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Article

The Influence of Spatial Grid Division on the Layout Analysis of Urban Functional Areas

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Abstract: The identification of urban functional areas is essential for urban planning and sustainable development. Spatial grids are the basic units for the implementation of urban plans and management by cities or development zones. The emergence of internet "big data" provides new ideas for the identification of urban functional areas. Based on point of interest (POI) data from Baidu Maps, the Xicheng District of Beijing was divided into grids with side lengths of 200, 500, and 1000 m in this study. The kernel density method was used to analyze the spatial structure of POI data. Two indicators, that is, the frequency density and category ratio, were then used to identify single- and mixed-functional areas. The results show that (1) commercial and financial areas are concentrated in the city center and multiple business centers have not developed; (2) scenic areas account for the largest proportion of single-functional areas in the Xicheng District of Beijing, followed by education and training, residence, and party and government organizations areas; and (3) the 200 × 200 m and 500 × 500 m grids are the most suitable for the identification of single- and mixed-functional areas, respectively.

Keywords: spatial grid; point of interest; function identification; spatial distribution

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1. Introduction

With the rapid development of cities, the urban spatial structure is not unchanged. It is also in a dynamic process of constant change, and in order to satisfy the daily needs of residents and the development of various industries, all kinds of types of cities have gradually formed. Urban functional areas refer to the division of areas according to the main functions of the city, forming relatively independent and connected functional areas, for example: recreational areas, commercial areas, residential areas, and other functional areas, etc. The rational layout and formation of urban functional areas can reduce the cost of living expenses, of traffic congestion, and of production logistics. These features effectively reduce the cost of large-scale production in cities, improve the quality of life and work efficiency of urban residents, and attract more other small0town residents to live in the city. At the same time, rapidly and reasonably identifying urban functional areas (1) can promote the development of various industries in the city; (2) can obtain the functions and characteristics of various spatial planning of the city, as the basic information of land planning; and (3) is of great significance for the effective allocation of resources and urban planning [1]. Research on the division and identification of urban functional areas must be conducted to obtain the smallest land unit of a city [2]. Two units can be used to organize the urban spatial morphology: grid and patch. Compared with the block mode, the grid mode focuses on space, showing superior order. Especially in terms of land division and management, a grid city is characterized by efficient and systematic land management and planning as well as land development volume and density [3,4]. The concept of a smart city and refined urban management leads to greater demands on the collection and organization of city information. Based on the division of the spatial grid using grid management, a collaborative work mode is used for the same grid. It is necessary to master various urban resources and information to achieve the purpose of urban resource system management and integration at all spatial levels from streets to plots [5,6]. Currently, urban functional areas are mainly identified by dividing cities into patch areas based on the urban road network [7]. However, there is a lack of studies of the division and identification of urban functional areas using grids. Grids have not been studied in detail with respect to the correlations among the size, number, and division and identification of urban functional areas. In addition, the increase in "big data" has led to new ideas for the identification of urban functional areas. Point of interest (POI) data are emerging point-shaped spatial data, which represent geographic entities such as bus stops, parks, shopping malls, and schools. They contain the name, category, longitude, and latitude of geographic entities. Compared with traditional data, POI data are large, easily accessible data, which reflect the spatial structure and function distribution of urban social and economic development and are widely used for the identification of urban centers, extraction of boundaries, and determination of temporal and spatial population changes [8–10].

In this study, POI data were used as follows: (1) kernel density analysis was used to analyze the spatial distribution of POI data, and the development trend of the city was determined from a macroscopic perspective based on the local POI distribution density and characteristics; (2) the city was divided into 200×200 m, 500×500 m, and 1000×1000 m grids using two indicators, that is, the frequency density (FD) and category ratio (CR), to quantitatively divide and identify urban functional areas based on POI data; and (3) urban single- and mixed-functional areas were visualized, and statistics were used to analyze the effect of the size of the segmented grid on the division and identification of urban functional areas. This research is of great significance for the division and identification of urban functional areas. On the one hand, POI data are large and rich in urban spatial information. The analysis of distribution characteristics can be used to determine the urban spatial structure and supplement existing research. On the other hand, the division and identification of urban functional areas based on POI data provides guidance and references for urban planners with respect to identifying the urban spatial structure and development patterns and formulating reasonable urban planning strategies.

2. Related Research

At present, an increasing number of data types is emerging because of the development of various sensors. The division and identification of urban functional areas is mainly based on the urban road network, POI, traffic trajectory, census information, remote-sensing image, and social platform data.

Sun et al. used the residential population and employment densities to compare and analyze the development of urban centers from time series [11]. Wang et al. used urban traffic trajectory data to identify functional areas in Beijing [12]. Zhong et al. used traffic trajectory data to create a directed graph, employed clustering and spatial analysis methods to detect urban centers and spatial structures and quantitatively detect urban activity centers and morphological changes [13,14]. Zhao et al. used location-based service data from 2015 to construct a relationship matrix, which fully describes the population migration in eastern and central China and analyzed the population of 31 provinces and cities in China based on the law of population migration, spatial patterns, and factors affecting migration [15]. Based on travel behavior data from 2010 and 2015 and kernel density analysis, Zhou et al. determined the boundary changes of Nanjing and then used multiple logit models to evaluate the effect of urban economic development on the residents' choices of transportation modes [16]. Based on the super object theory, Zhou et al. used remote-sensing images as data sources and SO-CNN convolutional neural networks to divide and identify urban functional areas [17]. Liu et al. extracted human activity patterns based on remote-sensing image land-use classification in combination with POI data and a taxi trajectory and superimposed the two data to achieve fine-grained urban functional area identification [18]. Song et al. combined multiple remote-sensing images, location-based service data (LBS), and nighttime light data (NTL) to identify urban functional areas [19]. Yan et al. used the coefficient of variation and Theil index to evaluate the urban economy based on DMSP/OLS NTL and utilized the standard deviation ellipse and spatial Markov chain (spatial Markov chain) to analyze the temporal and spatial characteristics of urban economic development [20]. Zheng et al. used the Google Earth Engine cloud platform in combination with daytime remote-sensing images and NTL remote-sensing data for the Yangtze River Delta Urban Agglomeration (YAR'ADUA) to perform spatiotemporal feature analysis to determine the status of the environment and urbanization intensity [21]. Deng et al. used density contour tree and POI data to analyze the structure and spatiotemporal characteristics of an urban center [22]. Yi et al. employed POI data and proposed a statistical significance test method (Fisher exact test method) for the quantitative identification of urban functional areas [23]. Zhang et al. combined the complex graph theory with OSM and POI data to divide a city into road networks, as the smallest research unit to identify a city's functional areas [24]. Lu et al. used POI data, the nearest-neighbor index, location entropy, and other methods to analyze the cluster-discrete spatial distribution structure [25]. Xing et al. combined POI data with semantic information and architecture at the object level (building area, edge, and structure) and used the random forest method to identify urban functional areas [26]. Liu et al. combined POI data and NTL data to extract high-density luminous leisure and POI areas and superimposed the data to determine the distribution of nighttime leisure activities in Beijing [27]. Chen et al. proposed a new method of co-location patterns based on POI data is proposed to identify and analyze the commonality and particularity of the spatial structure of 25 urban functional areas [28]. Andrade et al. developed a new program to automatically collect POI data, selected the most suitable POI data type for land-use classification, and used a convolutional neural network ANN to automatically identify urban functional areas [29].

