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# Food Retail Network Spatial Matching and Urban Planning Policy Implications: The Case of Beijing, China

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**Abstract:** Food is the core of urban daily life and socio-economic activities but is rarely the focus of urban planning. The spatial layout of food retail outlets is important for optimizing the urban food system, improving land resource allocation, and encouraging healthy food consumption. Based on food retail POI data, this study employed kernel density estimation, road network centrality, spatial autocorrelation analysis, and locational entropy to analyze the spatial characteristics of supermarkets, produce markets, and small stores in an urban center in Beijing, and explored street coupling and supply-demand matching. The results indicated that within the study area: (1) supermarkets had an obvious "core-periphery" distribution, produce markets had a polycentric distribution, and small stores had a relatively uniform distribution; (2) road network centrality indices revealed a differentiated multi-core-edge distribution; (3) streets with high locational entropy values for supermarkets and produce markets were mostly concentrated in the central area, whereas the matching distribution of small stores was relatively balanced. From the perspective of urban planning, policy implications are proposed based on spatial and social equity, urban-rural differences, population structure and distribution status, and a resilient supply chain. The study findings have practical significance for guiding the development of urban food systems in a healthy, just, and sustainable direction, as well as rational urban land planning.

**Keywords:** food retail outlets; spatial pattern; supply and demand matching; policy implications; urban land planning

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## 1. Introduction

Due to accelerating urbanization in recent decades, issues pertaining to urban inequality have attracted the attention of urban researchers and geographers. Studies have examined the economic, social, and environmental aspects of urban inequality, including residential segregation, commuting distances, food accessibility, health, and job availability [1,2]. Influenced by urbanization, regional functional differentiation, optimal allocation of production factors, and rapid expansion of transportation networks, the mobility of resource factors between regions has resulted in the inherent need for sustainable regional development. Food is needed to ensure the sustainable development of human society; thus, the acquisition and utilization of food is arguably the most basic and longest-standing form of interaction between humans and the environment. The food system, as the basic channel for establishing this human-earth interaction and realizing the nutritional and socioeconomic values of food, is an "open and complex mega-system" that encompasses social division of labor and consumption activities such as primary agricultural production, food processing, distribution, consumption, and waste disposal [3,4]. Strengthening urban-rural linkages through food systems contributes to poverty reduction, hunger eradication, job creation, infrastructure improvement, social inclusion, and sustainability in urban-rural integration [5]. The COVID-19 pandemic highlighted the weaknesses of the urban food supply chain. The pandemic dramatically affected the food retail sector and exacerbated inequalities in access to food, which were determined by restricted mobility, lockdowns, and social distancing measures, thus creating new food vulnerabilities. [6]. It also demonstrated the close connection between urban citizens and food. Although the pandemic did not cause a systemic failure, it suggested how citizens would accept, and indeed, support a transition towards more localized food production systems [7]. Therefore, the integration of urban food and land planning systems is necessary, and urban food distribution and security measures in response to such pandemic emergencies are important for the sustainable development of cities and national livelihoods. The global COVID-19 pandemic has reshaped lives and activities, the role of transport and land use, urban nature, public space, facilities and services, housing, and information and communications technology. The quality of life in cities was transformed as national and regional authorities reacted promptly to limit the spread of the coronavirus [8,9] with appropriate approaches to public health measures [10], quality of life for vulnerable groups like the elderly [9], effective walkability containment [11], alternative and sustainable models for post-COVID-19 urban cultural tourism [12], and a slowing of building activity for large projects in central areas [13].

Urban sprawl increases the challenges of urban spatial planning and spatial inequities. In particular, it increases inequities in access to infrastructure such as hospitals [14], education [15], and green spaces [16]. Similar to these infrastructures, food outlets are also an important part of the spatial inequality problem. However, the impacts of urban sprawl and the corresponding design and implementation of effective measures and governance have received little attention from researchers, urban spatial planners, and political decision makers [17]. Hatab et al. [18] revealed the interactions between urban food system components (resource use, agricultural production, and food security) in developing countries. They reported that high rates of urban sprawl cause land use changes that in turn affect the use of natural resources. Spatial planning is considered as a method to achieve increased sustainable use of land, because its mechanisms balance the quality and characteristics of different land areas and soil functions with competing objectives and private interests, such as those of urban developers [19]. For example, the Danish Spatial Planning Act strictly restricts the construction of large stores and shopping malls in green spaces outside large cities. Further, the spatial planning acts of some Austrian federal states allow for the identification and delineation of priority fertile agricultural soils and protected green spaces. Although soil conservation and land degradation reduction objectives are not explicitly mentioned in the Austrian planning acts, they are implicit based on the various roles of soils in ecosystem function [20]. Since the 1990s, strategic spatial planning has increasingly been undertaken at the city-regional level. Its goal is to define a coherent spatial development strategy to support the medium- and long-term development of urban areas, and establish major infrastructural development plans for land use, natural resource recognition, housing, and transportation [21,22].

Rationalizing land planning and spatial planning is a prerequisite to ensure equal access to food in urban environments under the context of urban sprawl. Inequality due to differences in the food environment, in which urban residents live, affects their dietary choices [23,24], and unequal transportation and economic costs to obtain food constitute the main components of food access inequality [25,26]. In many countries, especially developed countries, extensive research has been conducted to examine the relationships between socioeconomic and urban spatial factors, access to food, and nutritious diets, confirming that the distance residents travel to purchase food is closely related to their access to healthy food [27–31]. Larson et al. [32] demonstrated that improved accessibility to fresh food retail outlets helped residents make better dietary choices. Empirical analysis of research and geographical data suggests that longer travel distances add to the cost of food access, and food access inequality is directly influenced by the food retail environment, especially for fruit and vegetable consumption, which is closely related to the proximity of food retail outlets [33–35]. The integration of spatial, socioeconomic, and other multi-source data combined with spatial analysis methods to study urban food retailing patterns helps optimize the distribution of healthy food retail outlets, creates better community food retail environments, and contributes to addressing regional inequalities in food accessibility [36–38]. In North America and Europe, efforts to integrate food into local planning policies are underway, to the extent that in the broadest sense, food planning is arguably one of the most important social movements in developed countries at the beginning of the 21st century. Moreover, research demonstrates that retail policies can moderate spatial mismatches between retail outlets and housing, as well as trends in food access inequality, especially when it is embedded in spatial planning and applied at the national/urban level [39].

