Sensors and Materials, Vol. 34, No. 12 (2022) 4339–4353
MYU Tokyo

S & M 3114

Comparative Study on Functional Mixing Degree of Urban Land Use Based on Multi-source Data —Case Study of Zhuhai City, China

Junrong Li,[1] Peng Guo,[1*] Yanling Sun,[1**] Zifei Liu,[1]
Qiyi Chen,[1] Ying Zhang,[2] and Jie Liu[2]

[1]School of Geography and Environmental Science, Tianjin Normal University, Tianjin 300387, China
[2]Shanghai Citybeats Information Technology Co., Ltd., Shanghai 200433, China

(Received August 21, 2022; accepted October 3, 2022; online published November 24, 2022)

Keywords: mixed degree of urban functions, POIs, taxi GPS, mobile phone signaling data, Zhuhai

With increasing urbanization, the compact use of urban land has attracted increasing attention. The mixing degree of urban land use is an important way to realize intensive and efficient land use. In this study, three types of geographic spatiotemporal data, namely, point of interest (POI) data, taxi GPS data, and mobile phone signaling data, were used to identify and analyze the spatiotemporal differentiation characteristics of the functional mixing degree of urban land use in Zhuhai, China. We used correlation and regression analyses to demonstrate the rationality of using the three types of geographic spatiotemporal data in combination to evaluate the degree of functional mixing. We showed that the results obtained using the three types of geographic spatiotemporal data have different emphases, and their combined use can improve the accuracy of research results. On the whole, the functional mixing degree of land use in the study area was generally low and the spatial distribution varied, gradually decreasing away from the center of the old central city in the east of Zhuhai City to the central city in the west of Doumen District.

1. Introduction

A mixture of urban land use functions is an effective way to improve the vitality of a city and the intensity of land use. To realize the intensive and efficient use of land, it is particularly important to explore the compact use of urban land and improve the mixture of land use functions.(1) In urban land, the degree of mixing is considered to be the amount of mixing of residential, retail, office, entertainment, and other functional parcels in a specific area.(2) Its essence is to reflect the function of urban land agglomeration and the degree of synergy. There have been many studies on the evaluation of the mixed use of urban land. Hoppenbrouwer and Louw(3) divided functional mixing into sharing mixing, horizontal mixing, vertical mixing, and time dimension mixing. In terms of the research scale, according to the research purpose, the scope can be divided into different spatial scales, such as buildings,(4) grids,(5) block scales,(6) communities,(7) and urban local regions.(8) Common measurement methods include the entropy

*Corresponding author: e-mail: pguo@tjnu.edu.cn
**Corresponding author: e-mail: sunyanling@tjnu.edu.cn
https://doi.org/10.18494/SAM4089

ISSN 0914-4935 © MYU K.K.
https://myukk.org/

index, Simpson index, Shannon–Wiener index, balance index, dissimilarity index, fragmentation index, diversity index, and statistical index methods.[9–11] These methods have advantages and disadvantages, and different methods are applicable to different research scales and functional types of urban land use.[12]

With the advent of the era of big data, multisource data, particularly point of interest (POI) data, resident travel data, mobile phone signaling data, and microblog check-in data, has often been used to conduct functional hybrid research on urban land use.[13] For example, Li *et al.*[14] used POI data, information entropy, landscape pattern analysis, and association rule mining to explore the spatial differentiation characteristics of mixed land use. POI data, characterized by a wide coverage, a large amount of data, a simple access method, and high accuracy and timeliness, can provide a wide range of sources for urban land use research. However, it only considers entities related to urban life space (e.g., hospitals, schools, and shopping malls) and its attribute information (e.g., name, coordinates, and address), and people's travel trajectories and activity ranges are ignored.[15] Li *et al.*[16] used taxi origin–destination (OD) data to preliminarily identify the spatiotemporal differentiation of urban functional mixing in Beijing, and they further integrated POI data and used the information entropy model to quantitatively evaluate the functional mixing degree of urban land use. The taxi OD data was used to collect the activity information of people, cars, and other mobile objects in the city through the on-board GPS, and the dynamic law of the urban internal spatial structure can be reflected after processing the data. Previous studies have shown that taxi data can reflect the mixing degree of functional zoning within a city but cannot accurately reflect the spatial distribution characteristics of a population.[17] Niu *et al.*[18] analyzed the population on working and rest days using mobile phone signaling data, identified the urban spatial structure of the center of Shanghai City by a spatial clustering method, and analyzed the mixing degree of urban functions. Duan *et al.*[19] identified the urban spatial structure by analyzing big data. Their research showed that the mobile phone signaling data had high spatial and temporal accuracies, and the spatiotemporal law of residents' activities can reflect the mixing degree of urban land use to a certain extent.

According to the above studies, it is feasible to conduct functional hybrid studies of urban land use based on different data sources, but different data sources have different characteristics. Therefore, the functional mixing degree of cities cannot be accurately identified by only using a single type of data. The integration of multisource data can compensate for the sample deviation of data to a certain extent, and spatial information can be interpreted as comprehensively as possible to identify the functional mixing degree of a city.[20] However, previous studies on identifying the mixing degree of urban land use have been mainly based on a single type of data, and few studies on the functional mixing degree of urban land use have integrated multisource data such as POI data, resident travel data, and mobile phone signaling data.