In most previous studies, image and census data were used as data sources. However, census data are generally based on a survey containing population information and are affected by the sample size. They cannot reflect the distribution of the urban population in detail. Social media data have the same shortcomings. Remote-sensing image data used for the top-down design of urban structures cannot present the spatial structure of the city in detail. Therefore, in this study, POI data were used instead of surveys and social media data. Kernel density analysis including two indicators, that is, FD and CR, was employed and the urban grid was used as the smallest land unit to identify urban functional areas and analyze the effects of the number and size of urban grids on the urban spatial distribution. This article is divided into four parts. Section 2 reviews related work. In Section 3, based on POI data and kernel density analysis, the spatial layout of the Xicheng District, Beijing, was analyzed and visualized. In Section 4, the Xicheng District was divided into 200×200 m, 500×500 m, and 1000×1000 m grids using the FD and CR to quantitatively identify single- and mixed-functional areas; and in Section 5, the single- and mixed-functional areas identified in the three different grids were analyzed. In Section 6, the paper is concluded with a brief summary. The overall research framework is shown in Figure 1.

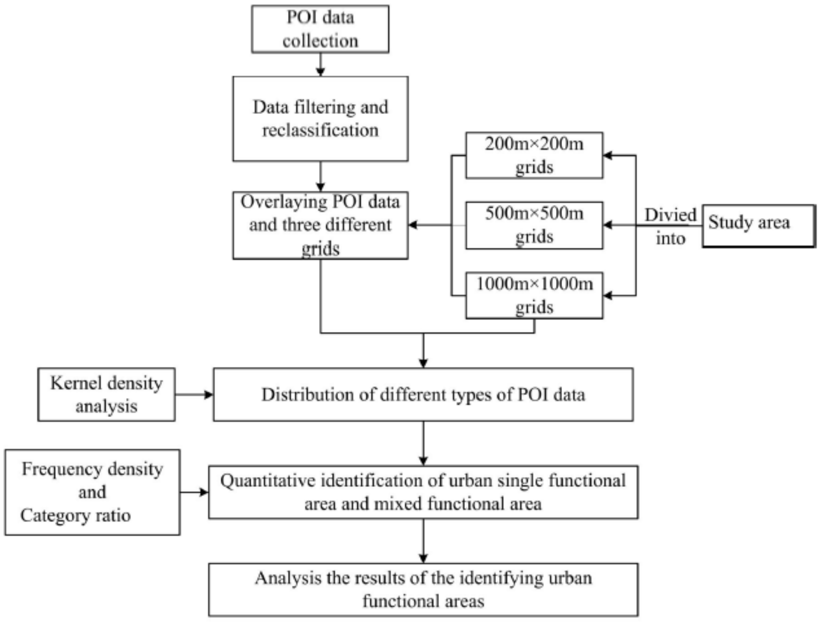


Figure 1. Research framework showing the steps employed in this study.

3. Research Area and Data

3.1. Study Area

Beijing is the capital of China. The Xicheng District is located west of central Beijing (Figure 2). Various cultures, such as royal and famous cultures, are highly integrated in this area. As of 2019, the district covers an area of 50.7 km^2 and has 15 blocks, 261 communities, a permanent population of 1.137 million people, and a gross regional domestic product (GDP) of 500.73 billion RMB. The Xicheng District is the functional core area and political center of the capital. Core areas, including cultural and economic centers, are important for the national image and international exchange. In addition, the Xicheng District is one of Beijing's old districts, characterized by a mix of old and new buildings, dense population, diverse industries, and numerous municipal facilities and pipelines. Therefore, understanding the urban spatial structure and division of functional areas of the Xicheng District, implementing refined management and development, and stimulating the vitality of the "old city" are important research topics [30,31].

3.2. Data Collection and Processing

In this study, Baidu Maps was used to obtain POI data and the administrative boundaries of the Xicheng District in Beijing. Based on the POI classification and characteristics of the Xicheng District [32], the POI data were divided into eight first-level categories, which were further divided into second- and third-level categories. The POI data were filtered and reclassified, and data with low public awareness, such as public toilets and newsstands, were removed. Finally, 20,622 POI data points were obtained. The classification is shown in Table 1.