As a developing country, the population growth and urban expansion resulting from urbanization in China pose a great challenge to the urban food system. In the face of urban expansion, consumption upgrading, and regional differentiation in consumption structure during the process of social and economic change, urban food supply and demand will eventually be matched by spatial resource allocation [40]. To alleviate the constraints in the food supply chain in China, the Ministry of Agriculture proposed the construction of the "shopping basket program" in 1988. The first phase of the program established central and local production bases for meat, eggs, milk, aquatic products, and vegetables, as well as breeding and feed processing services, to ensure that residents have access to fresh vegetables all year round. Until the mid-1990s, the program focused on solving the problem of market supply shortage. The "shopping basket program" products continued to grow rapidly, fundamentally reversing China's chronic shortage of food supplies. Except for dairy and fruits, the per capita share of all "shopping basket program" products reached or exceeded the world per capita level. Effective supply of these products at the micro-level has become a key issue for urban food security in China [41]. In assessing the "shopping basket program" system launched by the Chinese government in 2018 for 36 large and medium-sized cities, the distribution of retail outlets was used as an important evaluation index. Most of the existing studies in China have analyzed overall retail trade in cities based on POI data [42,43], but few studies have been conducted specifically on food retail outlets, except for sporadic studies in Nanjing and Hangzhou [44,45]. Adequate and reasonable geographic distribution of food resources is a prerequisite for the cultivation of healthy diets and an important factor for the development of healthy cities. Beijing, as the capital of China, has experienced a rapid metropolitan development phase and the urban infrastructure and living standards of the central urban area are relatively developed. Nevertheless, gaps in research on the geospatial analysis of food sources remain. Moreover, some studies report that the commercialization and land development pattern in Beijing, which is mainly newly developed land in the suburbs, has led to increased spatial inequality and social discontent [46,47].

Adjusting the spatial distribution of food supply resources is an important tool to promote equality of food accessibility among residents. Among existing studies, road network analysis using average road distance measurements to study the distribution of neighborhood food retail outlets and the level of food accessibility for residents has become a popular choice among scholars [42]; additionally, spatial analysis methods, such as kernel density distribution, synergistic spatial analysis, and the Moran index, have been applied [48,49]. Research exploring urban food systems in western countries is more advanced than in developing countries, with more studies and discussions regarding food access justice, food rights, and related policy formulation and implementation [50].

Similar to infrastructural developments, such as parks and hospitals, food outlets are important to ensure urban equity. However, existing research has rarely examined the comprehensive linkages and coordination between urban spatial planning and food systems in developing countries, especially in the form of quantitative analysis. Therefore, in this study, we used POI data to assess food retail outlets based on quantitative analysis methods, analyze the spatial distribution status and the matching between supply and demand, and propose targeted policy implications from the perspective of urban spatial planning to support the optimization of food retail outlet distribution, improve urban food safety, and provide a reference for the rational allocation of urban resources. Specifically, taking Beijing, China, as a case study, this research aimed to:

(1) To analyze the spatial distribution characteristics of three types of food retail outlets within the Fifth Ring Road of Beijing using the kernel density estimation method.
(2) To measure the accessibility of food retail outlets from a road-traffic perspective using the road network polycentricity evaluation model.
(3) To calculate the degree of matching between food retail outlets and population distribution in each street district using the locational entropy method.
(4) To propose policy recommendations for urban planning from the perspectives of spatial and social equity, urban-rural differences, population structure and distribution, and a resilient supply chain.

## 2. Data and Methods

### *2.1. Data Sources*

The urban area within the Fifth Ring Road of Beijing was the research area of this study (Figure 1). The POI data for retail outlets were divided into three categories based on product category, business scale, and service capability. Supermarkets were identified as large-scale businesses with a significant number of chain stores. Produce markets included exclusive markets for agricultural products, as well as newly emerging chain stores that specialize in selling fresh food. Small stores included vegetable shops and other non-chain specialized food stores, most of which had incomplete cold-chain facilities and few product categories. Residents typically need to visit more than one small store to purchase all of their daily food products. Road network data were sourced from the OpenStreetMap (OSM) platform. Beijing road network data were imported into ArcGIS 10.2 to establish a road network dataset. The POI data from food retail outlets were sourced from the amap open platform. After manual screening, removing duplicates, and correcting deviations, 4057 food retail outlets were obtained, which included 676 supermarkets, 792 produce markets, and 2589 small stores. The road network and distribution of food retail outlets are shown in Figures 1 and 2.

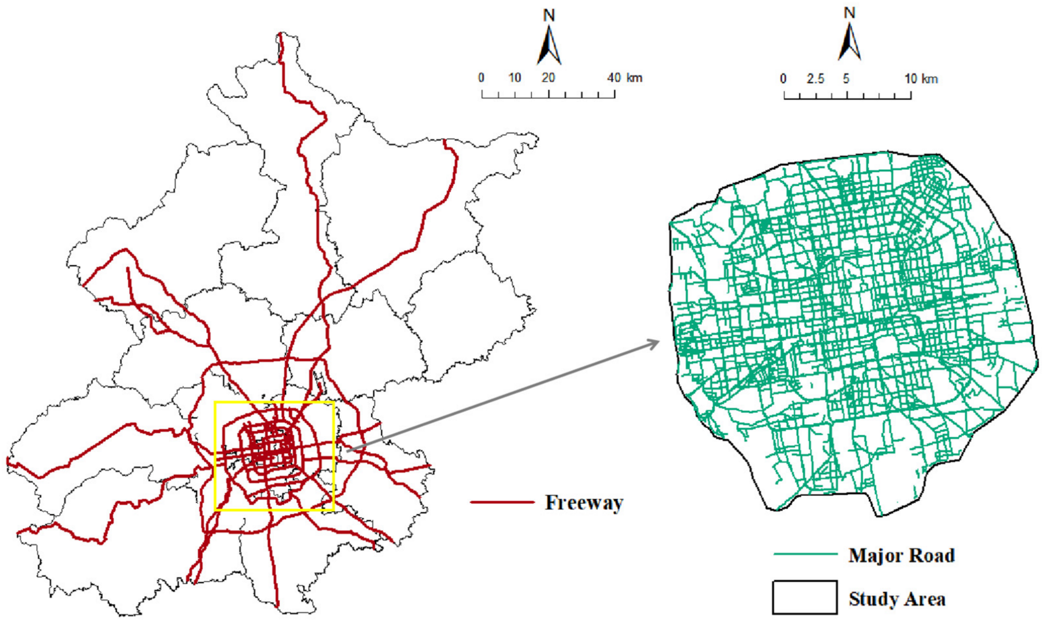


**Figure 1.** Roads and streets within the Fifth Ring Road in Beijing. The yellow square refers to the area within the Fifth Ring Road of Beijing.