Therefore, in this study, by integrating these three data sources, we first used the information entropy model to calculate the functional mixing degree of urban land use of a 500 m × 500 m grid in Zhuhai, China. We also analyzed and verified the mixing degree of urban land functions in Zhuhai from the three research perspectives of location, travel trajectory, and population distribution. Secondly, global and local spatial autocorrelation analyses were applied to the results of information entropy to detect agglomeration areas with high mixing degrees. Finally, correlation and regression analyses were used to verify the rationality of the combined use of three types of entropy to evaluate the functional mixing degree of urban land use, so as to provide a more scientific and reasonable reference for the future development of urban functional mixing.

2. Study Area and Data

2.1 Study area

Zhuhai is located in the central and southern parts of Guangdong Province, China (Fig. 1). The city has jurisdiction over Xiangzhou, Doumen, and Jinwan administrative regions and has five economic functional zones: Hengqin, Gaoxin, Baoshui, Wanshan, and Gaolan. At the end of 2020, the land area of Zhuhai was 1736.45 km^2. The permanent resident population was 2449600 and the urbanization rate was 90.47%. As one of the special economic zone cities in China, Zhuhai has become an important port city owing to its unique geographical location; it is the only city on the mainland connected to both Hong Kong and Macao by land. After more than 40 years of development since China's reform and opening up, Zhuhai has developed from a border town to one of the happiest cities in China, attracting population and industries, and the city has developed rapidly. In the Sustainable Development Blue Book: *China's Sustainable Development Evaluation Report*(21) released for three consecutive years from 2018 to 2020, Zhuhai ranks first in China for sustainable development. At the same time, urban land shortage has also become a problem in Zhuhai. Therefore, it is of great significance to carry out research on its urban functional mixing.

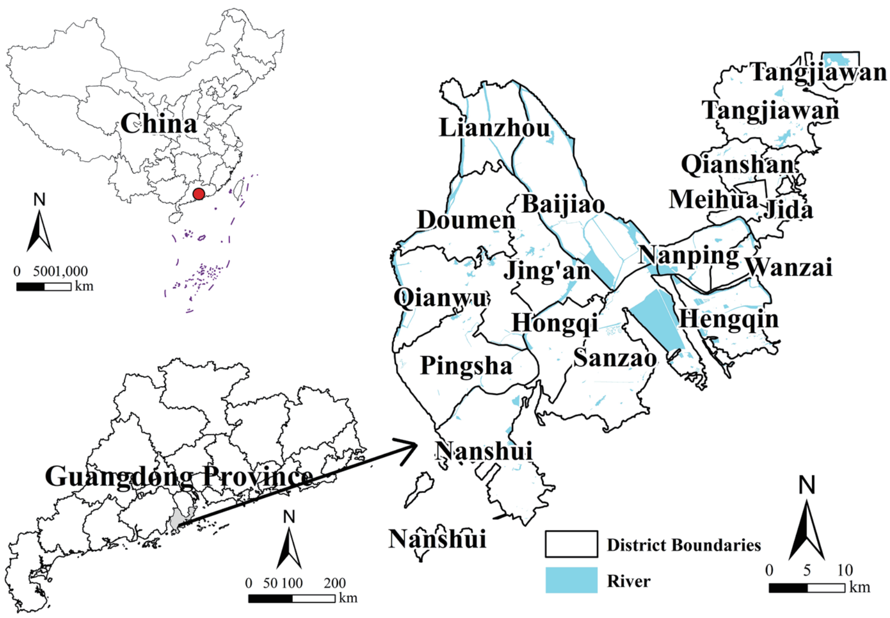

Fig. 1. (Color online) Location of the study area in China.

2.2 Data source

2.2.1 POI data

Based on the open application programming interface (API) of Amap (Gaode Map), we obtained POI data of Zhuhai in October 2020 through the Python web crawler. Each POI contains attribute information such as latitude and longitude coordinates, address, name, type, and administrative region. After pre-processing involving cleaning, rechecking, spatial positioning, definition projection, and coordinate transformation, 128949 effective POIs were finally obtained. In accordance with the National Economic Industry Classification and the Statistical Classification of Consumer Services (2019),(22,23) these POIs were divided into six categories and 14 subcategories, including life services, business, finance and insurance, public services, leisure and entertainment, and housing. The results of the specific classification are shown in Table 1.

After screening and classification, the POI point data was spatially visualized, superimposed, and interpreted with the administrative division data of each district in Zhuhai. Through the fishnet function of ArcGIS Geographic Information System software, Zhuhai was divided into a 500 m × 500 m unit grid, which was regarded as the computing unit. By combining the spatial distribution of POI point data and its access frequency data, the actual demand and usage of functional points in each city were investigated.

2.2.2 Taxi GPS data

Taxi GPS data contains a large amount of spatiotemporal information about urban residents' activities and mobility, and is widely used in urban research.(24) According to the monitoring index information of Zhuhai taxi market operation (2020), each taxi in the city carries about 35 passengers a day with an average daily mileage of 182.7 km. Therefore, the GPS data of Zhuhai taxis can reflect the travel trajectory and activity of urban residents to a certain extent. At the same time, this data can be used together with the mixing degree research method mentioned in the introduction to reveal the functional structure of the city and the mixing degree of urban functions. In this study, GPS data of 3284 taxis in Zhuhai City on weekdays in June 2020 was used. Each record included the taxi number, GPS time, longitude and latitude coordinates, whether passengers were being carried (1 = carrying passengers, 0 = no load), and mileage

Table 1
Types of POI data in Zhuhai.

