habibi and Zebardast, 2016; Song and Knaap, 2004) and the entropy index (Lu et al., 2018; Musakwa and Niekerk, 2013; Shi et al., 2016; Song et al., 2013). The three methods mentioned above are applicable to different research scales. The data required for methods (1) and (2) are generally obtained from questionnaires or field surveys, which require a large number of participants, material resources, and time, and are suitable for small-scale research such as blocks and communities. Method (3) is generally based on land use data obtained from remote sensing classification, which is suitable for large-scale research but cannot reflect the local functional compactness. However, the urban functional compactness reflects the rationality of urban layout based on functional zones, and the mixing degree of urban land use cannot express the rationality of urban layout based on functional zones. Therefore, the mixing degree of urban land use cannot explicitly indicate the urban functional compactness.

The increasing availability of public source data provides new insights into urban functional compactness. Along with the wide application of mobile intelligent terminals, a substantial amount of public source data are being generated, including mobile phone signaling, GPS-derived urban traffic trajectories, and points of interest (POIs). These data are easy to access with a low cost, are frequently updated, and have wide coverages. Compared with traditional data (e.g., remote sensing images), these emerging public source data not only are available in much larger quantities, but also reflect human behaviors and activities (Zhong et al., 2020). Researches have applied public source data to identify urban functional areas (Long and Shen, 2015; Song et al., 2018). Additionally, great progress has been made in earth observation technology using remote sensing and geographic information systems (GIS). A strong correlation has been found between the intensity of human activity and nighttime light intensity levels (Bennett and Smith, 2017; Xia et al., 2020), and nighttime light data have been widely used to estimate economic activity and detect and monitor urbanization (Elvidge et al., 1997; Lu et al., 2008). Compared with Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) nighttime light data, National Polar-orbiting Partnership (NPP) Visible Infrared Imaging Radiometer Suite (VIIRS) nighttime light data have a higher spatial and radiometric resolutions and can, therefore, better reflect the intensity of human activity (Bennett and Smith, 2017).

The compactness index (CI) was originally proposed by Thinh et al. (2002) to quantify urban physical compactness based on a gravitation approach supported by a land use database and GIS raster analysis. The main advantage of the CI is that it considers the filling level of sealed settlement surfaces as well as the distances between land patches in a city. However, the CI can only evaluate the urban physical compactness, and cannot indicate the differences in functional aspects among cities. This leads to our attempt to develop a new method that can reflect the overall and local functional compactness of cities, can be used to compare multiple cities, and can comprehensively reflect the intensity of human activity, the differentiation between residential zones and other functional zones, and the mixing degree of different functional zones. A functional compactness index (FCI) for development should meet at least three requirements: (1) it can distinguish the differences in the urban functional compactness among cities; (2) its computation procedure should be objective enough to ensure the soundness of its results; and (3) it should be suitable for large-scale research in term of input data avaibality.

## 2. Data and study area

### 2.1. Data source

The POIs refer to zero-dimensional elements involving specific real-world locations, such as historical sites, landmarks, public service facilities, shops, schools, and restaurants (Ye et al., 2019). The POIs used in this study were obtained from the Chinese internet map company Amap in 2018; each POI contains the name, category, longitude and latitude, address, and other information. The POIs are divided into 14 categories, namely catering services, shopping services, science and education and cultural services, scenic spots, public facilities, corporate enterprises, transportation facilities services, financial insurance services, business housing, life services, sports and leisure services, healthcare services, government agencies and social groups, and accommodation services. All POIs were cleaned and coordinate-converted for backup.

The NPP/VIIRS nighttime light data represent visible light (e.g., city lights, fishing-fleet lights, fires) captured by remote sensing satellites in cloudless conditions at night (Elvidge et al., 2013). These data were obtained from the National Oceanic and Atmospheric Administration's National Geoscience Data Center (NOAA/NGDC). The original nighttime light data are affected by cloud and include stray light, fires, and other ephemeral light. Therefore, annual composite data, in which the effects of these factors are reduced (Bennett and Smith, 2017), were used in this study. The annual composite data were available for 2015 and 2016, and the 2016 data were used in this study.

The Roads Network of OpenStreetMap (RNO) data are vector data for urban roads. First developed in University College London in July 2004, the OpenStreetMap (OSM) is a free, open source, editable mapping service created by the public (Haklay and Weber, 2008). OSM provides detailed information on road and road attributes, which can be used to map the basic spatial units required for analysis in this paper. We used the 2018 road network data, including roads and railways. Only above-ground railways were considered since these have an impact on the surface texture; underground railways were neglected since they have little impact on the surface texture.

### 2.2. Study areas

In order to explore the differences in functional compactness among cities of different sizes, we selected four Chinese cities whose urban areas have similar physical forms but which have different sizes as case studies, namely Beijing, Shanghai, Xi'an, and Xiamen (Fig. 1). Beijing (39°28′–41°03′N, 115°25′–117°35′E), the political center of China, is a