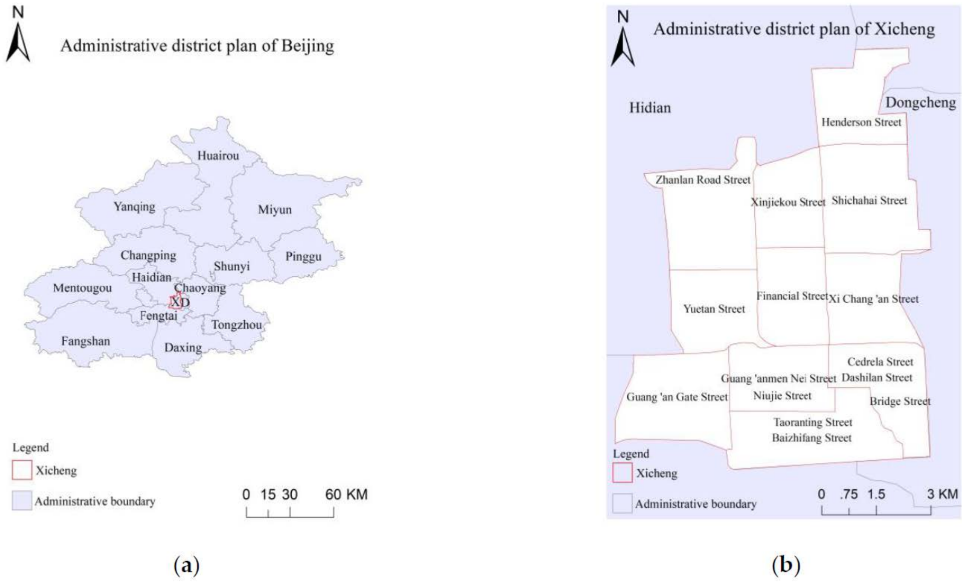


Figure 2. Maps of the study area (**a**) Xicheng District, Beijing; (**b**) division of the Xicheng District into 15 blocks: Baizhifang Street, Guang'an Gate Street, Guang'anmen Nei Street, Dashilan Street, Financial Street, Yuetan Street, Xi Chang'an Street, Xinjiekou Street, Shichahai Street, Zhanlan Road Street, Henderson Street, Cedrela Street, Bridge Street, Niujie Street, and Taoranting Street.

Table 1. Results of the reclassification of POI data.

Current Categories (Level One)	Current Categories (Level Two)	Current Categories (Level Three)
Residence	Water, electricity, gas service, life services, ticket office	Electricity repair, household management service, community service
Education and training	Low and middle education, continuing education, higher education	Primary school, high school, skill-training institution, university
Recreation and entertainment	Culture, recreation, sports and fitness	Museum, library cinema, amusement park swimming pool, gym
Medical and public health	Medical institutions, rehabilitation care, animal hospital	Hospital, clinic, convalescent hospital, animal hospital
Commercial and financial	Finance, shopping center, hotel	Bank, security, supermarket, catering, hotel, lodging
Incorporated business	Company, enterprise	Company, enterprise
Party and government organization	Government, administration	Public security, the People's courts
Scenic	Scenic area	Tourist attractions

4. Methods

4.1. Kernel Density Analysis

Density analysis can be used to express the spatial distribution structure. It can be used to determine the degree of local aggregation based on the positional relationship between spatial points. It is a statistical analysis process based on spatial smoothing and spatial interpolation technology, which accurately reflects spatial laws. Urban planning, management, and spatial structure characteristics allow for auxiliary decision-making. For example, Sun [33] used remote-sensing images and kernel density analysis to analyze the population density, reflecting the population distribution and social development laws. Zhou [34] and others used kernel density analysis to analyze the correlation between poverty and geographic environment in 124,000 poor villages in China. Common methods used for spatial point density analysis are the square density [35], kernel density, and Voronoi diagram methods [36,37]. (2) Based on both the square density and Voronoi diagram methods, the research area is divided into subareas, and the point density is calculated. Data processing is simple, but the degree of aggregation of spatial points in the subregion and the continuity of spatial phenomena can be easily ignored [38]. The main idea of the kernel density method is to produce a smooth surface above a spatial point A. The surface value is the largest at the position of spatial point A. When the distance between spatial point A and other points increases, the surface value gradually decreases and approaches zero [39]. The density of each point is the sum of all surface values superimposed on that point (Figure 3).

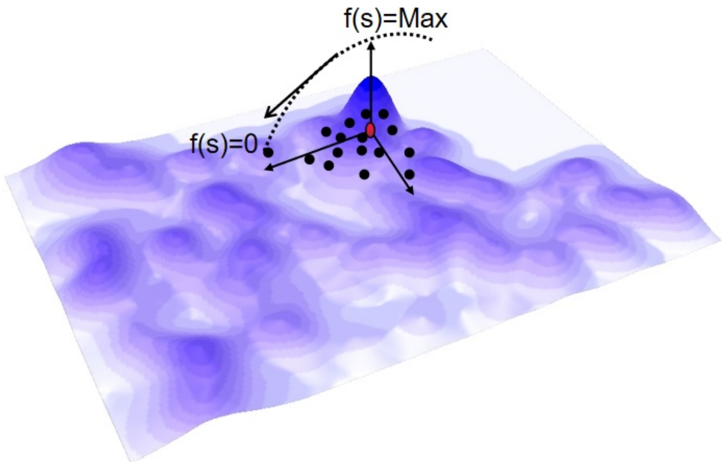


Figure 3. Diagram of the kernel density calculation.

If the spatial points $X_1, X_2, \ldots, X_n$ are independent and identically distributed random samples with an unknown probability density function $f(x)$, the equation of the probability density function $f(x)$ at any point x in samples based on kernel density estimation is as follows:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{x - X_i}{h}) \tag{1}$$

where n represents the number of samples; h is the bandwidth, where the optimal bandwidth proposed by Silverman [40] was used in this study; and $K(x)$ is the kernel function. The Gaussian kernel function was used in this study:

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}x^2)\ ,\ x \in R, \tag{2}$$

4.2. Grid Size Determination

Since 1929, Graneau, a Finnish geographer, adopted a 1 km grid to analyze social development, geographic analysis based on urban grids of different size has gradually developed into a geological analysis method [41]. With the development of GIS technology, Socioeconomic Data and Applications Center (SEDAC) used the NOAA AVHRR data from 1990 to establish a 1 km grid of population density and land-use relational database; Gallup et al. based on the grids to explore the spatial relationship between land-use status and social economy; Jiang et al., Liao et al., and Tian et al. used various geographic data and socioeconomic development data to establish a 1 km grid data model [42]. What is more, Japan, Finland, the Netherlands and other countries have established grid-based databases, which are widely used in urban development and infrastructure planning [43]. Before identifying urban functional areas, the research area must be divided into several basic research units-grids. According to geometry and division method, the commonly used grid division models are as follows: the model of latitude–longitude grid, adaptive-grid model, regular-polyhedron grid model, and global equal-area quadtree grid model [44]. In previous studies, most grid sizes are divided based on administrative boundary and road network data. Although this method can be divided naturally, calculation results are skipped at the boundary, and the level of detail is not enough. Therefore, in order to reflect the internal spatial structure of the city in detail, the size of the research unit is the key. If the grid size is too large, it cannot reflect the complexity of the city, and if the grid size is too small, the function of the city may also be overanalyzed. The research area in this article is relatively small; therefore, the quadrilateral grids model in the regular-polyhedron grid model was selected as the research unit. We used the density of POI data and the road network data to determine the grid size. A grid must contain a certain number of buildings and sufficient POI data to identify urban functional areas. In other words, when the average density of POI data is large, we think that a grid contains more POI data, and when the standard deviation of the average density of POI data is small, we believe that the amount of POI data contained in each grid is stable. The density of POI data function was used in this study:

$$f(x) = \frac{n}{s}, \tag{3}$$

where $f(x)$ represents the density of POI data, n represents the number of POI data in a grid, and s represents the area of a grid.