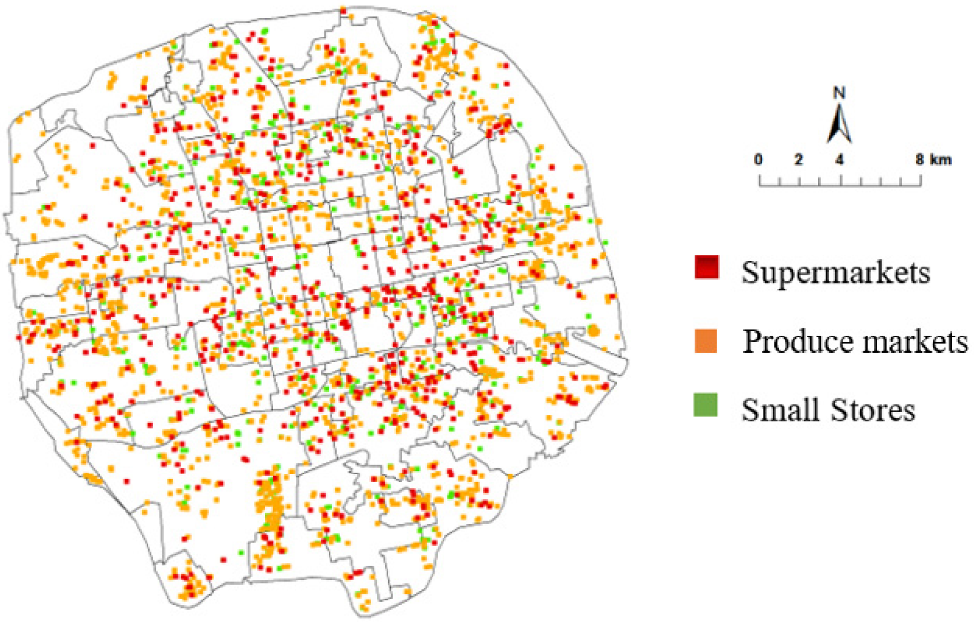


**Figure 2.** Distribution of the three types of food retail outlets.

## *2.2. Research Methods*

### 2.2.1. Kernel Density Estimation Method

Kernel density estimation (KDE) was employed to interpolate the POI data for food retail outlets and the three indices of road network centrality to reflect their spatial clustering characteristics within the study area. Based on Tobler's first law of geography, KDE uses different calculation methods according to different spatial distance concepts, thereby obtaining high-quality probability density estimation results. In addition, KDE can transform different spatial elements into the same spatial unit and facilitates the study of the relationship between different spatial elements. KDE is widely used in research to investigate micro-spatial distributions.

KDE uses $x_1$, $x_2$ ... , $x_n$, for independent, identically distributed samples of the population with the distribution density function $f$. $f(x)$ is defined as follows:

$$f_n(x) = \frac{1}{nh}\sum_{i=1}^{n} k(\frac{x - x_i}{h}) \quad (1)$$

where $k(\cdot)$ is the kernel function, $h$ is the bandwidth, and $x - x_i$ is the distance from estimation point $x$ to sample $x_i$.

Using ArcGIS software, the POI data for the food retail outlets and the three index values from the road network multiple centrality assessment model were stored using KDE, considering 100 m × 100 m image elements and 3000 m bandwidth, to transform the two data layers into the same spatial unit to facilitate correlation analysis between them.

### 2.2.2. Multiple Centrality Assessment Model

The Urban Network Analysis (UNA) tool was used to measure the centrality of the road network in ArcGIS software. The UNA tool analyzed network layers geometrically and topologically, abstracted road routes at the network edges, considered the intersection and endpoints of a road as the node of the connecting edges, and then calculates the distance between nodes along the actual network path. Closeness, betweenness, and straightness were selected as the centrality indices for the road network analysis in the study area.

The closeness centrality measures the proximity of a node to all other nodes in the network by reversing the average value of the path distance from each node to all other nodes along the shortest path. Closeness is defined as follows:

$$C_i^C = \frac{N-1}{\sum_{j=1;j\neq i}^{N} dij} \tag{2}$$

where *i* and *j* are the nodes, *N* is the total number of nodes in the road network, and *d* is the shortest path distance between nodes *i* and *j*.

The betweenness centrality represents the frequency of the shortest distance between any two nodes that pass through a node. Betweenness, which measures the traffic flow at that node, is defined as follows:

$$C_i^B = \frac{1}{(N-1)(N-2)} \sum_{j=1,k=1,j\neq k\neq i}^{N} \frac{n_{jk}(i)}{n_{jk}} \tag{3}$$

where $n_{jk}$ is the number of shortest paths between nodes *k* and *j*, and $n_{jk}(i)$ is the number of times that the shortest path between nodes *k* and *j* passes through node *i*.

The straightness centrality represents the deviation from the distance of the shortest path from one node to another and its Euclidean distance. Straightness, which measures the efficiency of the road network and identifiability of the nodes, is defined as follows:

$$C_i^S = \frac{1}{N-1} \sum_{j=1,j\neq i}^{N} \frac{d_{ij}^{Eucl}}{d_{ij}} \tag{4}$$

where *N* is the total number of nodes in the road network, $d^{Eucl}$ is the Euclidean distance between nodes *i* and *j*, and $d_{ij}$ is the shortest distance between nodes *i* and *j*.

#### 2.2.3. Moran's *I* Model

Global spatial autocorrelation describes the spatial distribution characteristics of a certain attribute value in an entire region. Local spatial autocorrelation measures the attribute correlation between different spatial positions and their adjacent spatial positions in a region. The global Moran's *I* model is defined as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} C_{ij}(X_i^a - \overline{X}_a)(X_j^b - \overline{X}_b)}{\sum_{j=1}^{n}\sum_{j=1}^{n} C_{ij}\sum_{i=1}^{n}(X_i^a - \overline{X}_a)(X_j^b - \overline{X}_b)} \tag{5}$$

where *n* is the number of spatial units, $C_{ij}$ is the weight matrix used to measure the adjacency relation between spatial units *i* and *j*, and ${X^a}_i$ and ${X^b}_j$ are the values of attribute *a* of spatial unit *i* and attribute *b* of spatial unit *j*, respectively.

The bivariate local Moran's *I* model is defined as follows:

$$I_{kl} = \frac{X_k^i - \overline{X}_k}{\sigma_k} \sum_{j=1}^{n} W_{ij} \frac{(X_l^j - \overline{X}_l)}{\sigma_l} \tag{6}$$

where $I_{kl}$ is the local bivariate spatial autocorrelation coefficient, ${X^i}_k$ is the value of attribute *k* of the spatial unit *i*, ${X^j}_l$ is the value of attribute *l* of spatial unit *j*, $\sigma_k$ and $\sigma_l$ are the variances for attributes *k* and *l*, respectively, and $W_{ij}$ is the spatial weight matrix between spatial units *i* and *j*.