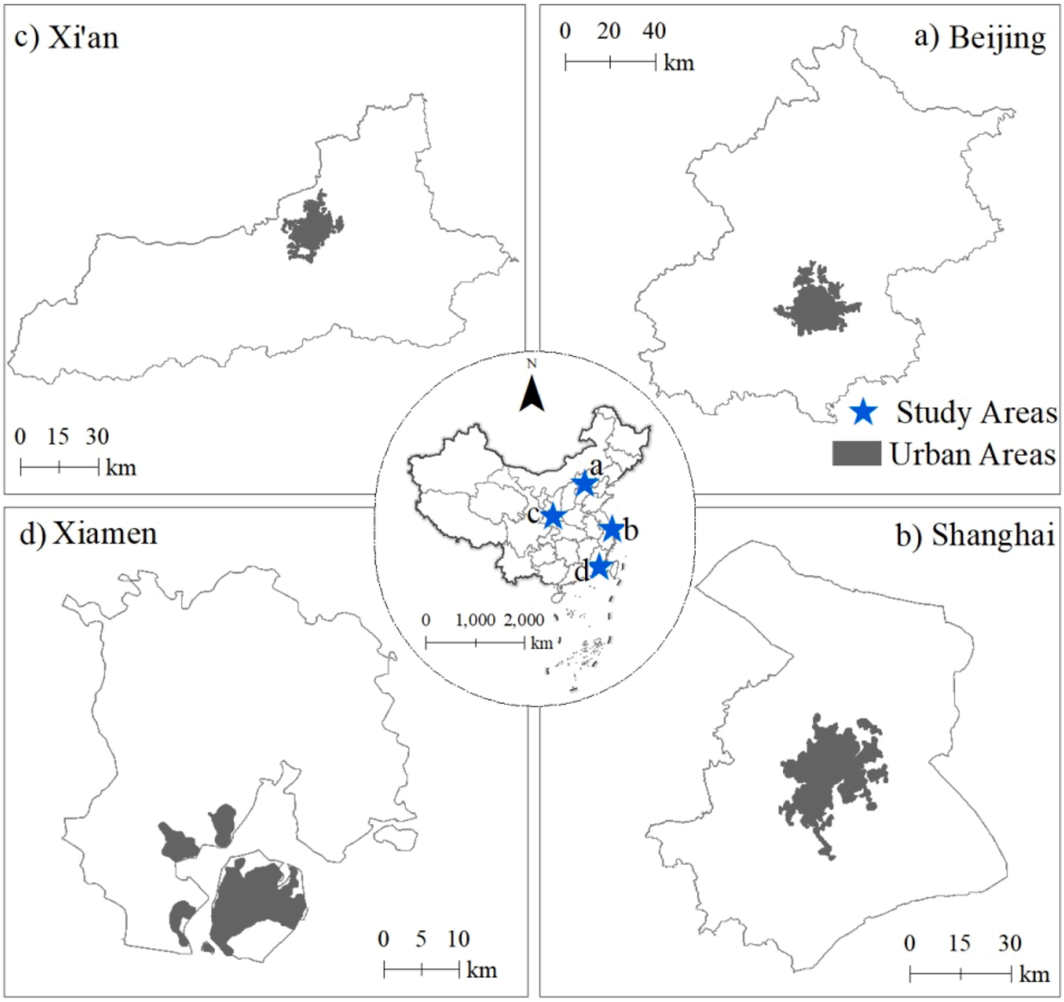


**Fig. 1.** The study areas.

typical plain city with regular circular development. Shanghai (30°40′–31°53′N, 120°52′–122°12′E), the economic center of China, lies in the Yangtze River Delta alluvial plain on flat terrain. Xi'an (33°25′–34°27′N, 107°24′–109°29′E) is an important city in Western China with high terrain in the southeast, northwest, and southwest. Xiamen (24°23′–24°54′N, 117°53′–118°26′E), an important city on China's southeast coast, is a typical topographically restricted city with coastal plains, platforms, and hills as its main terrain (Sun et al., 2019).

## 3. The FCI development

Compact urban function requires the effective mixing of urban residential zones, commercial zones, public service zones, transport zones, and other zones. In compact urban areas, people can carry out their daily activities within a small area, which maximizes the intensity of human activity in such areas. We developed the FCI, a comprehensive index that can indicate the intensity of human activity and the differentiation of residential zones and other zones as well as assist in mapping the mixing degree of different functional zones. Within urban areas, the FCI takes the street blocks in RNO data as the basic spatial analysis unit. Then, the FCI identifies the functional attributes of each street block according to the POIs. Finally, it uses NPP/VIIRS nighttime light data to determine the intensity of human activity in functional zones.

### 3.1. *Urban area and functional zoning*

#### 3.1.1. *Urban area*

In this study, POIs were used to identify the functional attributes of street blocks. The degree of correspondence between POIs and real-world locations is related to the accuracy of the functional zoning. Therefore, the urban areas which are rich in POIs were taken as the main research area. Urban areas are regions where economic, political, cultural, and other activities take place and are the core areas of urban public activities. Based on many experiments using nighttime light data in the United States, Imhoff et al. (1997) proposed the Sudden Change Detection method to map urban areas. Based on this idea, in this study, we extracted urban areas according to the change in POI density. Firstly, we analyzed the change trend of POI density in cities and thus extracted the POI density contour. The polygon corresponding to the density contour is the POI density *iso*-surface. The value of the density contour gradually decreases from the city center to the city limits, while the area of the *iso*-surface gradually increases from the city center to the city limits. When the area of the *iso*-surface changes suddenly, the threshold before sudden change was used to map the initial urban area. Finally, the largest area and the areas connected to the largest area by roads whose length does not exceed 500 m were set as the final urban area.

#### 3.1.2. *Functional zoning*

The basic spatial units for analysis must be determined before dividing the functional zoning. Regular grids (e.g., square grids) (Thinh et al., 2002) and irregular grids (Song et al., 2018) are two main forms of basic spatial unit. The street blocks used in this study are irregular grids. Street blocks are the basic units of urban form structure, urban function, urban management, and urban cognition (Jiang and Liu, 2012). Each street block has a dominant functional attribute, which is determined by the POIs that dominate the block. According to the Chinese national standard *Code for the Classification of Urban Land Use and Planning Standards of Development Land*, urban functions are divided into six categories: (1) residential zone, referring to the area zoned for residential development; (2) commercial zone, referring to the area used for commercial development; (3) public service zone, referring to land used for government agencies and social organizations, press and other publications, scientific, education, and cultural services, and health and public facilities; (4) transport zone, referring to transportation infrastructure; (5) tourism/recreational zone; and (6) other zones. The classification of POIs is shown in Table 1.

After analyzing the POIs, it was found that the residential POIs have a smaller number of points; In contrast, commercial POIs, have a larger number of points. Specifically, a residential building is usually represented by only one POI whereas a commercial building is usually denoted by many POIs. Therefore, different types of POIs have different weights when identifying the attributes of street blocks. The residential POIs were processed separately from the other four categories of POIs.

Firstly, POIs were divided into two categories: residential POIs and non-residential POIs. The residential POIs include two categories: residential POIs and commercial POIs (residential POIs in commercial zone). In order to map the residential zone more accurately, a correction index was added to the residential POIs to distinguish commercial POIs from residential POIs. This index was calculated using the kernel density of the commercial POIs, and the sudden change detection method described in Section 3.1.1 was used to define the commercial zone as the area where the commercial density undergoes a sudden change. The categories of non-residential POIs were identified based on the proportion of each kind of POI (Eq. (1)); for example, if commercial POIs account for the largest proportion in a block, it can be determined that the block belongs to a commercial zone. The workflow of the mapping of functional zones is shown in Fig. 2.

$$F_i = \frac{n_i}{N} \tag{1}$$

where, $i$ represents the type of POI under examination, $n_i$ is the number of POIs of type $i$ in the research unit, $N$ is the total number of POIs in the research unit, and $F_i$ is the proportion of the number of POIs of type $i$ to the total number of POIs in the research unit.

After the classification of non-residential POIs, most of the blocks had been assigned attributes; however, there were still a small number of blocks for which the functional attributes could not be judged since there are no POIs in these blocks. For these blocks, the attributes were determined based on the size of the blocks. The functional properties of blocks with an area of more than 90,000 $m^2$ were comprehensively judged based on Google Earth images and the attributes of the surrounding POIs, while blocks with an area of less than 90,000 $m^2$ were set as transport zone, since 90,000 $m^2$ is the average size of residential blocks in China.