4.3. Quantitative Identification of Functional Areas

After using the kernel density method to analyze the distribution and spatial characteristics of the POI data, two indicators were employed, that is, frequency density (FD) and category ratio (CR), to identify the functional area of each sample square.

$$F_i = \frac{n_i}{N_i}, \tag{4}$$

$$C_i = \frac{F_i}{\sum_{i=0}^{8} F_i}, \tag{5}$$

where i represents the POI type; n_i represents the number of POI data of type i in the sample square; N_i represents the total number of POI data of type i; F_i represents the frequency density of type i POI data in the sample square; and C_i represents the ratio of the frequency density of type i POI data in the sample square to the total frequency density of POI.

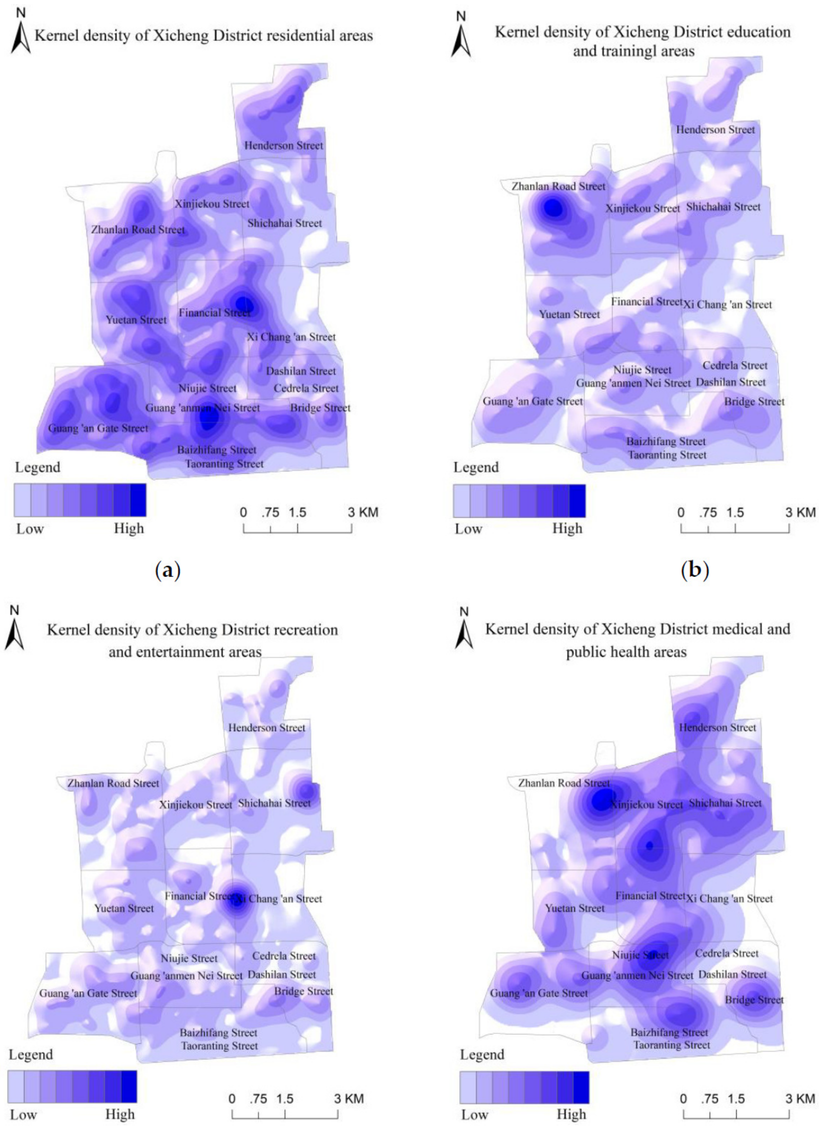
When the C_i value of a certain type of POI data in a square is $\geq$50%, its functional nature is determined by the type of POI data, and it is a single-functional area of that type. When the C_i of all POI types is <50%, its functional nature is determined by the two types of POI data with the largest proportions in the unit sample squares, that is, the mixed-functional area. Sometimes, the sample square does not contain POI data (area without data).

5. Results and Discussion

5.1. Kernel Density Analysis of POI Data

The eight types of POIs in Beijing's Xicheng District, including residential, education and training, recreation and entertainment, medical and public health, commercial and finance, incorporated and business, party and government organization, and scenic areas, were identified using the kernel density analysis method, and each type of POI space was visualized, and its distribution was determined. The results are shown in Figure 4.

Different types of POI data have different spatial distributions. Residential areas are distributed in the middle and south of the Xicheng District; they are concentrated at the junctions of Financial Street and Shichahai Street, Guang'anmen Nei Street and Taoranting Street, and Guang'an Gate Street. Education and training areas are distributed in the northwest of the Xicheng District; they are concentrated on Zhanlan Road. Recreation and entertainment areas are distributed in the middle and northeast of the Xicheng District; they are concentrated at the junction of Financial Street and Shichahai Street. Medical and public health areas can be found along the central line extending from north–south in the Xicheng District. Commercial and financial areas are distributed in the middle of the Xicheng District; they are concentrated at the junction of Financial Street and Shichahai Street. Incorporated business areas can be found on Henderson Street in the northeast of the Xicheng District, at the junction of Xinjiekou Street and Zhanlan Road Street in the northwest, and at the junction of Guang'an Gate Street, Guang'anmen Nei Street, Niujie Street, Taoranting Street, and Baizhifang Street in the southwest. The distribution of party and government organizations is similar to that of medical and health areas, that is, along the central line extending from north–south. Scenic areas are distributed in the east of the Xicheng District and are concentrated on Shichahai Street.