The kernel density values for food retail outlets extracted by ArcGIS software and the kernel density values for the road network centrality indicators of the same location were used as variables and imported into GeoDa software, and the corresponding global and local bivariate spatial autocorrelation models were used to analyze the spatial correlation between the road network centrality indicators and the three types of food retail outlets from a large regional level to the local level.

#### 2.2.4. Human Settlement Index

The Human Settlement Index (HSI) was used to simulate the population distribution at street scale by combining Luojia-1 nighttime light (NTL) remote sensing data, OpenStreetMap (OSM) data, and Landsat-8 multispectral images [51,52].

(1) Normalized vegetation index

First, OSM data for water bodies, forests, historical sites, and tourist landscapes in Beijing were extracted to exclude the influence of the non-residential surface environment on NTL data. Next, Landsat-8 multispectral images of Beijing with less than 10% cloud cover in April 2018 were selected to calculate the normalized vegetation index (NDVI), which is calculated as follows:

$$NDVI = \frac{NIR - R}{NIR + R} \tag{7}$$

where *NIR* is the near-infrared band of the Landsat-8 multispectral image and *R* is the red band.

(2) Human settlement index

Radiation-corrected and image-aligned NTL data were subsequently normalized using the following equation:

$$NTL'(i,j) = \frac{NTL(i,j) - NTL_{\min}}{NTL_{\max} + NTL_{\min}} \tag{8}$$

where $NTL$ is the unnormalized NTL data, $NTL_{\max}$ and $NTL_{\min}$ are the maximum and minimum values of the unnormalized NTL data, respectively, and *(i,j)* are the pixel coordinates.

The final calculation for *HSI* was performed using the following formula:

$$HSI = \frac{(1 - NDVI) + NTL'}{(1 - NTL') + NDVI + NTL' \times NDVI} \tag{9}$$

#### 2.2.5. Locational Entropy

Locational entropy (LE) in this study represented the ratio of retail store occupancy relative to the population in the jurisdiction to retail store occupancy relative to the total population in the study area using HSI as an indicator of population size and each street jurisdiction divided into one spatial unit for each street data. LE was calculated as follows:

$$LQ_j = (N_j/P_j)/(N/P) \tag{10}$$

where $LQ_j$ is the LE value of the $j$th street, $N_j$ is the number of food retail outlets on the $j$th street, $P_j$ is the number of residents on the $j$th street, $N$ is the total number of food retail outlets in the study area, and $P$ is the total population of the study area. If $LQ_j > 1$, the per capita enjoyment level of the spatial unit is higher than the overall level of the study area range; if $LQ_j < 1$, the per capita enjoyment level within the spatial unit is lower than the overall level of the study area range.

According to the requirements of the Urban Residential Planning and Design Standards (http://www.mohurd.gov.cn/wjfb/201811/W020181130044801.pdf, accessed on 10 July 2018), service areas are subdivided in different types of food retail stores. Thus, 15-, 10-, and 5-min living circles are applicable to supermarkets, produce markets, and small stores, respectively. The number of residents served by the three types of living circle infrastructure differs, with twice the number of people served by supermarkets compared to produce markets and four times that of small stores. The LE values for supermarkets, produce markets, and small stores were first calculated, and then the LE values for overall food retail outlets in relation to the population were calculated by taking the number of residents served by the three types of living circles as a reference.

## 3. Results

### *3.1. Spatial Patterns and Road Coupling Analysis of Food Retail Outlets*

#### 3.1.1. Spatial Patterns of Food Retail Outlets

Using the KDE method, spatial interpolation was performed on the POI data for the study area. In general, the density distribution of food retail outlets diffused from the center to the outside edge of the study area. Areas with low KDE values were mostly distributed outside the Fourth Ring Road (Figure 3). The distribution of food retail outlets was relatively concentrated in the southeast. Meanwhile, the northeast region had few areas with high KDE values. Scenic spots and natural landscapes, along with their surrounding areas, constituted the areas with low-KDE values for the three types of food retail outlets.

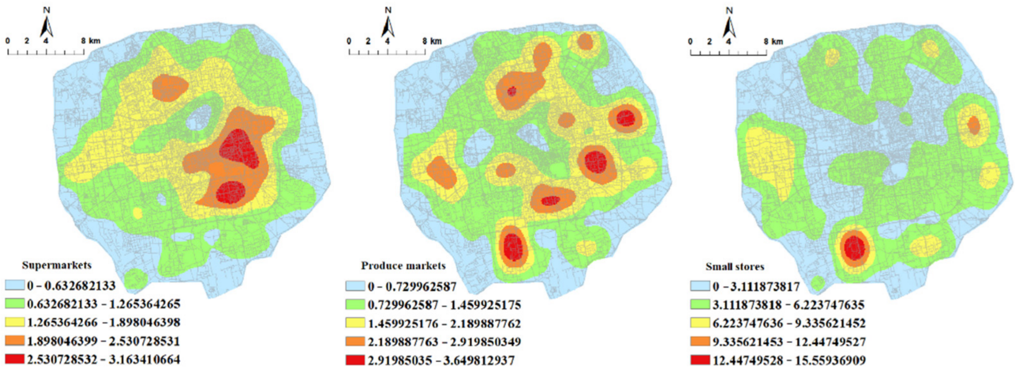


**Figure 3.** Distribution of kernel density estimation values for the three types of food retail outlets.

Chain supermarkets displayed an obvious "core-periphery" spatial distribution. Two areas had the highest core density in the southeastern area of the Fourth Ring Road, which were located at the junctions of Dongcheng and Chaoyang Districts and Dongcheng and Fengtai Districts. As the main urban area with a high density of permanent residents, residents of Dongcheng District have high demand for one-stop food purchases. However, supermarkets were scattered around scenic spots. For example, the area around the Forbidden City inside the Second Ring Road had the lowest KDE value. Other areas with low KDE values were located outside the Fourth Ring Road. If residents in these areas choose supermarkets as their purchase point for food, they will need to cover a relatively longer distance.

The spatial patterns for produce markets and supermarkets differed significantly, with a more obvious multi-center distribution trend. Multiple high-density areas were far removed from each other, displaying a scattered distribution. The five areas with the highest KDE values for produce markets included two areas located near the area with the highest KDE value for supermarkets, both of which were located southeast of the Fourth Ring Road. The remaining three areas were around the Xinfadi Market, Shilibao Road (east of the East Fourth Ring Road), and Jingshi Road (south of the North Third Ring Road). Among them, Xinfadi Market is the largest wholesale market for agricultural products in Beijing and plays an important role in the safe and stable supply of agricultural products in the capital. In the early 20th century, Liulitun and other streets around Shilipo Road were relatively backward "urban villages" in Beijing with a dense distribution of agricultural product stores.