**Table 1**
The classification of points of interest (POIs).

| Functional zoning | POI |
|---|---|
| Residential zone | Residential community |
| Commercial zone | Restaurants, shopping services, life services, motorcycle services, car services, car sales companies, car maintenance companies, security services, financial insurance companies, banks, bank-related services, security companies, office buildings, general companies, accommodation services, sports leisure services, indoor facilities |
| Public Service zone | Scientific services, education and cultural services, government agencies and social organizations, medical and health services, public facilities, sports land |
| Transport zone | Airports, railway stations, transport services, road ancillary facilities, parking lots, ports, bus stations, railway stations |
| Tourism/ recreational zone | Places of interest, green land |
| Other zone | Bare land, agricultural land, water |

### 3.2. The FCI and its significance

Street blocks were abstracted into points. A block corresponds to a point, and each point has two attributes: functional type and intensity of human activity. Among them, the functional type is determined by POIs and the intensity of human activity is extracted from NPP/VIIRS nighttime light data. The average nighttime light intensity of each block was used to represent the intensity of human activity in that block. Fig. 3 shows an example of street blocks which were abstracted into the points that were required for the calculation of the FCI. Taking residential zones as the center, the gravitation between residential zones and the other four types of zone was calculated according to the gravitation formula (Thinh et al., 2002). The average gravitation between the intensity of human activity in the residential zone and that in another kind of zone is taken as the functional compactness between the residential zone and this other kind of zone (Eq. (2)). The functional compactness of a city is taken as the sum of the functional compactness of the residential zone and the functional compactnesses of the four other types of zone (Eq. (3)):

$$F_{RX} = \frac{1}{MN}\sum_{i\in\varphi_i}\sum_{j\in\varphi_j}\frac{1}{c}\frac{R_iX_j}{d^2(i,j)} \tag{2}$$

$$\mathrm{FCI} = \sum F_{RX}(X = 2,3,4,5) \tag{3}$$

where, $F_{RX}$ is the spatial gravitation between the intensity of human activity of the residential zone and that of another zone; $R$ represents the intensity of human activity of the residential zone; $X$ represents the intensity of human activity of either the commercial zone, public service zone, transport zone, or tourism/recreational zone, in which cases it takes values of 2, 3, 4, and 5, respectively; $\varphi_i$ is the set of point i;$\varphi_j$ is the set of point j; $R_i$ is the intensity of human activity of point $i$ in the residential zone; $X_j$ is the intensity of human activity of point $j$ in class $X$; $d$ is the Euclidean distance between point $i$ and point $j$; $M$ is the total number of points in the residential zone; $N$ is the total number of points in any of the other four classes; and $c$, equals 100 $(\mathrm{nW\ cm^{-2}\ sr^{-1}})^2\ \mathrm{m^{-2}}$, makes $F_{RX}$ non-dimensional and more readable. The FCI was used as the final estimate of the urban spatial functional compactness of the city. The greater the value of the FCI, the more compact is the urban spatial function.

## 4. Results

### 4.1. The FCI examinations

#### 4.1.1. The mapping of urban area and the precision of functional division

The POIs are zero-dimensional elements of geographic entities, and the closer they are to the city center, the more complete they are. Choosing an urban area with a relatively large amount of POIs as the research area can improve the division accuracy of functional areas to a certain extent. The availability of POIs, RNO data, and NPP/VIIRS nighttime light data makes it possible to compare the functional compactness of cities on a large scale.

The functional zoning of each of the studied cities was obtained using the method in Section 3.1.2. Random points were generated for each city (Beijing: 199; Shanghai: 190; Xi'an: 180; Xiamen: 164). The properties of random points were judged using a combination of Amap street view images, Google Earth images, and nearby POI points. By comparing the attributes of random points with the attributes of functional zones, the division accuracy of functional zones in each city was obtained. The