(**a**) (**b**) (**c**) (**d**)

Figure 4. *Cont.*

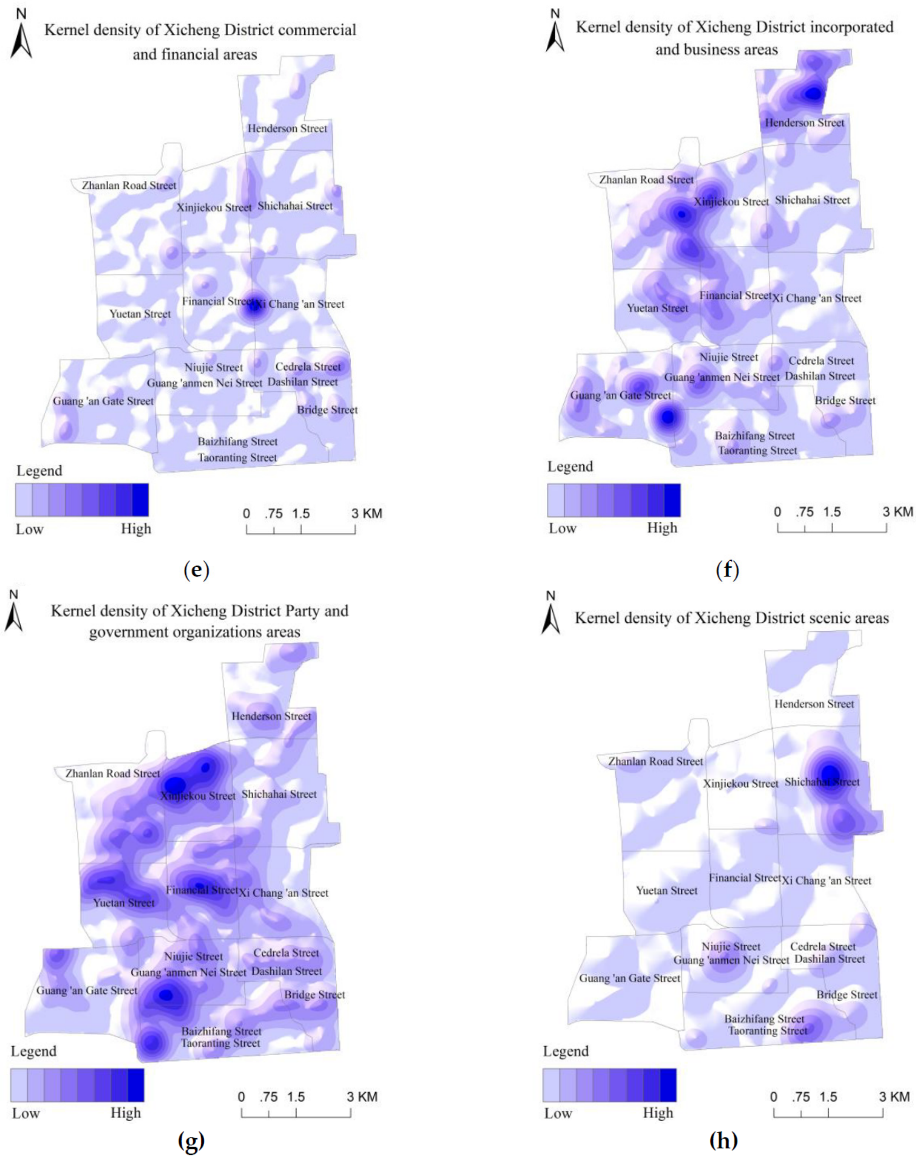


Figure 4. Kernel density analysis of point of interest (POI) data.

Overall, Beijing's Xicheng District mainly consists of residential, medical and health, and party and government organizations areas and their spatial distributions, indicating that the development of these three types of areas is inseparable. The north–south distribution of medical and public health areas as well as party and government organizations is very convenient for all residents in the Xicheng District. In addition, the spatial distribution of recreation and entertainment areas is similar to that of commercial and financial areas. They are both concentrated in the center of the Xicheng District. Multiple business centers have not developed, which is not conducive to the economic development of other areas in the city, reduces the cost of living of the residents, alleviates urban traffic pressure, and stabilizes housing prices [45]. Most of the incorporated business areas are concentrated between two blocks, which is convenient for residents of the respective two blocks with respect to work and travel.

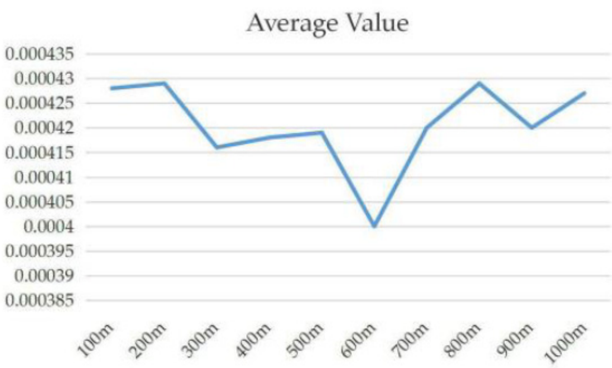
5.2. Grid Size

To obtain the road network data of Xicheng from OpenStreetMap, the primary roas, second road, thired road and highway are screened out. The footway, residential road, cycleway, living street, and outher roads in Xicheng District are left as experimental data. According to statistics, a 100 m road in Xicheng District is about the length of a building, and the longest road in Xicheng District is along Beihai Park, about 1381 m, as shown in (Figure 5).Therefore, the grid side length range is selected as 100~1000 m. The Xicheng District of Beijing is divided into grids of 100 × 100 m, 200 × 200 m, 300 × 300 m, 400 × 400 m, 500 × 500 m, 600 × 600 m, 700 × 700 m, 800 × 800 m, 900 × 900 m, and 1000 × 1000 m. Then, the average density of POI data in the unit grid and the standard deviation of the average density of POI data were calculated, and the results as shown in (Figure 6). Considering the two calculation results comprehensively, we chose the grid size of 200, 500, and 1000 m with larger average density of POI data and smaller standard deviation as three sets of comparative experiments to explore the influence between grid size and the identification of urban functional areas.