Small stores were abundant and had a relatively balanced spatial distribution, displaying a "high outside-low inside" spatial pattern. Around Xinfadi Market (south of the South Fourth Ring Road), specialty stores for meat, fruits, vegetables, and other agricultural products formed the only area with high KDE values. The overall distribution of small stores was scattered, and areas with relatively high KDE values were distributed outside the Fourth Ring Road.

### 3.1.2. Coupling between Food Retail Outlets and Road Network

The three centrality indices for the road network showed differential spatial patterns in the core and periphery of the study area (Figure 4). Closeness was distributed across multiple centers, while betweenness and straightness demonstrated significant "core-periphery" distribution patterns. Straightness had the largest "core-periphery" area, with the center located north of the study area.

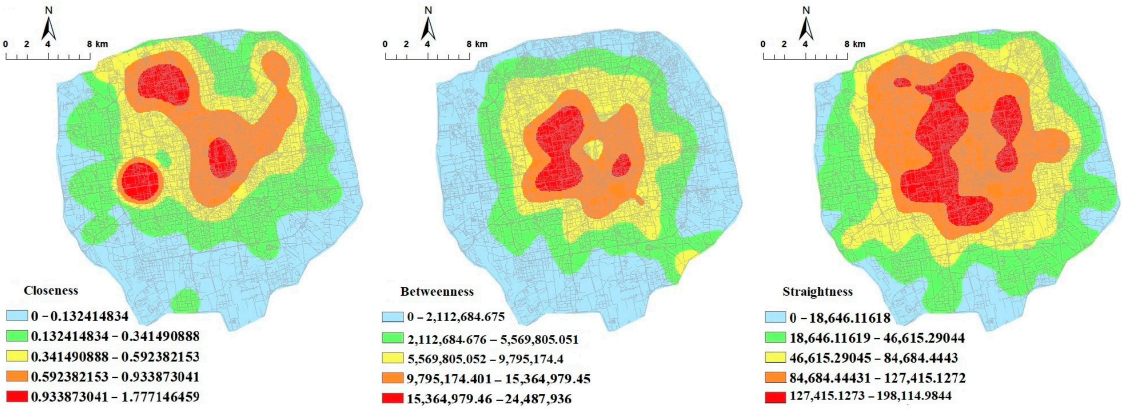


**Figure 4.** Distribution of kernel density estimation values for the centrality indices of the road network.

Geoda 1.20.0 software was employed to extract the KDE values for road network centrality indices and retail outlet locations to conduct spatial autocorrelation analysis. Global Moran's *I* values for the three types of food retail outlets with road network centrality are listed in Table 1. The bivariate global autocorrelation coefficients for supermarkets and road network closeness, betweenness, and straightness indices were 0.288, 0.483, and 0.463, respectively. Thus, the road network centrality indices were positively correlated with the distribution of supermarkets in the study area to different degrees, indicating that supermarkets were more conveniently located and accessible. Among them, supermarkets had the strongest positive spatial correlations with betweenness and straightness. The bivariate global autocorrelation coefficients for produce markets and the KDE values for the three indices were relatively low and had different positive and negative coefficients, indicating a differentiated spatial relationship between road network centrality indices and the distribution of produce markets in the study area. The bivariate global autocorrelation coefficients for small stores and the KDE values for the three centrality indices were all negative with low to medium level values. Further, the scatter distribution indicated that small stores had similar significant negative spatial correlations with the three indices. Small stores were more densely distributed in areas with low road network centrality. Few points were observed in the first quadrant of the scatter plot, indicating the lack of areas with high road network centrality and small stores clustered in the study area.

**Table 1.** Moran's Index values for road network centrality indices for food retail outlets.

| | Closeness | Betweenness | Straightness |
|---|---|---|---|
| Supermarkets | 0.288 | 0.483 | 0.463 |
| Produce markets | −0.017 | 0.086 | 0.150 |
| Small stores | −0.300 | −0.349 | −0.335 |

Using the local bivariate spatial autocorrelation model, a bivariate LISA cluster map of road network centrality and food retail outlets was obtained, and the clustering characteristics were analyzed (Figure 5). The spatial autocorrelations between different road network centrality indices and food retail outlets showed four types of aggregation areas, namely low–high, high–low, high–high, and low–low areas. Low–high areas had low road network centrality and densely distributed food retail outlets, whereas high–low areas had high road network centrality and sparsely distributed food retail outlets, showing spatially incompatible relationships.