POI type	Quantity (unit)	POI type	Quantity (unit)
Auto services	3946	Scenic spots	701
Food and beverage services	19005	Commercial housing	4076
Shopping services	28438	Government agencies	3510
Life services	19275	Science, education, and culture	5351
Sports and leisure services	2289	Traffic facilities	5056
Health care services	3507	Financial insurance	1847
Accommodation services	28438	Companies	3510

information. After cleaning the original GPS trajectory data, the passenger travel record data was obtained by using different passenger carrying states. After performing statistics, 1.214 million travel records were finally obtained. To conduct spatial analysis, the grid of 500 m × 500 m was taken as the analysis unit, and the travel distance of each trip in the grid was determined. The record format of each trip included the taxi number, boarding time, boarding grid number, getting off time, getting off grid number, travel distance, and travel time. By analyzing the obtained data, we determined the 24 h average passenger flow of a working day.

2.2.3 Mobile phone signaling data

The mobile phone signaling data used in this study originated from China Mobile operators in Zhuhai, and the data acquisition time was consistent with the taxi data. By identifying the stop point and analyzing the origin and destination of travel, the travel data was counted on the same 500 m × 500 m grid, and 6.023 million travel records were obtained. The format of each record was similar to that of a taxi record, including the departure time of an anonymous user with an identification number, the origin grid number, the arrival time, and the arrival grid number.

3. Methods

3.1 Calculation of mixing degree

3.1.1 Spatial dimension information entropy calculation based on POI data

The information entropy can measure the imbalance degree of the distribution of geographical elements and characterize the spatial homogeneity or heterogeneity of urban space.[25] In the study of urban land use and internal functional areas, the level of information entropy can reflect the equilibrium degree of urban land use. A higher entropy corresponds to more land use types with different functions, richer urban functions, and a higher mixing degree. In this paper, we quantitatively describe the functions of different types of urban land use through the information entropy models of different types of POI data that integrate information and fractal theories. The information entropy is calculated as follows:

Let the total number of POI data be A. In this study, there are 14 types of data (n = 14) and the number of each type of POI is A_i (i = 1, 2, ..., 14). Thus, A is

$$A = \sum_{i=1}^{n} A_i \, . \tag{1}$$

The proportion P_i of each type of POI of the total POI is

$$P_i = \frac{A_i}{A} = \frac{A_i}{\sum_{i=1}^{n} A_i} \, . \tag{2}$$

Then, the formula for the information entropy of the urban land use function is

$$H = -\sum_{i=1}^{n} P_i \times \log P_i \,. \tag{3}$$

ArcGIS is used to grid the urban space. The grid size is 500 m × 500 m and has m rows and n columns in total. When investigating the spatial distribution of the POI of different land use function types, it is necessary to keep the total number of POI types invariant. Suppose that the number of POIs of a certain type in the grid of row i and column j is A_{ij}, the total number of all POI types in the grid of row i and column j is A_k, which is defined as

$$P_{ij} = \frac{A_{ij}}{A_k} \,. \tag{4}$$

Then, the formula for the spatial information entropy H_s is

$$H_s = -\sum_{i}^{m}\sum_{j}^{n} P_{ij} \times \log P_{ij} \,. \tag{5}$$

H_s reflects the mixing degree of urban functions. The higher the value of H_s, the more functional types of urban land use there are and the less the difference in the number of functional types of urban land use. In contrast, a lower H_s means fewer functional types of urban land use and a greater difference in the number of functional types of urban land use.

3.1.2 Entropy calculation of spatiotemporal information based on taxi GPS data and mobile phone signaling data

In accordance with the above calculation model of information entropy, a calculation model of spatiotemporal entropy based on taxi OD points and mobile phone signaling data was constructed. To accurately reflect people's activities in different time periods, it was divided into t time segments (t = 14 days × 24 h), and the space–time entropies of OD data based on taxi data and the OD data of mobile phone signaling data in each grid were calculated as

$$H_{st} = -\sum_{i}^{m}\sum_{j}^{n}\sum_{h}^{t} P_t \times \log P_t \,. \tag{6}$$

This formula is applicable to the calculation of the OD spatiotemporal entropies of taxis and mobile phones, where H_{st} is the spatiotemporal entropy. P_t is the proportion of the passenger flow at point O (origin place) or point D (arrival place) in the grid at row i, column j, and hour h relative to the passenger flow at all statistical times. In the calculation of the spatiotemporal entropy of mobile phone signaling data, P_t is the proportion of the population in the grid at row i, column j, and hour h relative to the total population at the statistical time. According to the characteristics of the taxi GPS data, to some extent, the space–time OD distribution can characterize the behavior characteristics and regularity of different people, and the mobile phone signaling data can reflect the real-time distribution of the population. With increasing spatial and temporal entropies of the taxi GPS data and mobile phone signaling data, the OD number and the mixing degree increase, which also means that for a higher population density, the function type of the city also becomes more complex.