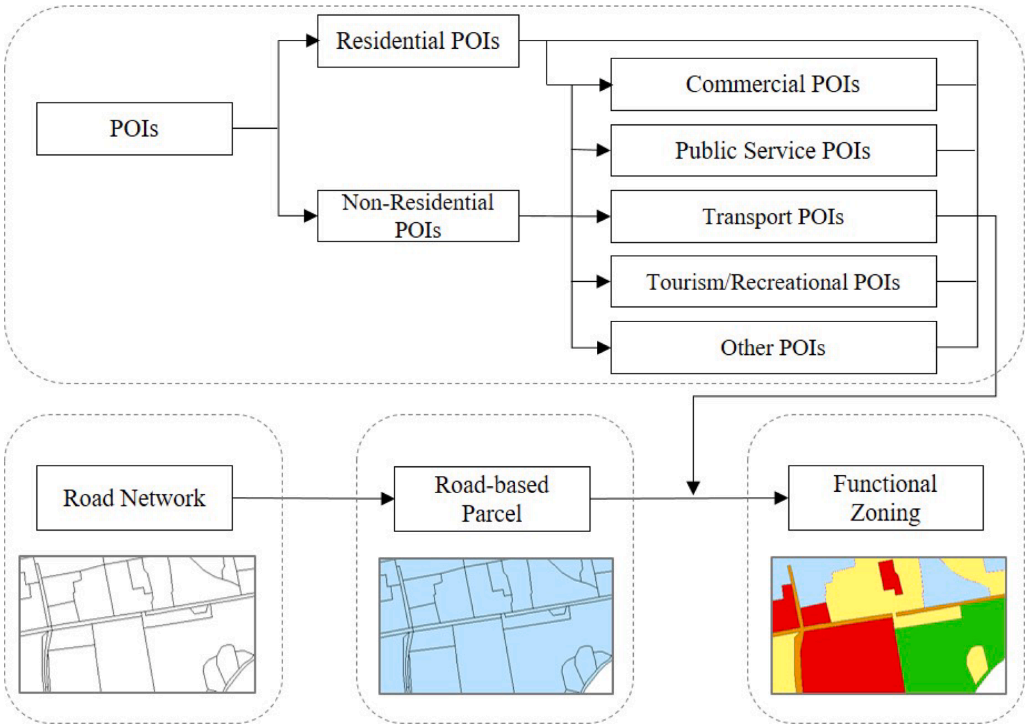


**Fig. 2.** The workflow of the mapping of functional zones.

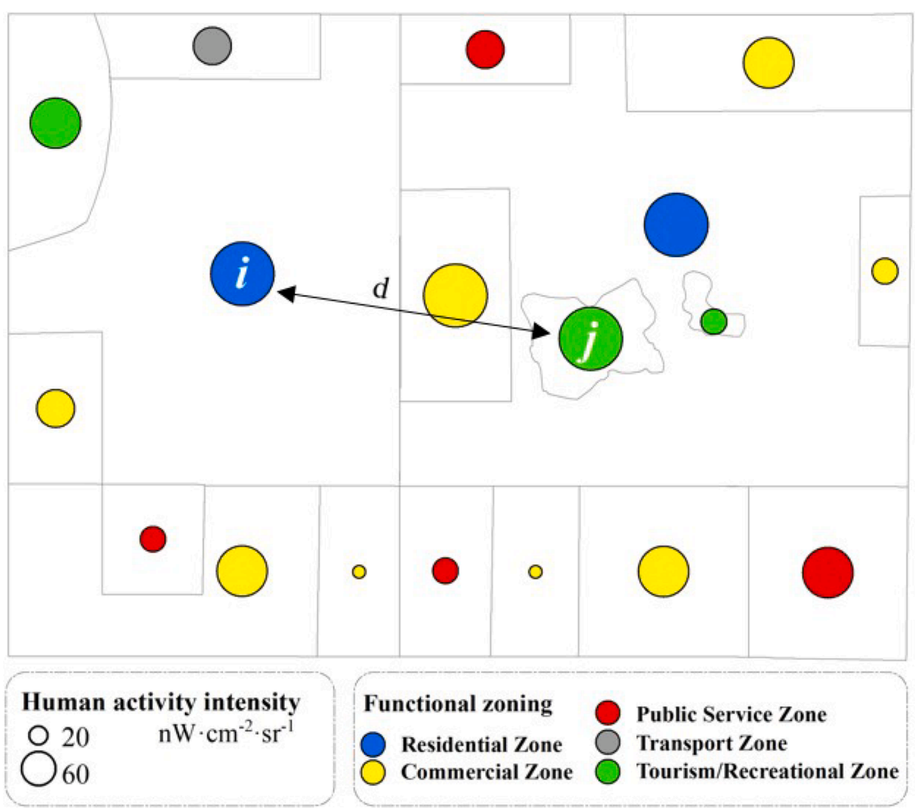


**Fig. 3.** Street blocks abstracted into the points that are required for the calculation of the functional compactness index (FCI). Points are used to represent the characteristics of street blocks.

determined accuracies were 95.48, 92.63, 94.44, and 87.20% for Beijing, Shanghai, Xi'an, and Xiamen, respectively. The blocks in the northern cities (Beijing and Xi'an) are more regular than those in the southern cities (Shanghai and Xiamen), and thus the accuracy of functional zone division is higher in the former cities; additionally, in the more developed cities (Beijing and Shanghai), the accuracy of functional zone division is higher.

*4.1.2. Scenario analysis*

Based on the actual situation of urban planning, we examined the effectiveness of the FCI on estimating urban functional compactness under four land use scenarios (Fig. 4). The block size in all four scenarios is 300 m × 300 m. Scenarios a, b, and c simulate the changes in the FCI under the same intensity of human activity but for different degrees of land use mixing. Specifically, in scenarios a, b, and c, the commercial, public service, transport, and tourism/recreational zones are clustered together, and then the mixing degree between the residential zone and these four types of zone, respectively, are changed. In Scenario a, the residential, commercial, public service, transport, and tourism/recreational zones are completely clustered and the residential zone is distributed among the four other types of zone. In Scenario b, the residential zone is mixed with the four other types of zone and the residential zone is partly surrounded by these four types of zone while other types of land are completely clustered. In Scenario c, the residential zone is mixed with the four other types of zone, however, the residential zone is completely distributed on the peripheries of the other types of zone. For the three scenarios, the value of FCI follows the order: Scenario b (75.75) > Scenario a (72.96) > Scenario c (57.46). This indicates that, for the layout in which the residential zone is surrounded by other zones, the degree of mixing between the residential zone and the other zones is greater, the average distance between the residential zone and other zones is shorter, and the urban function is more compact. Scenarios a and d simulate the relationship between the intensity of human activity and the FCI when the distribution of functional zones is exactly the same. In Scenario d, the FCI is 278.84, meaning that the overall intensity of human activity is greater than that in Scenario a. The results show that the higher the intensity of human activity, the more compact the urban function is.

*4.1.3. Analysis of the service radius of residential zones*

Additionally, we analyzed the relationship between the FCI and the service radius of residential zones. The service radiuses of residential zones for the four cities are shown in Fig. 5. By analyzing the changes in the FCI of all residential zones for different service radiuses, it was found that (1) when the service radius is within 1–8 km, the FCI increases rapidly with increasing service radius, (2) when the service radius is more than 8 km, the FCI increases less rapidly with increasing service radius, and (3) when the service radius reaches 20 km, the FCI is basically stable with increasing service radius, with only a slight increase (Fig. 6). Therefore, it was concluded that it is unnecessary to consider the size of the residential service radius when calculating the FCI.