(**a**) A 100 m road

(**b**) A 1381 m road

Figure 5. Schematic diagram of the road network in Xicheng District, Beijing.



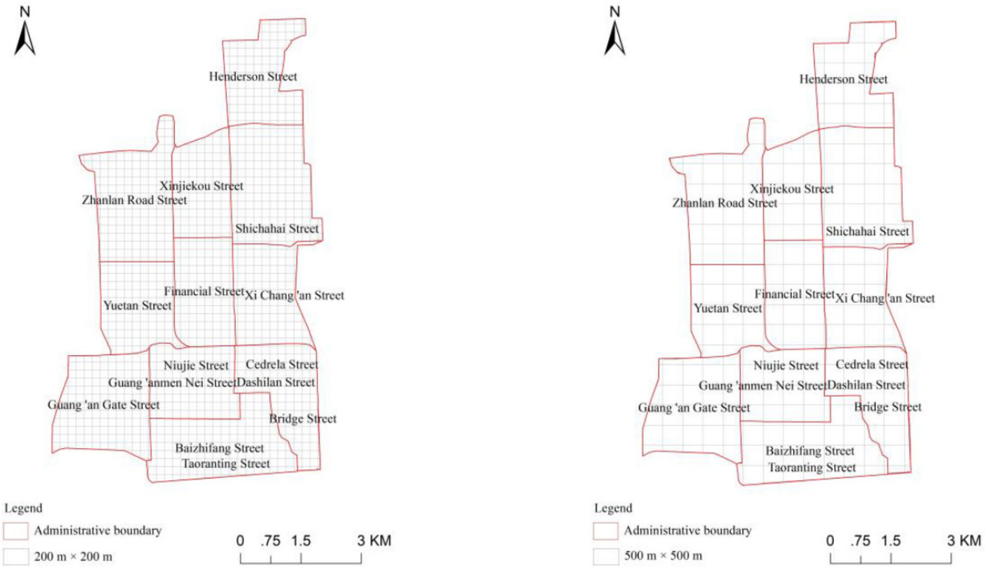
(**a**)

(**b**)

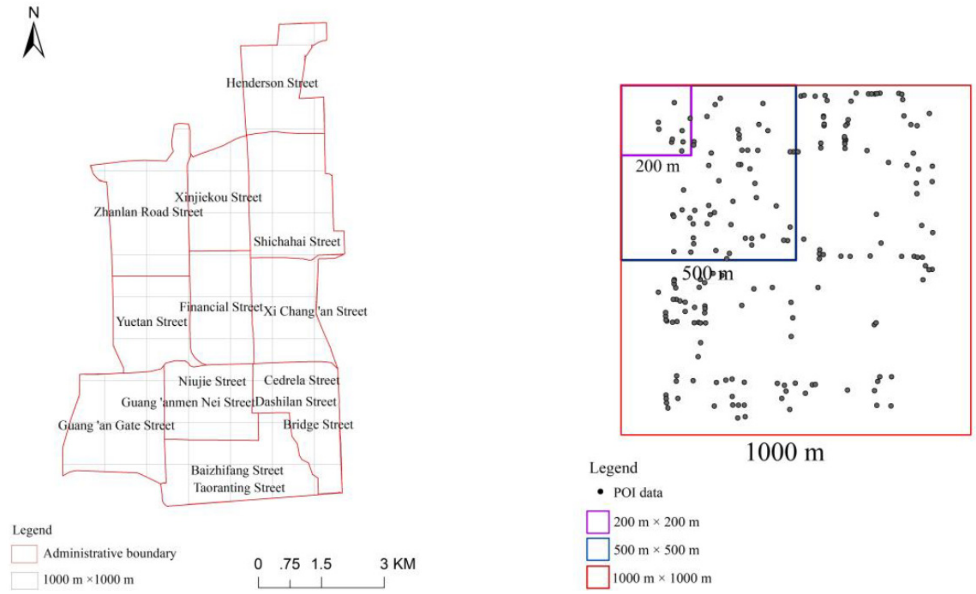
Figure 6. The average density of the POI data and the standard deviation of the average density.

Then, the Xicheng District of Beijing was divided into spatial grids with dimensions of 200 × 200 m, 500 × 500 m, and 1000 × 1000 m. The number of sample squares was 1361, 243, and 69, respectively (Figure 7). Based on the kernel density method, FD, and CR, the POI data were used to quantitatively identify and visualize the functional areas of the

Xicheng District, Beijing, and reflect the spatial distribution structure of the district, which is of significance for urban planning and management.



(**a**) 200 × 200 m grid of the Xicheng District and (**b**) 500 × 500 m grid of the Xicheng District



(**c**) 1000 × 1000 m grid of the Xicheng District and (**d**) grids with different side lengths

Figure 7. Division of the Xicheng District into grids with dimensions of 200 × 200 m, 500 × 500 m, and 1000 × 1000 m.

5.3. Identification of Functional Areas

5.3.1. Single-Functional Area

The Xicheng District of Beijing can be divided into eight single-functional areas. Figure 8 shows the distribution of single-functional areas in the Xicheng District based on 200 × 200 m, 500 × 500 m, and 1000 × 1000 m grids. Each single-functional area is represented by a different color.