3.2 Spatial autocorrelation analysis

3.2.1 Global spatial autocorrelation

Global spatial autocorrelation usually uses global Moran's I index to judge whether the observed variables in the whole study area have aggregation characteristics in space. Its value is generally between −1 and 1, with a value less than 0 indicating a negative correlation, a value greater than 0 indicating a positive correlation, and a value of 0 indicating no correlation. The closer the absolute value is to 1, the more similar the properties are between units; the closer it is to 0, the less correlated the units are. The calculation formula of Moran's I index is

$$\text{Moran's } I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij}\left(x_i-\overline{x}\right)\left(x_j-\overline{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij}\sum_{i=1}^{n}\left(x_i-\overline{x}\right)^2}, \tag{7}$$

where I is the total number of spatial units; m is the number of units neighboring spatial unit i; w_{ij} is an element of the spatial weight matrix. When spatial elements i and j are adjacent, $w_{ij} = 1$, otherwise $w_{ij} = 0$; x_i and x_j are the element attribute values of spatial elements i and j, respectively. x is the attribute value of the factors of the evaluation unit and $\overline{x}$ is the average of all data.

3.2.2 Local spatial autocorrelation

Local Moran's I (LISA) statistic is the most commonly used statistic in local spatial autocorrelation analysis to show the degree of aggregation and the stability of the scope of a local space. It is calculated as

$$I_i = \frac{\left(x_i-\overline{x}\right)\sum_{j=1,j\neq i}^{n} w_{ij}\left(x_j-\overline{x}\right)}{S^2}, \tag{8}$$

where x_i, x, x_j, m, w_{ij}, and n have the same meaning as above and s^2 represents the variance of the proportion of spatial units.

4. Results

4.1 Analysis of spatial distribution characteristics of land use functional mixing degree based on three data sources

As shown in Fig. 2(a), the overall pattern of the POI mixing degree in Zhuhai is high in the east and low in the west. The high-value area in the east has a blocklike distribution, whereas the high-value area in the west has a ribbonlike distribution. The grid with non-zero mixing degree covers 447.71 km^2. The eastern high-value area is the central city of Zhuhai, and the mixing degree decreases gradually from the center to the periphery. The high-value area in the west is distributed in Doumen and Jinwan Districts. The mixing degree of the urban POI in Lianzhou and Nanshui Towns, respectively in the north and south of the western part of Zhuhai, is generally low. Consider the mixing degrees of the O and D points based on taxi GPS data [Figs. 2(b) and 2(c), respectively]. According to the statistics, the grid coverage area with non-zero mixing degree is 304.07 km^2, which is markedly smaller than the non-zero mixing degree grid coverage area of POI data. Similar to the distribution characteristics of the POI mixing degree, the O point area of taxi GPS data with high mixing degree in the eastern area of Zhuhai showed