*4.1.4. Relationship between FCI and CI*

Fig. 7 shows the impervious surface areas in the urban areas of the

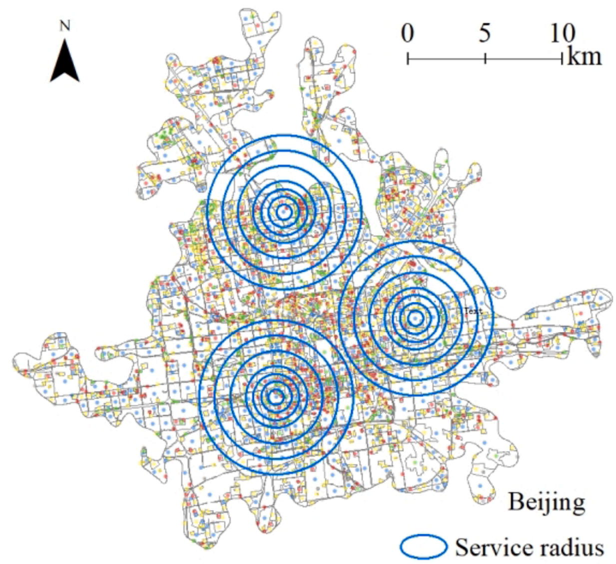


**Fig. 5.** Service radiuses of residential zones.

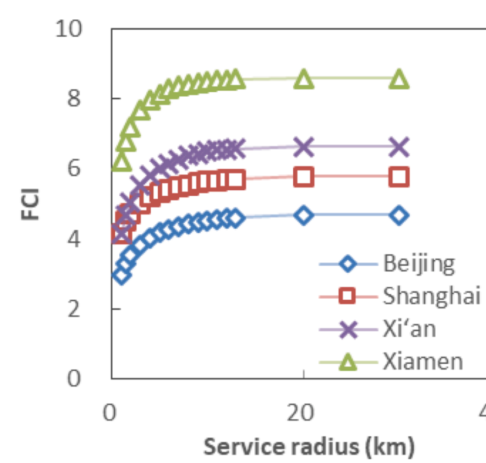


**Fig. 6.** The relationship between the FCI and the service radius of residential zones for the four studied cities.

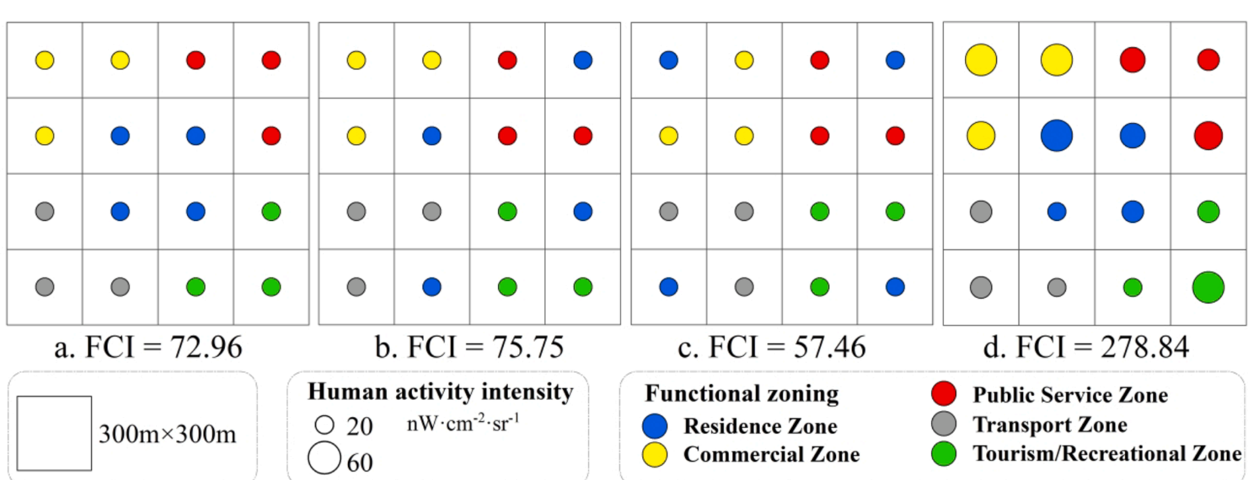


**Fig. 4.** Values of the FCI for different degrees of functional zone mixing.

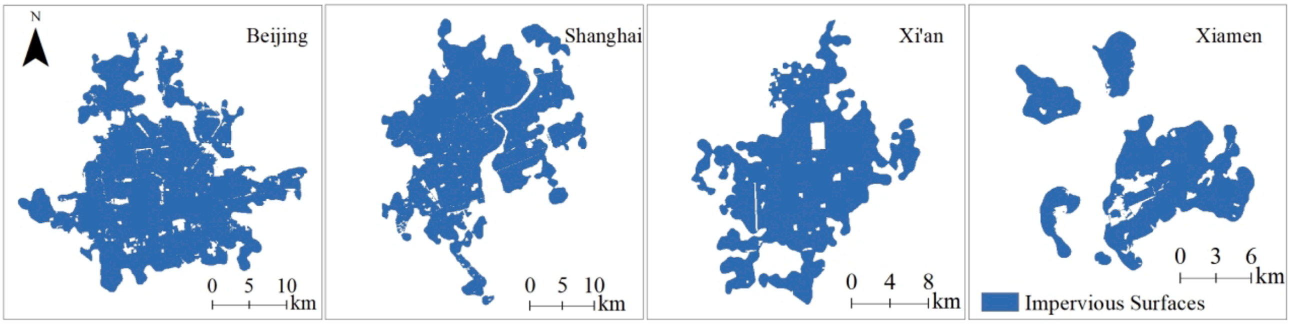


**Fig. 7.** Impervious surface area of the study areas in the urban areas.

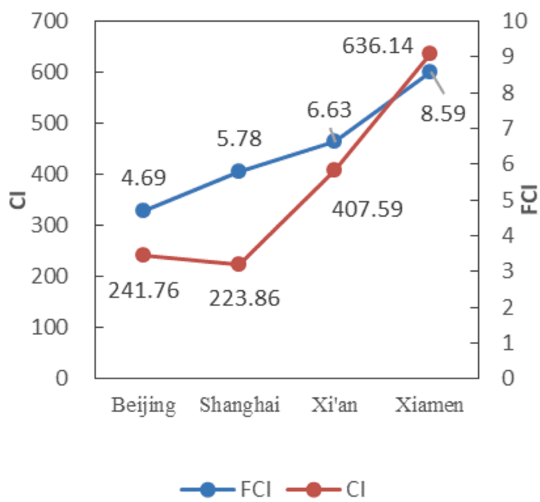


**Fig. 8.** Values of the FCI and compactness index (CI) in the four studied cities.

four studied cities. Based on these impervious surface areas, the CI was calculated for each city, as shown in Fig. 8. As can be seen in the figure, the calculated CIs were different for the four cities. The CI is lowest in Shanghai. This can be attributed to the city's large size and the fact that it is divided into two parts by the Huangpu River. The CI of Beijing is the second-lowest. Xi'an and Xiamen, which are smaller than Beijing and Shanghai, have the second-highest and highest CI, respectively. There were significant differences in the FCI and CI among the four cities. The FCI in Xiamen was the largest (8.59), followed by Xi'an, Shanghai, and Beijing.

The FCIs for residential and commercial zones ($F_{R2}$), residential and public service zones ($F_{R3}$), residential and transport zones ($F_{R4}$), and residential and tourism/recreational zones ($F_{R5}$) are shown in Table 2. The FCI between residential zones and public service zones is relatively large, which indicates that the distribution of public service zones and residential zones match well. The spatial gravitation between residential zones and tourism/recreational zones is relatively small, which means that the distribution of residential zones is not well matched with that of tourism/recreational zones; however, Shanghai is an exception to this, since its main tourist sights are located in the downtown business district. Of the four cities, Beijing has the highest FCI between residential and public service zones, Shanghai has the highest FCI between residential and tourism/recreational zones, and Xi'an and Xiamen have the highest FCI between residential and transport zones.

**Table 2**
Functional compactness index (FCI) in the four studied cities and the FCI between residential zones and commercial, public service, transport, and tourism/recreational zones.

| City | FCI | $F_{R2}$ | $F_{R3}$ | $F_{R4}$ | $F_{R5}$ |
|---|---|---|---|---|---|
| Beijing | 4.69 | 1.06 | 1.34 | 1.29 | 1.00 |
| Shanghai | 5.78 | 1.29 | 1.60 | 1.17 | 1.70 |
| Xi'an | 6.63 | 1.48 | 1.83 | 1.90 | 1.41 |
| Xiamen | 8.59 | 2.03 | 2.26 | 2.50 | 1.81 |

Note: $F_{R2}$ is the FCI between residential and commercial zones, $F_{R3}$ is the FCI between residential and public service zones, $F_{R4}$ is the FCI between residential and transport zones, and $F_{R5}$ is the FCI between residential and tourism/recreational zones.

On the whole, the FCI values of the four cities are inversely proportional to the city size. Taking the geometric center of the city as the origin and circular buffer zones with radiuses increasing from one km to the city limits, the FCI was calculated for different radiuses (Fig. 9). In all cities aside from Xiamen, the largest FCI was obtained for a radius of one km, with values of 1459 in Shanghai, 473 in Beijing, and 535 in Xi'an. With increasing circle radius, the FCI values decreased sharply. For radiuses of 1–13 km, Shanghai has the highest FCI, followed by Xi'an and Beijing, whose FCI values are similar, while Xiamen has the lowest FCI. For radiuses above 13 km, the FCI value of Xiamen is the highest, followed by Shanghai, Xi'an, and Beijing, which means that the intensity of human activity in Shanghai, Beijing, and Xi'an is low. That is, with expanding urban area, the FCI values of the larger cities—Beijing, Shanghai, and Xi'an—decline rapidly, while the FCI values of the smaller city—Xiamen—decline slowly and eventually surpass those of Xi'an and Beijing (at 10–11 km) and Shanghai (at 13 km).