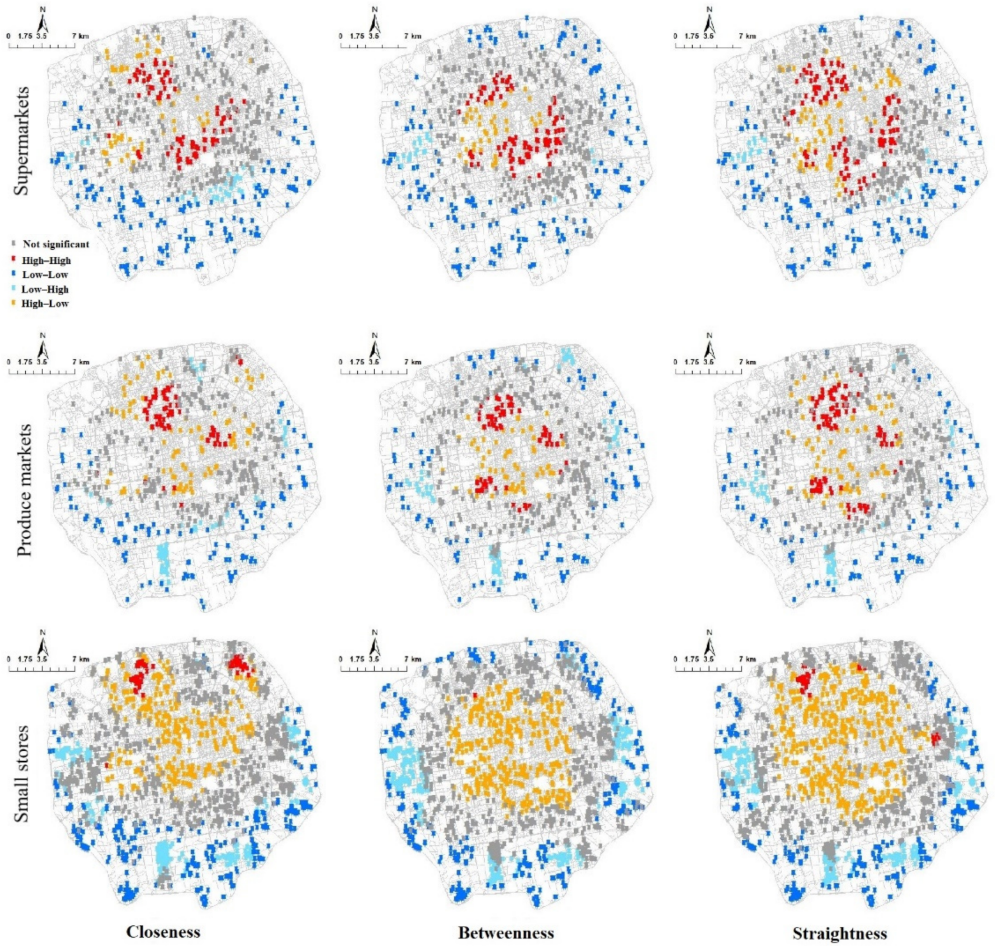


**Figure 5.** Results of bivariate LISA analysis for the three types of food retail outlets. The red (High–High) and blue (Low–Low) indicate a positive spatial correlation between the road network centrality and food retail outlets. The green (Low–High) areas had low road network centrality and densely distributed food retail outlets, whereas yellow (High–Low) areas had high road network centrality and sparsely distributed food retail outlets, showing spatially incompatible relationships. And gray (Not significant) indicate there is no significant relationship between the two variables.

Supermarkets had the largest range of high–high areas, almost all of which were distributed inside the Fourth Ring Road. Low–low areas of supermarkets were mostly distributed in the outer area of the Fourth Ring Road, whereas most low-high areas were close to the Fourth Ring Road. High–low areas had a small distribution range and were mainly distributed close to the Second Ring Road, which is characterized by historical sites and nearby cultural attractions. The clustering characteristics of produce markets and supermarkets demonstrated certain spatial similarities. The range of high–high areas of produce markets was smaller than that of supermarkets and almost entirely distributed inside the Fourth Ring Road. Low-low clusters of produce markets were mostly distributed outside the Fourth Ring Road. Low–high areas had a small range, most of which were dotted between low–low areas. High–low areas also had a small range, distributed within the Fourth Ring Road and north of the North Fourth Ring Road. Regarding small stores, high–high areas were rather small and distributed close to the Fourth Ring Road. No autocorrelation was determined with betweenness. The ranges of low–low and low–high areas of small stores were large, most of which were distributed outside the Fourth Ring

Road. High–low areas of small stores were large and mostly concentrated within the Fourth Ring Road.

### *3.2. Food Retail Outlet Spatial Matching Analysis*

In this study, food retail stores within the Fifth Ring Road of Beijing were considered to be social public service facilities, so the spatial matching evaluation method of public resources was applied to analyze their spatial matching pattern. Using LE values to express the ratio of retail outlet occupancy by residents in the jurisdiction relative to retail outlet occupancy by the entire population in the study area, the degree of spatial matching between food retail stores and population distribution in each street unit was analyzed. Further, the variability of spatial matching between food retail outlets and population distribution in each street unit was analyzed.

HSI was calculated from NTL and multispectral image data (Figure 6), and the spatial variability characteristics of the habitat area were analyzed. Further, HSI values of each street unit in the study area were counted to obtain the ratio of the habitat area of each street unit to the overall habitat area of the study area.

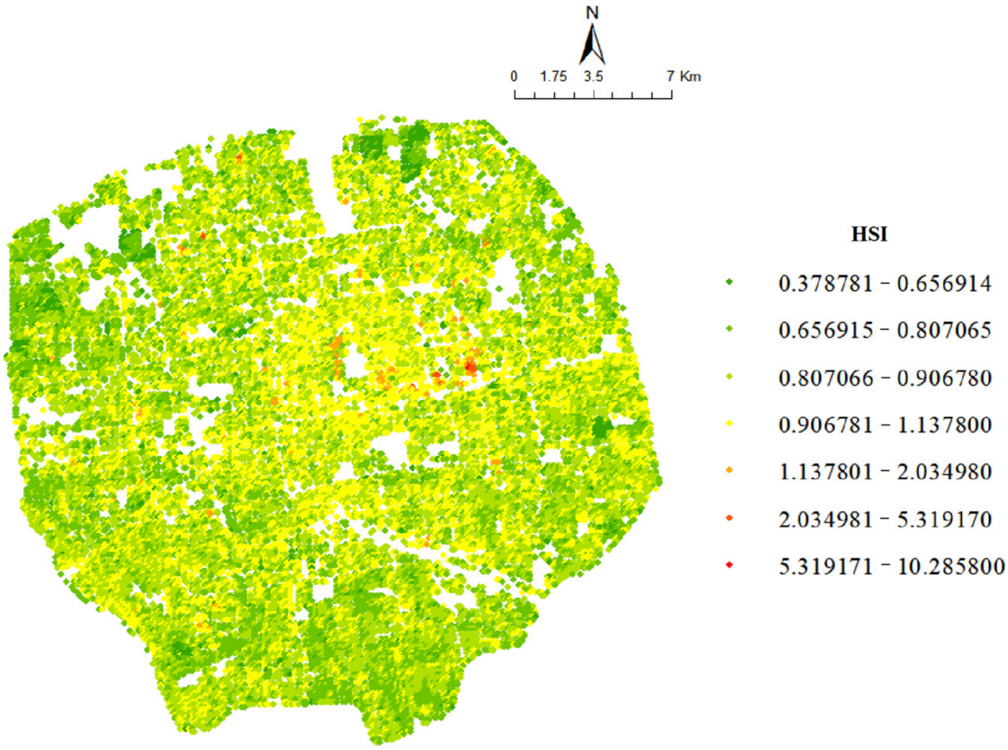


**Figure 6.** Spatial distribution of the human settlement index values within the Fifth Ring Road in Beijing.

Spatial mismatch between the spatial distribution of food retail outlets and the living and working areas of the residents is an important component of urban food inequality, and a direct manifestation of irrational urban spatial planning. To delineate the occupancy of the three types of food retail outlets and overall food retail outlets by residents in different street units, the distribution match of this resource relative to the population in the study area was quantitatively determined and compared according to LE theory. The LE values for each street unit were ranked according to the natural fracture method to analyze the quantitative distribution, spatial layout characteristics, and spatial differentiation status of resource-advantaged and -disadvantaged areas.

### 3.2.1. LE Values for Supermarkets

The LE values for supermarkets were divided into five classes using the natural fracture method, and the difference between the LE values for supermarkets in each street unit was >3, showing some spatial variability in the distribution of the number of supermarkets in each street. The LE values for supermarkets in each street of the study area were measured relative to the population, and the distribution of the LE values for sub-street locations was plotted (Figure 7). Most streets with very high LE values were located inside or around the Second Ring Road, and these streets had sufficient supermarket resources in their jurisdictions. The distribution of streets with extremely low LE values was more dispersed, mostly located around and outside the Fourth Ring Road. The results indicated that the layout of supermarkets in the periphery of the Fourth Ring Road warrants improvement, and the layout of supermarkets in the city center also has a certain degree of unevenness.