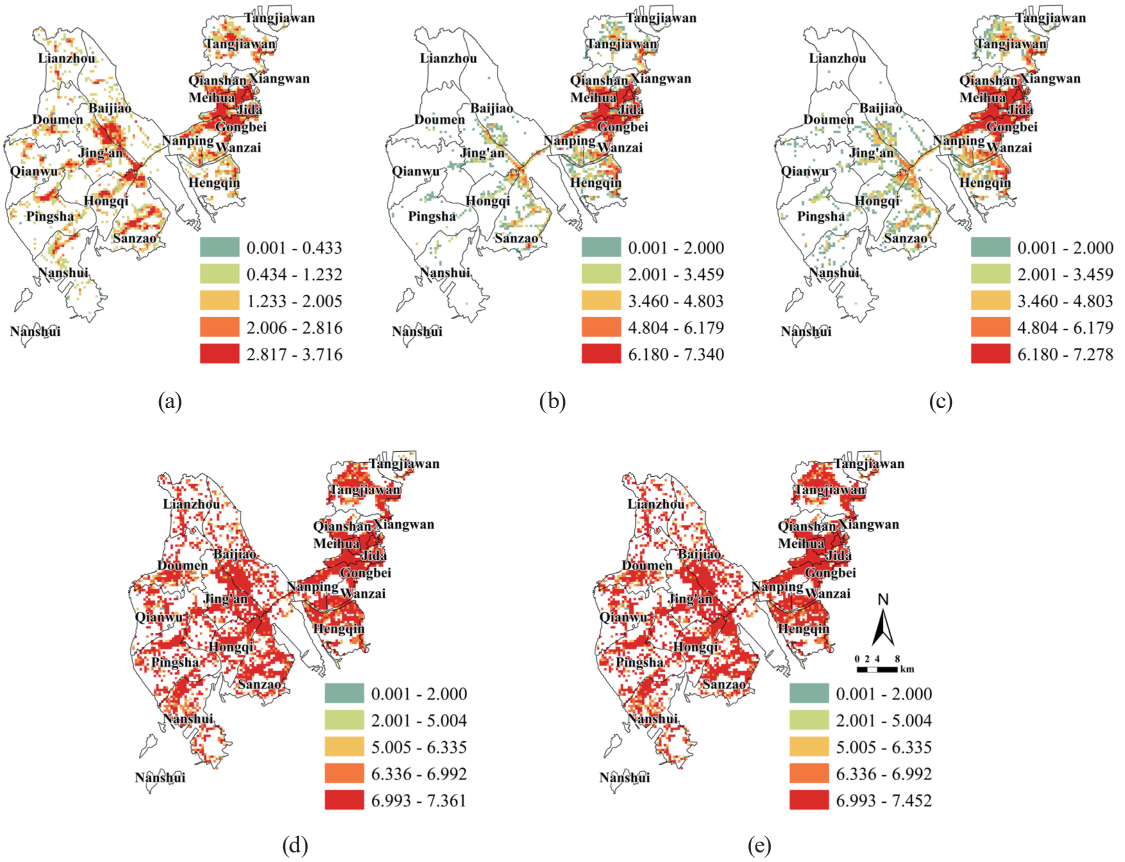

Fig. 2. (Color online) (Color online) Distribution of functional mixing degree of urban land use obtained from three data sources: (a) POI, (b) taxi point O, (c) taxi point D, (d) mobile phone signaling point O, and (e) mobile phone signaling point D.

a clumpy distribution, while the area with high mixing degree in the western area showed a banded distribution. The mixing degree of point D is slightly lower than that of point O, shows the same spatial pattern, and decreases from both the eastern central city and the western central city to the surrounding suburbs. Next, consider the spatial distribution maps of the mixing degree of the starting and ending points of mobile phone signaling data [Figs. 2(d) and 2(e), respectively]. According to the statistics, the grid coverage area where the mixing degree of the starting and ending points of mobile phone signaling data is non-zero is as high as 712.52 km^2, much higher than the range covered by the mixing degree of the POI and taxi data. Similar to the results obtained from the previous two types of data, the high-value areas are mainly concentrated in the central and western central cities, but the distribution range of the areas with a high mixing degree of the starting and ending points of mobile phone signaling data is wider. Compared with the mixing degree of the starting point of mobile phone signaling data, it can be easily seen that the mixing degree of the ending point of mobile phone signaling data is significantly higher, but its mixing degree distribution characteristics are still consistent with those of the starting point of mobile phone signaling data. This indicates that the mixing degree of the starting point is higher than that of the ending point in the busy commercial area.

On the whole, the distribution of the urban functional mixing degree in Zhuhai is not uniform, showing a high value in the east and a low value in the west. The area with a high mixing degree in the east of Zhuhai is also the central part of the city, with a highly developed infrastructure, a large human flow, a high consumption level, and a high agglomeration of facilities such as food, accommodation, travel, tourism, shopping, and entertainment. The areas with a high mixing degree in the western region are unevenly distributed, mainly because of the wide spread of farmland in these regions. Compared with the eastern central urban area, the high-value area in the western region has fewer local villages, a lower population, fewer POI types, and a lower travel demand, resulting in a low mixing degree of the urban land use function. Most of the low-value areas in Zhuhai are distributed in the western region, which is mainly affected by the wide spread of mountains, which limits the development of the city. Urban land with a single type of use forms low-value areas, which also indicates that the infrastructure of such land needs to be improved.

4.2 Spatial autocorrelation analysis of functional mixing degree of land use based on three data sources

As can be seen from Table 2, in the global autocorrelation analysis of the spatiotemporal entropy obtained from the three different data sources, the global Moran's I index in the study area is always greater than 0 and P is always less than 0.01, which passes the 99% confidence test. That is, Z is always greater than 2.58, indicating a positive spatial correlation. This shows that the spatiotemporal entropies corresponding to the three data sources have different degrees of the agglomeration effect. Among the three types of data, the global Moran's I index of the taxi O and D points is the largest, and the corresponding Z is also the largest, followed by the POI data, and finally the mobile phone signaling points O and D, indicating that the global spatial autocorrelation of the taxi data is greater than that of the other two types of data.

Table 2
Global spatial autocorrelation indices of land use function mixing degrees of the three data sources.

Data	Moran's I index	Z	P
POI	0.677	81.113	0.000
Taxi point O	0.788	94.403	0.000
Taxi point D	0.789	94.498	0.000
Mobile phone signaling point O	0.458	54.907	0.000
Mobile phone signaling point D	0.459	54.941	0.000

Local autocorrelation analysis was conducted on the spatiotemporal entropies of the three types of heterogeneous data, as shown in Fig. 3. The spatial heterogeneity was explored, and the local areas with high agglomeration were found. Note that in the visualization results, the spatial clustering measurement results of the high-value points are the most obvious, while those of low-value points are not obvious. In the local spatial autocorrelation analysis of the POI data spatial entropy [Fig. 3(a)], the clusters of high-value areas of spatial information entropy in Zhuhai are mainly distributed near the old and western central cities, and other areas are not significant because of their small entropy. In the local spatial autocorrelation analysis of the spatiotemporal entropy between taxi points O and D [Figs. 3(b) and 3(c)], the clusters with high values are more obvious in the eastern old city of Zhuhai, mainly because the development history of the eastern old city is relatively long, the infrastructure is highly developed, and the mixing degree is high. In the local spatial autocorrelation analysis of the spatiotemporal entropies of points O and D of mobile phone signaling [Figs. 3(d) and 3(e)], it can be clearly seen that the clusters with high values occupy a larger range than those for the POI and taxi data, which is related to the wide range and high precision of mobile phone signaling data acquisition. In addition, there are sporadic high-low (H-L) and low-high (L-H) agglomeration areas in the western part of Zhuhai, among which sporadic L-H agglomeration areas appear around the high-agglomeration areas in the western part of Zhuhai. This is mainly because the land use function mixing degree is lower than that in the surrounding areas. These areas are surrounded by high-agglomeration areas but have not developed into high-agglomeration areas, indicating that there is no positive interaction between them and the areas with a high mixing degree of land use function in the surrounding cities. Therefore, these areas should strengthen their industrial cooperation with the high-agglomeration areas and improve the functional mixing degree of land use. Compared with the L-H agglomeration areas, the H-L agglomeration areas have a wider range and are mainly distributed from Lianzhou Town in the north of the west of Zhuhai to Nanshui Town in the south. These areas are advantageous for improving the functional mixing degree of urban land use and also have potential for future development.