### 4.2. *Intensity of human activity and functional types*

The intensity of human activity and the functional types are the basic data used to calculate the FCI. In order to facilitate their interpretation, these two data types were visualized using the ArcGIS software (Esri, Redlands, CA, USA; Fig. 10).

#### 4.2.1. *Intensity of human activity*

Taking the central business district (CBD) of the city as the city center, rectangular strips with a width of one km were created in each of the four studied cities. Then, the total intensity of human activity in each strip was calculated (Fig. 11). It was found that the maximum intensity of human activity in each city is located in or close to the city center. For all four cities, the intensity of human activity gradually decreases from the city center to the city limits, increases again in the sub-center, and then decreases again. The intensity of human activity is the weakest at the edge of the urban area. Of the four cities, Beijing has the highest intensity of human activity, followed by Shanghai, Xi'an, and Xiamen. The areas with the highest intensity of human activity in Beijing are Beijing railway station, Wangfujing, Sanlitun, Shuangjing, and Beijing Antique City. The areas with the highest intensity of human activity in Shanghai are the Bund and Lujiazui. The areas with the highest intensity of human activity in Xi'an are mainly located within the ancient city walls and in the south of the city. The highest intensity of human activity in Xiamen is located on Xiamen Island, and there is little difference in the intensity of human activity across the city.

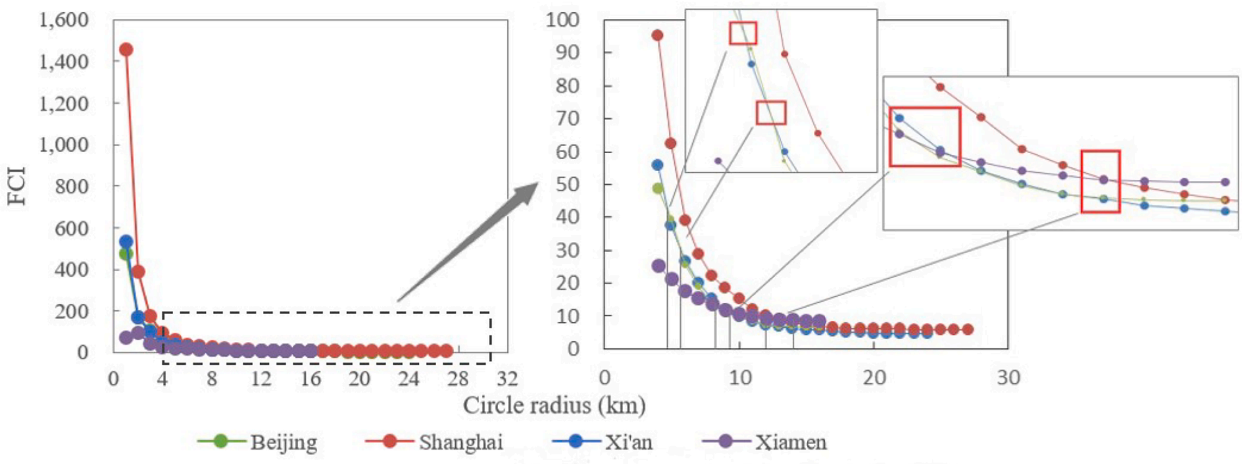


**Fig. 9.** The FCI measured within circles of different radiuses centered on the city center for the four studied cities.