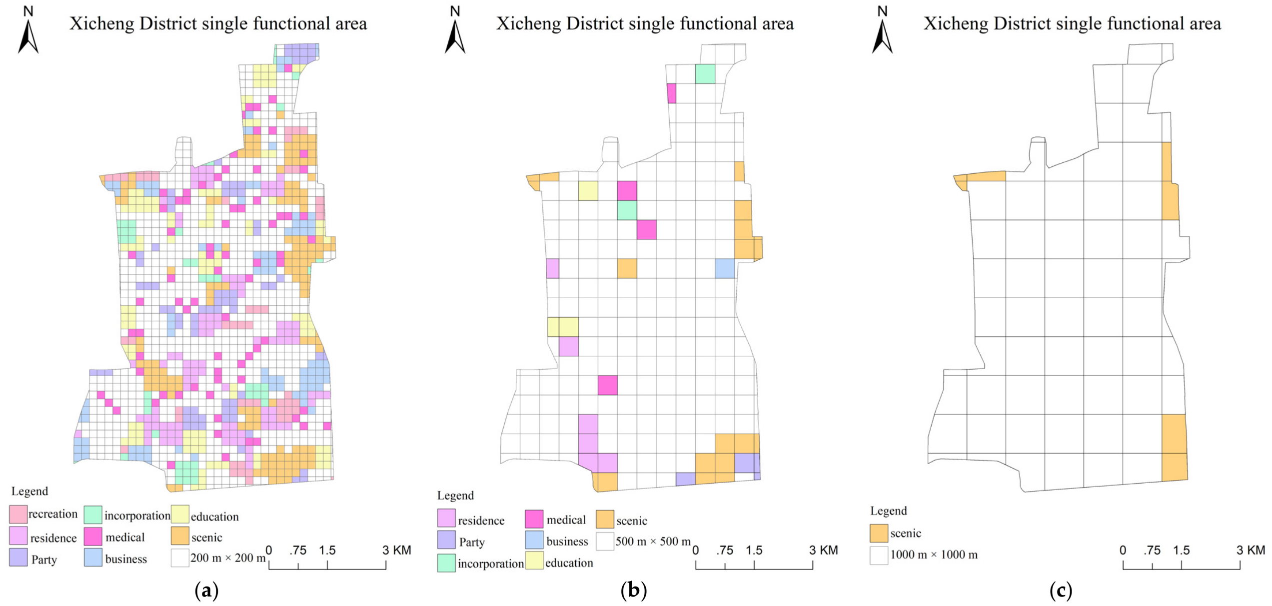
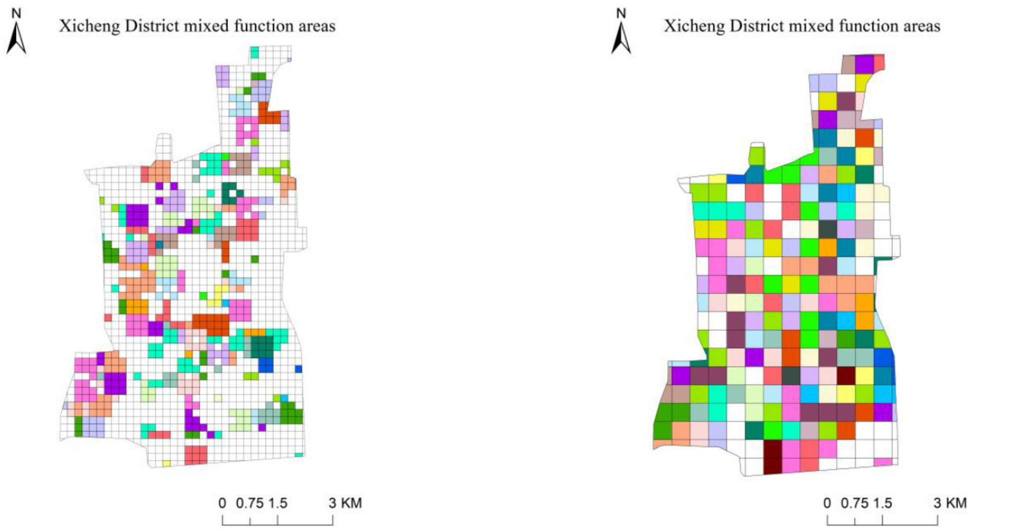


Figure 8. Single-functional areas in the Xicheng District: recreation stands for recreation and entertainment areas; residence stands for residence areas; party stands for party and government organization areas; incorporated stands for incorporated business areas; medical stands for medical and public health areas; business stands for commercial and financial areas; education stands for education and training areas; and scenic stands for scenic areas.

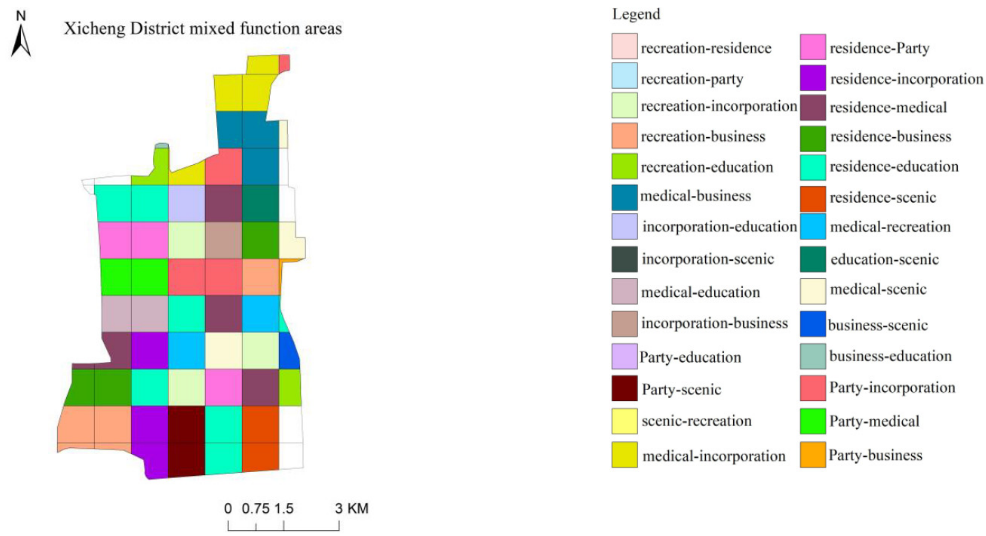
The 200 × 200 m, 500 × 500 m, and 1000 × 1000 m grids contain 696, 40, and 7 single-functional areas, respectively. In the 200 m × 200 m grid, scenic areas account for the largest proportion (152 sample squares). The proportions of single-functional areas gradually decrease in the following order: education and training, residential, commercial and finance, party and government organization, medical and public health, recreation and entertainment, and incorporated and business areas. In the 500 × 500 m grid, scenic areas account for the largest proportion (20 sample squares). The proportions of single-functional areas gradually decrease in the following order: residential, party and government organizations, medical and public health, education and training, incorporated and business, and commercial and financial areas. The single-functional area for recreation and entertainment is zero, indicating that recreational and entertainment functional areas and other functional areas become mixed-functional areas. The 1000 × 1000 m grid contains only one single-functional area for scenic areas. All other areas are mixed-functional areas. The number of sample squares corresponding to a single-functional area in the Xicheng District differs depending on the grid size. The shorter the side length of the sample square in the same area is, the less POI types the sample square contains and the more the single-functional area is divided. The opposite is true for a longer side length.