4.3 Correlation analysis of functional mixing degree of land use based on three data sources

To better explain the urban mixing degree of Zhuhai, the entropies calculated from the above three types of data are used to examine the spatial correlation. Firstly, the spatial entropy of the POIs was spatially correlated with the spatiotemporal entropies of taxi O and D points, and three

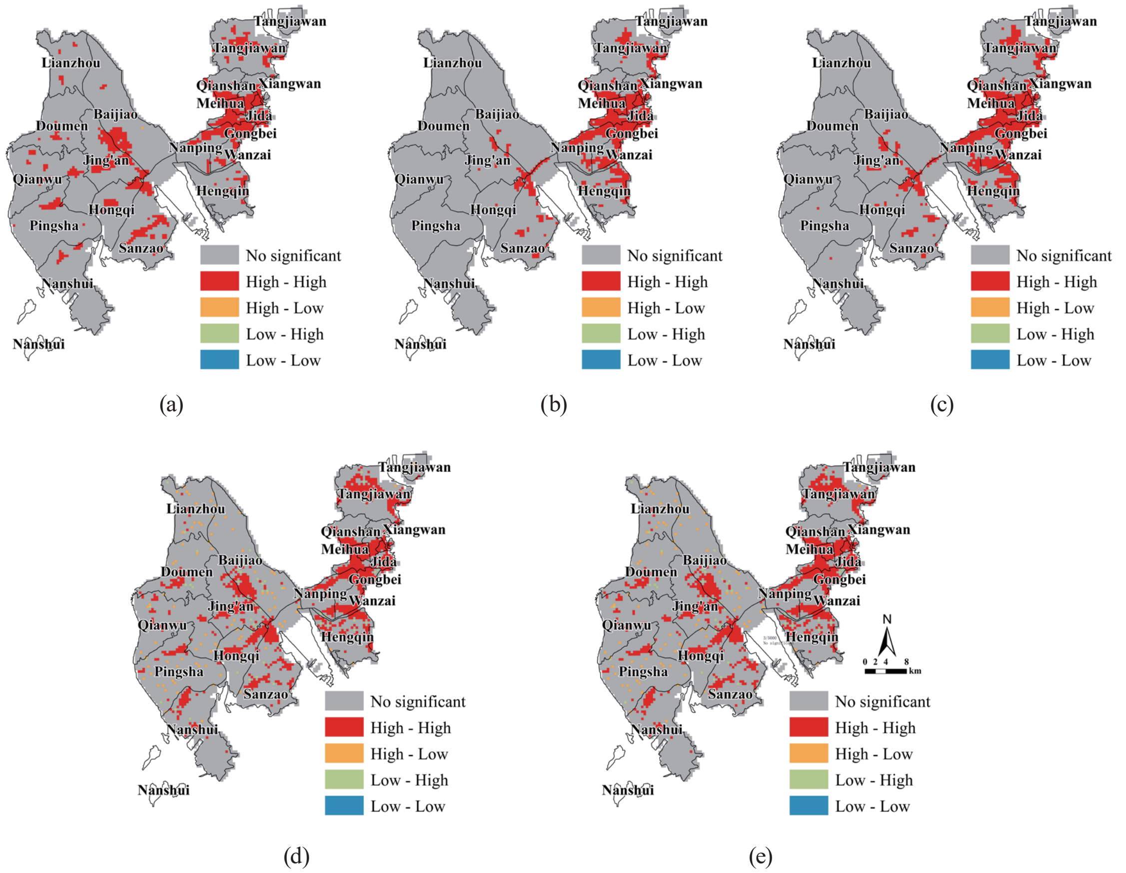

Fig. 3. (Color online) Local autocorrelation of functional mixing degrees of urban land use obtained from three data sources: (a) POI, (b) taxi point O, (c) taxi point D, (d) mobile phone signaling point O, and (e) mobile phone signaling point D.

spatial entropies corresponding to the tabulated space were obtained by spatial sampling. Accordingly, the correlation between points O and D was calculated. The spatiotemporal entropies of taxi points O and D passed the significance test and the correlation coefficient was 0.916, indicating that the two points were highly correlated. In addition, the spatial entropy of the POIs and the spatiotemporal entropies of taxi points O and D both passed the significance test with correlation coefficients of 0.442 and 0.438, respectively, showing good correlation degree (Table 3). Secondly, the spatial entropy of the POIs was analyzed by regression with the spatiotemporal entropies of points O and D of mobile phone signaling, and three entropies corresponding to the tabulated space were also obtained through spatial sampling (Table 4). Accordingly, the correlation between points O and D was calculated. The spatiotemporal entropies of taxi points O and D passed the significance test and the correlation coefficient was 0.990, which also showed a high correlation between the points. The POI spatial entropy of the POIs and the spatiotemporal entropies of points O and D of mobile phone signaling passed the significance test, and the R^2 test values between them were 0.271 and 0.260, respectively, showing good correlation. Finally, taking the spatiotemporal entropies of points O and D of mobile phone signaling as a bivariate function, regression analysis was conducted between the

Table 3
Spatial correlation analysis of POI and spatiotemporal entropies of taxi points O and D.