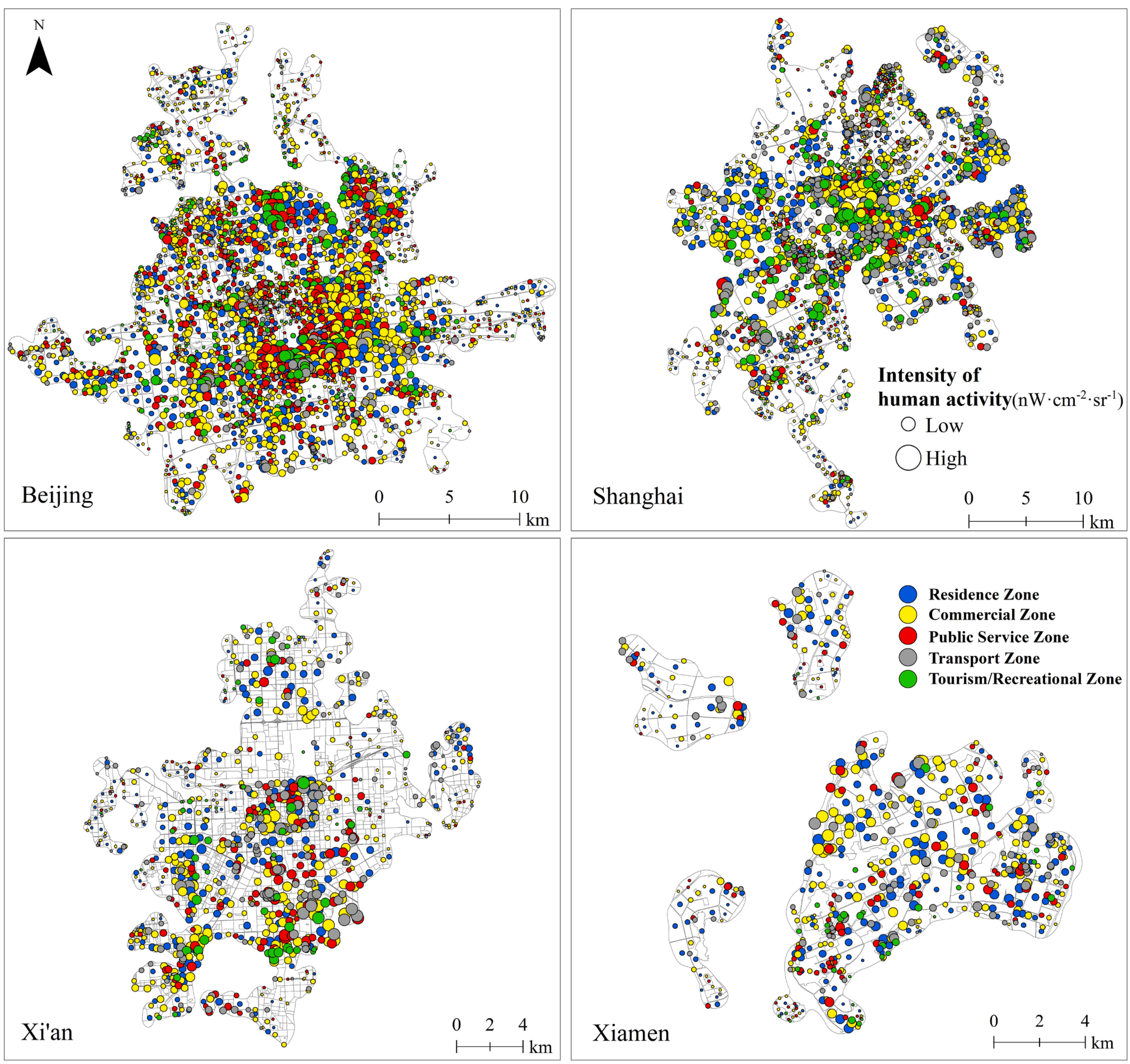


**Fig. 10.** Visualization of the intensity of human activity for different functional types.

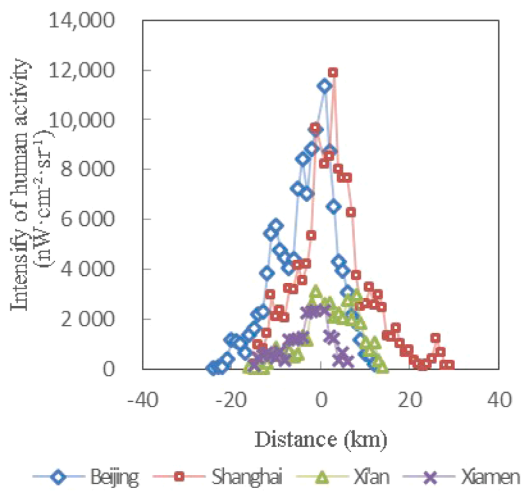


**Fig. 11.** An analysis of the intensity of human activity in the four studied cities. Taking the central business district (CBD) of the city as the city center, rectangular strips with a width of one km were created for each city. Then, the total intensity of human activity in each strip was calculated.

#### 4.2.2. Functional types

A grid of 1 km × 1 km was established for each city except Xiamen, for which a grid of 0.5 km × 0.5 km was established due to the city's smaller size. Street blocks were abstracted into points as described in Section 3.2. The number of points of each type of each grid were summed separately to obtain residential zone, commercial zone, public service zone, transport zone, and tourism/recreational zone. Then, the relationship between the residential zones and the other four types of zone was analyzed using the local indicator of spatial association (LISA; Anselin, 1995). Bivariate LISA maps between residential zones and other types of zone are shown in Fig. 12. On the whole, there is a positive spatial correlation between residential zone and the other four kinds of zone. For all four cities, H-H clusters (i.e., spatial clustering of high values (i.e., those that exceed the mean) [Pili et al., 2017]) are mainly distributed in the city center. Specifically, there are a large amount of L-H (low values [i.e., those that are lower than the mean] surrounded by high values) and H-L (high values surrounded by low values) clusters in the correlation analysis between residential zones and tourism/recreational zones. Of the four cities, the correlation between residential zones and public service zones is strongest for Beijing, where L-L clusters (that is, spatial clustering of low values) are mainly distributed at the edge of the urban area. The correlation between residential zones and commercial zones is the strongest in Shanghai, and H-L clusters are distributed at the edge of the city. The correlation between residential zones and transport zones is strongest in Xi'an, where H-L clusters are also distributed at the edge of the city. The relationship between residential zones and transport zones is strongest in Xiamen, where H-L clusters are distributed at the inner edge of Xiamen Island and outside Xiamen Island.

## 5. Discussion

### 5.1. Advantages of the FCI

The FCI proposed in this study can be used to assess the rationality of city layouts based on the spatial distribution of functional zones. By considering four scenarios, it was found that the greater the intensity of human activity, the more compact the city functions, the more mixing there is between residential zones and other functional zones, and the more compact the city is. The results of this study show that the FCI can comprehensively reflect the intensity of human activity, the differentiation between residential zones and other zones, and the degree of mixing of different functional zones. However, the urban functional compactness cannot be effectively improved by simply mixing different types of functional zone while ignoring the locations of residential zones. By shortening the average distance between residential zones and other zones, urban activity can be increased and urban functional compactness can be improved. Moreover, this study found that the service radius of residential zones has no effect on the FCI. Different kinds of facility can have different optimal service radiuses (e.g., the service radius of primary schools should not be greater than 500 m and that of middle schools should not be greater than 1000 m). In this work, it was found that, with increasing service radius, the FCI first increases rapidly, then increases slowly, and finally reaches stability. Therefore, it is not necessary to consider the residential service radius when calculating the FCI. Additionally, it was shown that the FCI can reflect both the overall functional compactness and local functional compactness of a city. It was found that Xiamen has the largest functional compactness of the four studied cities, with an FCI of 8.59, followed by Xi'an, Shanghai, and Beijing, with FCIs of 6.63, 5.78, and 4.69, respectively. By further analyzing the relationship between the FCI and city size, it was found that in the larger cities—Shanghai, Beijing, and Xi'an—the FCI is high in the center of the city and low in the periphery, and there are large regional differences in the intensity of human activity. However, in the smaller city—Xiamen—the intensity of human activity is more balanced and the overall functional compactness is optimal.

### 5.2. FCI and CI

The FCI is based on a gravitation equation and takes into account the spatial distances between parcels of a city, as does the CI (Thinh et al., 2002). However, there are three main differences between the FCI and the CI: (1) The basic spatial units of the two indexes are different. The basic spatial unit of the CI is a regular grid, and the CI changes with changing grid scale; hence, it is necessary to analyze the scale and select the appropriate grid scale when calculating the CI. For example, Zhao et al. (2011) selected a 300 m × 300 m grid. Additionally, after evaluating the relationship between grid scale and the CI, Thinh et al. (2002) selected 500 m × 500 m as the final grid size. In this study, the irregular street block was taken as the basic spatial analysis unit for the calculation of the FCI. As the basic spatial unit of the intensity of human activity, street blocks have unique advantages for reflecting the spatial layout of functional zoning. In the calculation of a city's FCI, there is no need to consider the scale; (2) The data involved in the calculation of the indexes are different. The basic data needed to calculate the CI are the urban impervious surface area or urban built-up area (Jia et al., 2019), these data are generally obtained from remote sensing image classification or land use databases. On the other hand, the basic data required to calculate the FCI are urban functional zoning and the intensity of human activity, which can be obtained from the POIs and NPP/VIIRS nighttime light data, respectively; (3) The meaning of the two indexes is different. The CI, which is a physical compactness index, describes the degree of correlation between urban parcels, while the FCI considers the rationality of urban layout based on functional zones and reflects the gravitational attraction of the intensity of human activity in different functional zones.