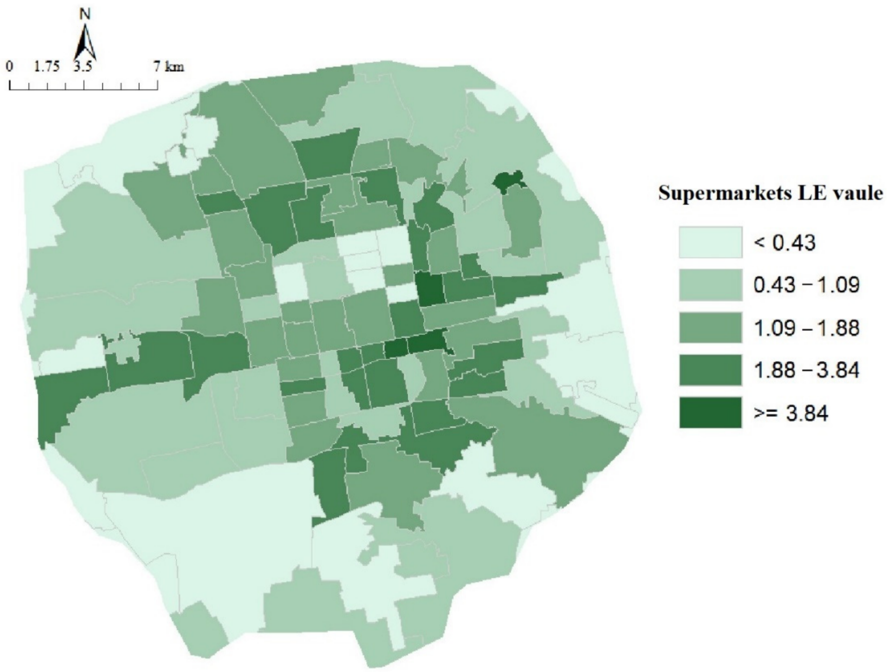


**Figure 7.** Distribution of the supermarket locational entropy values for streets within the Fifth Ring Road in Beijing.

### 3.2.2. LE Values for Produce Markets

Similar to supermarkets, the LE values for produce markets in each street were divided into five classes using the natural fracture method, and the difference between the LE values in each street unit was relatively small. The distribution of LE values for produce markets by street is shown in Figure 8. Compared with supermarkets, more streets had extremely high LE values for produce markets and they were more dispersed, mostly distributed inside and around the Third Ring Road. Further, the layout of produce markets in the jurisdiction of these streets was relatively more populated. The distribution of streets with extremely low LE values for produce markets was more dispersed and they were distributed in all Ring Road areas, whereas streets with low LE values for produce markets inside and around the Second Ring Road were closer to the streets with extremely high LE values. Therefore, residents who prefer to buy food from produce markets in some of the low LE value streets may still be able to reach produce markets within a convenient travel range. On the whole, significant spatial variation in the street LE values for produce markets was observed in the central area, while street LE values in peripheral areas were mostly in the middle and lower range. There were significantly more streets with low and extremely low LE values than those with high and extremely high LE values. Combined with the current development trend of decommissioning non-capital functions and industrial upgrading in

Beijing, some old produce markets in the main urban area have been closed and the scale and environmental protection requirements for new produce markets have been improved. In the future, upgrading development of produce markets to supermarkets will gradually improve the quality of products and services while matching food retail outlet distribution to the population.

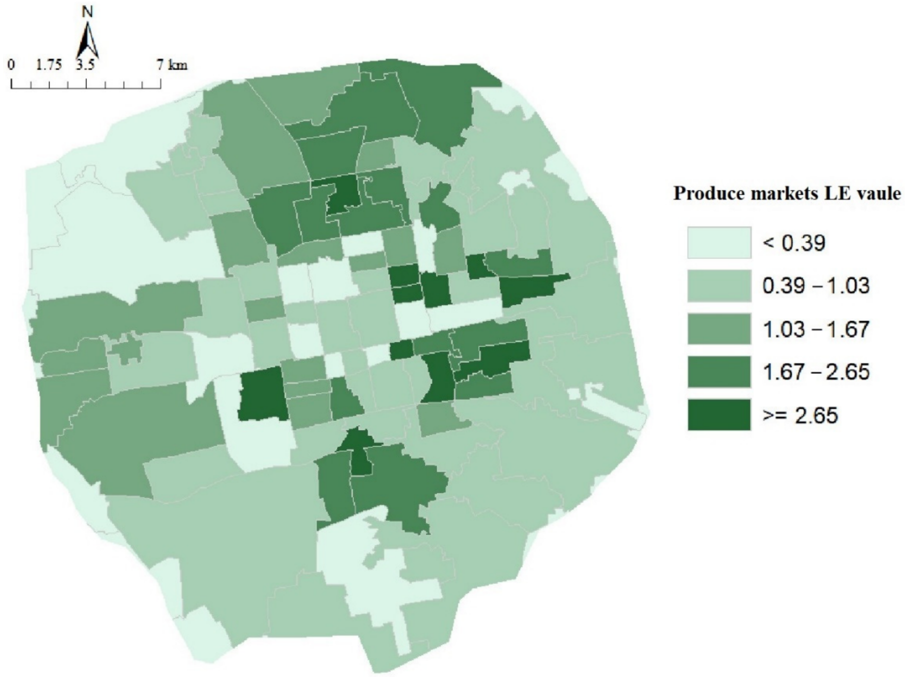


**Figure 8.** Distribution of the produce market locational entropy values for streets within the Fifth Ring Road in Beijing.

### 3.2.3. LE Values for Small Stores

The distribution of the LE values for small stores by street is shown in Figure 9. The small number of street units with extremely low and extremely high LE values indicated that the distribution of small stores relative to the population in most streets was close to the average. At the same time, unlike supermarkets and produce markets, small stores showed an overall "low inside-high outside" distribution trend, and differences between the LE values were further reduced. These results indicated that spatial matching of small stores in each street was less diverse relative to the population. The only street with an extremely high LE value was Jiuxianqiao Street in Chaoyang District, which is a small area with a high-tech park, a deep foundation for industrial cluster development, and convenient transportation between the Capital Airport Expressway and the Fourth Ring Road. Streets with extremely low LE values were mostly located at the edge of the Fifth Ring Road, and the distribution of small stores in this area relative to the population was much lower than the average for the study area, which did not have excellent matching conditions for small-scale specialty franchise stores. On the whole, differences in the street LE values for small stores were small between districts and spatial distribution was more balanced.