	POI	Taxi point O	Taxi point D
POI	1	0.442	0.438
Taxi point O	0.442	1	0.916
Taxi point D	0.438	0.916	1

Table 4
Spatial correlation analysis of POI and spatiotemporal entropies of points O and D of mobile phone signaling.

	POI	Mobile phone signaling point O	Mobile phone signaling point D
POI	1	0.271	0.260
Mobile phone signaling point O	0.271	1	0.990
Mobile phone signaling point D	0.260	0.990	1

Table 5
Spatial correlation analysis of spatiotemporal entropy between points O and D of mobile phone signaling and taxi points O and D.

	Mobile phone signaling point O	Mobile phone signaling point D	Taxi point O	Taxi point D
Mobile phone signaling point O	1	0.990	0.167	0.194
Mobile phone signaling point D	0.990	1	0.171	0.202
Taxi point O	0.167	0.171	1	0.916
Taxi point D	0.194	0.202	0.916	1

spatiotemporal entropies of taxi points O and D (Table 5); the results passed the significance test with R^2 test values of 0.167, 0.194, 0.171, and 0.202, respectively. Through the above data analysis, it can be seen that the three types of data sources show the urban function mixing degree to some extent and have a certain association among each other. Their income entropy has similarity to the spatial distribution characteristics, and the combination of the three types of data sources can be simultaneously used to increase the evaluation accuracy of the degree of urban function mixing.

5. Discussion

We integrated spatiotemporal big data, overcame the limitations of traditional research data, and incorporated the actual needs of residents into the calculation of the functional mixing of urban land use, so as to quantitatively analyze the functional mixing degree of urban land use. We evaluated the functional mixing degree of urban land use mainly by combining POI data, taxi GPS data, and mobile phone signaling data. The conclusion of the analysis was basically in line with the actual situation of Zhuhai. Our study demonstrates that, based on the POI data, taxi OD data, and the mobile phone signaling data, constructing the entropy model of the mixing degree of urban functions has certain accuracy and rationality. Because of its precision, the model also has some reference value for urban space and urban development planning, providing an in-depth understanding of the mixing characteristics of all types of functions, coordinating the development direction of various functional areas, and improving the sustainability of urban development.

Although we used spatiotemporal big data to analyze and study the functional mixing degree of urban land use, it cannot fully reflect the mixing degree of land use. While studying the mixing degree, the factors affecting the functional mixing degree of urban land use should also be considered. Owing to the limitation of data, we did not take these factors into account, which should be attempted in the future. Secondly, we adopted the entropy index method to analyze the functional mixing degree of urban land use, because this method is suitable for the data adopted in this paper. However, the entropy index method also has some limitations; for example, it is easily affected by the vector plot size. The larger the plot size, the higher the mixing degree. This method is used to measure the mixture of urban land use functions from a planar perspective, but a city is 3D, and this method cannot reflect the difference in the mixture caused by a 3D layout. Therefore, an important research direction is to explore the functional mixing degree of urban land use from a 3D perspective. Finally, this paper only provides a case study of the functional mixing degree of urban land use in Zhuhai, giving it certain significance as a reference for optimizing the spatial structure of urban functions in Zhuhai, but it is not generally representative. Obtaining richer data in the future will enable us to overcome the above shortcomings.

6. Conclusions

We calculated the Zhuhai POI space entropy, taxi OD points, and mobile phone signal entropy of space and time, and thus analyzed the mixing degree of Zhuhai City land functions. We mainly used three types of heterogeneous data, namely, POI data, taxi GPS data, and mobile phone signaling data, to perform our analysis from the three aspects of location, travel, and the main body. Then, we studied the correlation among three types of heterogeneous data and verified the rationality of the results. The results show the following:

(1) The functional mixing degree of land use in the study area is generally low, and the spatial distribution of the functional mixing degree between the eastern and western regions is considerably different. In terms of the spatial distribution, the old central urban area in the east of Zhuhai and the central urban area in Doumen District in the west of Zhuhai have agglomeration areas with high mixing degree, and the edge effect is obvious. From the center to the periphery, the mixing degree gradually decreases. Owing to the mountainous terrain, the mixing degree of the high-value area has a circular distribution. This also reflects the large amount of high construction around the old city and the small amount of construction intensity in the urban fringe.

(2) The spatial autocorrelation analyses of POI data, taxi GPS data, and mobile phone signaling data all showed a significant positive spatial autocorrelation of the land use mixture in Zhuhai. The high-agglomeration area is mainly concentrated at the centers of the two urban areas of Zhuhai, while the low-agglomeration area is mostly distributed in the periphery of the urban area, resulting in an obvious edge effect.