### 5.3. Extraction of urban areas and data processing

In this study, urban areas were extracted for each city based on the change of the POIs density. In previous studies, the urban area has generally been obtained by extracting urban impervious surface area or built-up area from remote sensing image data (Jiao, 2015). For large-scale research, the collection and processing of remote sensing images is a time-consuming and laborious task. Therefore, in this work, it was chosen to extract urban areas using POIs in order to reduce the time requirements, which is conducive to the faster comparison of the functional compactness of multiple cities. Furthermore, since POIs in urban areas are more abundant than suburban areas, selecting urban areas as

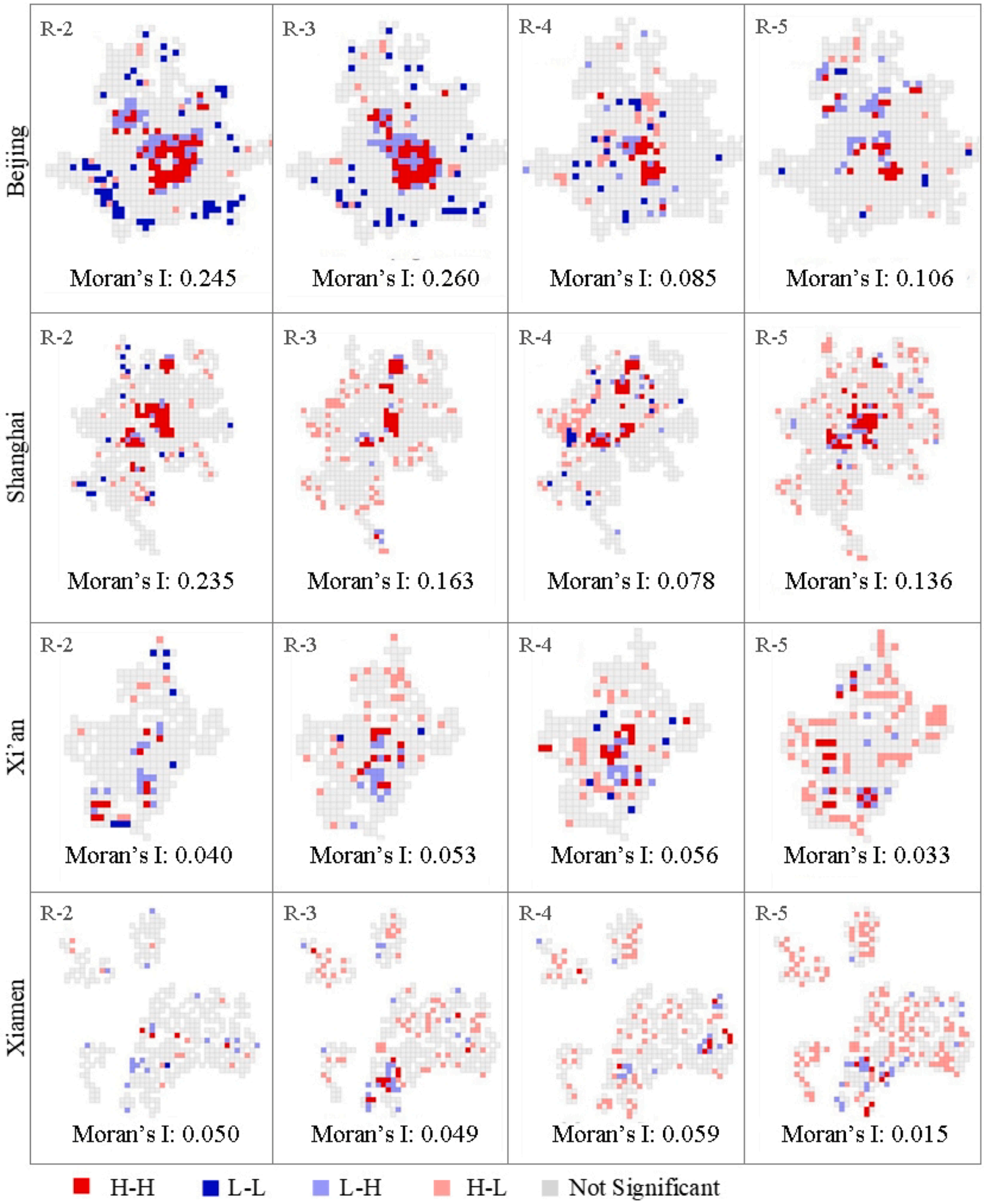


**Fig. 12.** Local spatial correlations between residential zones and: commercial zones (R-2), public service zones (R-3), transport zones (R-4), and tourism/recreational zones (R-5). H-H indicates spatial clustering of high values (i.e., those that are larger than the mean); L-L indicates spatial clustering of low values (i.e., those that are lower than the mean); L-H indicates the spatial association of low values surrounded by high values; and H-L indicates the spatial association of high values surrounded by low values.

the research target can improve the division accuracy of functional zones.

The method of quantifying urban functional zones that was used in this study is different from that used in previous studies (Song et al., 2018). In our study, POIs were divided into two categories, namely residential POIs and non-residential POIs. The achieved division accuracy was above 87% for all four cities. Compared with the southern cities (Shanghai and Xiamen), the street blocks in the northern cities (Beijing and Xi'an) are more regular, and the division accuracy is consequently higher in the latter cities. Additionally, a higher division accuracy was obtained for the more developed cities (Beijing and Shanghai), which is consistent with the higher availability of POIs in these cities. The functional zoning method proposed in this paper has high accuracy and good applicability, thus validating the applicability of the proposed FCI.

### 5.4. Limitations and prospects

There are some shortcomings to this study. First, the intensity of human activity was estimated using only nighttime light data. However, due to the restriction of human movement and the protection of cultural relics, nighttime light do not necessarily reflect the true intensity of human activity in some locations, which may introduce bias into the results of this study. In the future, the improvement in measuring the intensity of human activity would be helpful. Moreover, the POIs that were used in this study were obtained from the company Amap. Although a large amount of data are available, it cannot be guaranteed that all geographical entities are fully included, especially in suburban areas. This potential lack of data may lead to errors in the division of functional zones. For this reason, this study chose urban areas with relatively complete POI data while ignoring suburban areas.

## 6. Conclusions

In this study, we developed a novel index called FCI for quantifying the functional compactness of urban space. The performance of the FCI proved satisfactory. This index takes street blocks as the basic analysis unit and mainly considers the functional zoning and the intensity of human activity, unlike the CI and other indicators that only measure the physical compactness of cities. Four land use scenarios and four Chinese cities were considered to examine the effectiveness of the FCI. The results show that the FCI is not affected by scale effects or the service radius of residential zones and thus, can reflect the overall and local functional compactness of a city. We found that the correlation between residential zones and other functional zones was different among the four studied cities, which could help infer the main characteristics of the cities (e.g., political cities, economic cities, and tourist cities).

In the development and planning of big cities, on the one hand, it is necessary to consider the effective spatial matching of residential zones and other functional zones to reduce commuting time and improve the compactness of city; on the other hand, it is important to note that city “compactness” does not refer to a larger population or building density but appropriate population or building density. Therefore, future research on urban compactness should explore optimal ranges of compactness to help the sustainable development of cities.

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## CRediT authorship contribution statement

**Ting Lan:** Conceptualization, Methodology, Software, Data curation, Visualization, Investigation, Validation. **Guofan Shao:** Supervision, Writing - review & editing. **Zhibang Xu:** Methodology, Software. **Lina Tang:** Conceptualization, Methodology, Supervision. **Lang Sun:** Writing - review & editing.

## Declaration of Competing Interest

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

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