5.3.2. Mixed-Functional Area

In this study, different colors were used to indicate different mixed-functional areas in the Xicheng District. The spatial distribution of the mixed-functional areas of the Xicheng District in the 200 × 200 m, 500 × 500 m, and 1000 × 1000 m grids is shown in Figure 9 (note that residential–residence and residence–residential are considered to be the same type of mixed-functional area in this study, and other types of mixed areas are the same).



(**a**) Mixed-functional areas of 200 × 200 m grid and (**b**) mixed-functional areas of 500 × 500 m grid



(**c**) Mixed-functional areas of 1000 × 1000 m grid and (**d**) legend for functional areas types

Figure 9. Mixed-functional areas in the Xicheng District.

The statistics with respect to the number of mixed-functional areas in the Xicheng District of Beijing are shown in Table 2. The 200 × 200 m grid contains 24 types of mixed-functional areas. Among them, the numbers of recreation–business (58 sample squares), residence–party (58 sample squares), and residence–education (57 sample squares) areas are the largest, followed by residence–incorporated (38 sample squares), residence–business (32 samples), and party–incorporation (37 sample squares) areas. The 500 × 500 m grid contains 28 types of mixed-functional areas. Among them, the numbers of recreation–education (14 sample squares), residence–Party (12 sample squares), residence–medical, party–medical, and party–public (11 sample squares) areas are the highest, followed by recreation–business, incorporation–education, and medical–scenic (10 sample squares) areas. The 1000 × 1000 m grid contains 23 types of mixed-functional areas. Among them, the numbers of residence–education (seven sample squares), recreation–business, and recreation–residence (five sample squares) areas are the highest, followed by incorporation–medical and party–scenic (four sample squares) areas.

Table 2. Mixed-functional areas in the Xicheng District, Beijing.

	Recreation	Residence	Party	Incorporated	Medical	Business	Education	Scenic
(a) Functional areas in the 200 m × 200 m grid								
Recreation	53	21	13	14	1	46	6	1
Residence	7	98	36	25	0	26	36	10
Party	7	22	75	18	0	7	7	0
Incorporated	22	13	19	46	0	15	11	0
Medical	1	0	1	0	74	1	1	1
Business	12	6	4	0	0	88	14	5
Education	7	21	12	11	0	5	110	0
Scenic	5	14	0	0	0	0	15	152
(b) Functional areas in the 500 × 500 m grid								
Recreation	0	4	4	3	0	2	5	0
Residence	5	6	6	3	1	3	2	1
Party	5	6	4	1	3	1	3	2
Incorporated	2	2	10	2	2	5	2	2
Medical	5	10	8	4	4	8	5	8
Business	8	1	2	0	0	1	4	2
Education	9	4	4	8	1	2	3	1
Scenic	4	4	7	2	2	2	5	20
(c) Functional areas in the 1000 × 1000 m grid								
Recreation	0	1	0	0	0	4	1	0
Residence	0	0	0	2	0	1	4	0
Party	0	3	0	3	0	0	0	2
Incorporated	1	1	1	0	1	1	1	0
Medical	2	5	2	3	0	3	2	0
Business	1	2	1	0	0	0	0	1
Education	1	3	0	0	0	2	0	1
Scenic	0	2	0	0	3	0	0	7

6. Conclusions

In this study, the Xicheng District of Beijing was divided into 200 × 200 m, 500 × 500 m, and 1000 × 1000 m grids based on POI data. The kernel density analysis method was used to analyze the spatial distribution of eight types of data. Two indicators, that is, the FD and CR, were used to quantitatively identify urban functional areas and analyze the effects of the grid size and number on the division and identification of functional areas. The results provide guidance for decision-making with respect to reasonable urban planning and management. The statistical results are shown in Table 3. The following conclusions can be drawn: (1) with increasing grid size, the proportion of single-functional areas to the total area gradually decreases; (2) with increasing grid size, the proportion of mixed-functional areas to the total area gradually increases, and the 200 × 200 m, 500 × 500 m, and 1000 × 1000 m grids contain 24, 28, and 23 types of mixed-functional areas, respectively; and (3) with increasing grid size, the proportion of the area without data to the total area gradually decreases.

Table 3. Impact of the different grid sizes on the identification of urban functional areas.

Grids	200 × 200 m	500 × 500 m	1000 × 1000 m
Total number of quadrats	1361	243	69
Number of single-functional areas	696	40	7
Number of mixed-functional areas	550	200	62
Number of no-data areas	115	3	0
$\frac{\text{Numberofsinglefunctionalareas}}{\text{Totalnumberofquadrats}}$	51.14%	16.46%	10.14%
$\frac{\text{Numberofmixedfunctionalareas}}{\text{Totalnumberofquadrats}}$	40.41%	82.30%	89.86%
$\frac{\text{Numberofnodataareas}}{\text{Totalnumberofquadrats}}$	8.45%	1.65%	0%

Generally, the Xicheng District of Beijing, which is the political center of the country, contains large proportions of residential, party and government organization, and education and training functional areas, which agrees with the Xicheng District plan. In addition, the grid size affects the division and identification of urban functional areas. With respect to the identification of single-functional areas in the Xicheng District, the 200 × 200 m grid represents the most detailed division. With respect to the identification of mixed-functional areas, more types of mixed-functional areas are identified in the 500 × 500 m grid compared with the 1000 × 1000 m grid, this shows that the division results of urban mixed-functional areas with 500 × 500 m grid are more detailed. Therefore, the 200 × 200 m and 500 × 500 m grids are the most suitable for the division and identification of single- and mixed-functional areas in the Xicheng District (50.7 km^2). These results are of significance for the urban management and functional area identification of other cities with different areas.

However, this study has several limitations and improvements can be made in the future. For example, we would like to expand the scope of the research and continue to explore the correlation between the area of the grid and identification of urban functional areas. In addition, the results obtained for urban mixed-functional areas should be further analyzed, and we could also analyze the temporal evolution of the functional areas and even predict the evolution of these areas, which will be based on this article in the future.

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