(3) From the perspective of the correlation of the three types of heterogeneous data, the results all passed the significance test, and different data provide different explanations for the mixing degree of urban land use. POI data can be used for the preliminary identification of the distribution of urban functional areas, taxi GPS data can help to observe the travel activities and routes of the population, cellphone signal data can identify the actual distribution of the population, and the combination of the space–time entropies obtained from the three types of data can make the evaluation of the urban land function mixing degree more reasonable.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant Nos. 41001022 and 41971306).

References

1 G. Zhao and J. Song: Urban Plann. Forum **1** (2022) 51. https://doi.org/10.16361/j.upf.202201007
2 S. L. Handy, M. G. Boarnet, R. Ewing, and R. E. Killingsworth: Am. J. Prev. Med. **23** (2002) 64. https://doi.org/10.1016/S0749-3797(02)00475-0
3 E. Hoppenbrouwer and E. Louw: Eur. Plan. Stud. **13** (2005) 967. https://doi.org/10.1080/09654310500242048
4 A. Coupland: Reclaiming the City: Mixed use development (Routledge, London, 1996) 1st ed., Chap. 3. https://doi.org/10.4324/9780203985465
5 C. J. Crisioni, P. Rietveld, E. Koomen, and E. Tranos: Environ. Plann. A **46** (2014) 2769. https://doi.org/10.1068/a130309p
6 M. Fuller and R. Moore: An Analysis of Jane Jacobs's: The Death and Life of Great American Cities (Macat Library, London, 2017) 1st ed., Chap. 2. https://doi.org/10.4324/9781912282661
7 X. Yang: Exploring the influence of environmental features on residential burglary using spatial-temporal pattern analysis (University of Florida, Florida, 2006). https://www.proquest.com/openview/a96270c429b1bcc84a802b45ba3ea0de/1?pq-origsite=gscholar&cbl=18750&diss=y
8 J. Grant: J. Am. Plann. Assoc. **68** (2002) 71. https://doi.org/10.1080/01944360208977192
9 L. D. Frankand and G. Pivo: The 73rd Annual Meeting of the Transportation Research Board (TRB, 1994) 1466. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.368.4497&rep=rep1&type=pdf
10 D. Comer and J. S. Greene: Appl. Geogr. **60** (2015) 46. https://doi.org/10.1016/j.apgeog.2015.02.015
11 T. Li, Y. Liang, and B. Zhang: Land Use Pol. **69** (2017) 427. https://doi.org/10.1016/j.landusepol.2017.09.036
12 Y. Song, L. Merlin, and D. Rodriguez: Comput. Environ. Urban Syst. **42** (2013) 1. https://doi.org/10.1016/j.compenvurbsys.2013.08.001
13 D. Zhou, W. Zhong, T. Zhou, and J. Qi: Chin. Land Sci. **35** (2021) 96. https://kns.cnki.net/kcms/detail/detail.aspx?FileName=ZTKX202108011&DbName=CJFQ2021
14 J. Li, X. Qi, and W. Yuan: Progr. Geogr. **41** (2022) 239. https://kns.cnki.net/kcms/detail/detail.aspx?FileName=DLKJ202202005&DbName=DKFX2022
15 X. Hu, X. Li, and F. Wei: J. Southwest Univ. (Natural Science Edition) **43** (2021) 164. https://kns.cnki.net/kcms/detail/detail.aspx?FileName=XNND202101019&DbName=DKFX2021
16 M. Li, Y. Ma, X. Sun, J. Wang, and A. Dang: City Plann. Rev. **42** (2018) 97. https://kns.cnki.net/kcms/detail/detail.aspx?FileName=CSGH201802017&DbName=CJFQ2018
17 Y. Liu, Y. Xiao, S. Gao, C. Kang, and Y. Wang: Geogr. Geo-Inf. Sci. **27** (2011) 8. https://kns.cnki.net/kcms/detail/detail.aspx?FileName=DLGT201104003&DbName=CJFQ2011
18 X. Niu, L. Ding, and X. Song: Urban Plann. Forum **6** (2014) 61. https://kns.cnki.net/kcms/detail/detail.aspx?FileName=CXGH201406011&DbName=CJFQ2014
19 Y. Duan, Y. Liu, X. Liu, and D. He: Progr. Geogr. **38** (2019) 1957. https://kns.cnki.net/kcms/detail/detail.aspx?FileName=DLKJ201912011&DbName=CJFQ2019
20 Y. Liu, F. Wang, Y. Xiao, and S. Gao: Landsc. Urban Plann. **106** (2012) 73. https://doi.org/10.1016/j.landurbplan.2012.02.012

21 China Center for International Economic Exchanges: https://www.ssap.com.cn/c/2019-08-30/1080457.shtml (accessed August 2022).
22 National Bureau of Statistics of China: https://zhuanlan.zhihu.com/p/469981569 (accessed August 2022).
23 National Bureau of Statistics of China: https://wenku.baidu.com/view/7d6157276f85ec3a87c24028915f804d2b16872a.html (accessed August 2022).
24 T. Jia and P. Yan: IEEE Trans. Intell. Transp. Syst. **22** (2021) 3900. https://ieeexplore.ieee.org/document/9444609
25 L. Liu, Z. Peng, and H. Wu: City Plann. Rev. **45** (2021) 27. https://kns.cnki.net/kcms/detail/detail.aspx?FileName=CSGH202112004&DbName=CJFQ2021