### 3.2.4. LE Values for Overall Food Retail Outlets

Using the number of residents served by the living circle infrastructure as a reference, supermarkets and produce markets were equated to four and two small stores, respectively. Subsequently, the LE values for overall food retail outlets were integrated and calculated relative to the population. The distribution of LE values for overall food retail outlets by street is shown in Figure 10. Streets with extremely high LE value were located south of the northeast-southwest axis of the study area. Among streets with extremely high LE value streets, Jiuxianqiao Street had extremely high LE values for both supermarkets and small stores, Xiluoyuan Street (in Fengtai District) had an extremely high LE value for produce markets, and the other three streets had very high LE values for supermarkets, demonstrating differences in the composition of the food retail environment among the streets with extremely high LE values. The distribution of streets with extremely low LE values was more dispersed, did not display agglomeration characteristics, and was distributed in all Ring Road areas. Overall, the spatial distribution of the street LE values for overall food retail outlets was more balanced and higher, and streets with extremely high LE values were found in the central area rather than in the peripheral areas of the study area.

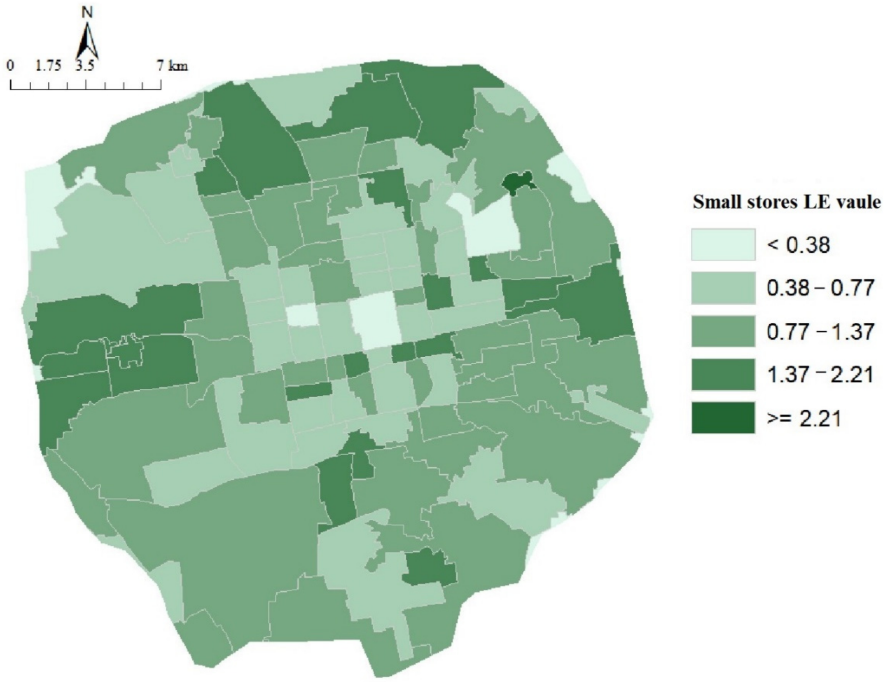


**Figure 9.** Distribution of the small store locational entropy values for streets within the Fifth Ring Road in Beijing.

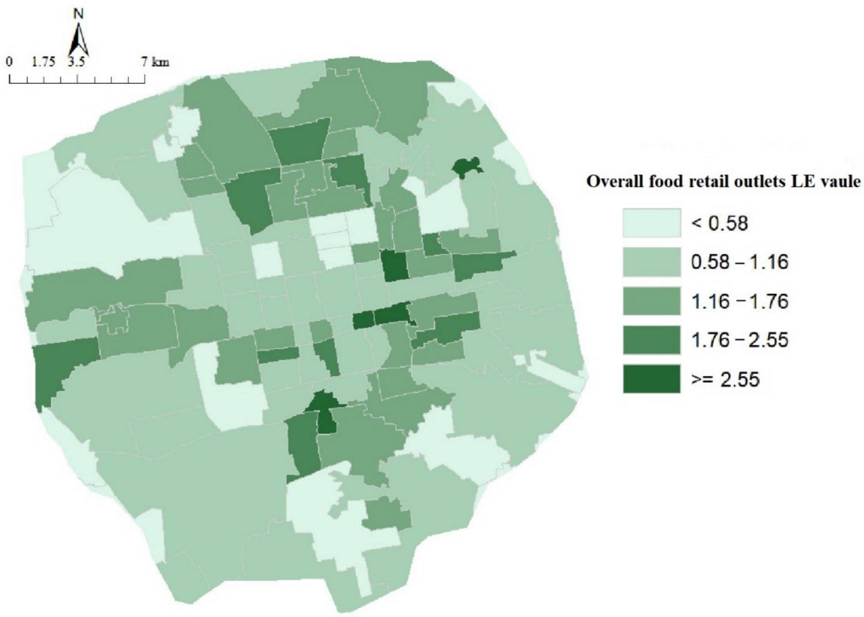


**Figure 10.** Distribution of the overall food retail outlet locational entropy values for streets within the Fifth Ring Road in Beijing.

## 4. Discussion

Food accessibility is a major social issue related to health, quality of life, and social equity. At present, most developing countries are in the early and middle stages of urbanization, and social functions and public services are undergoing structural optimization [53]. Consequently, consumers are demanding higher service quality and specialty stores. Future increased ownership of private cars and its impact on transportation will also change the retail layout. The distribution characteristics of food retail outlets are strongly related to urban development characteristics and road network distribution. Beijing's urban layout is characterized by a primary center interacting with seven surrounding secondary centers [54]. This layout is also reflected in the city's road network. Roads are important factors that affect the location and distribution of supermarkets. Supermarkets tended to be located in areas with the shortest path to main roads and heavy traffic flow to attract more consumers. Macroeconomic developmental factors, such as the construction environment and commercial competition, are also important factors [45]. The number of core produce markets was large, and they were distributed on each Ring Road. The spatial pattern of cluster areas for produce markets was similar to that of supermarkets, but the overall spatial autocorrelation with road network centrality was weak, possibly because the distribution of produce markets is more related to government planning and residential consumption habits [46,55]. Considering the flexibility in construction of small stores and rent costs, the spatial pattern of small stores does not typically adhere to the orientation of road network centrality [56]. In Beijing, few densely distributed small stores were found in areas with excellent road network centrality and heavy traffic flow. Indeed, the distribution of small stores was relatively balanced, showing a multi-center spatial pattern. Based on the above findings, the following policy implications are suggested for urban land and spatial planning to ensure the future supply security of food outlets.

(1) Optimize the urban food supply network. In urban planning, more attention should be paid to the layout of food retail outlets, which should be considered and planned systematically. Food outlets should be considered an important part of urban public services, and more attention should be paid to optimizing the ratio of different types of food retail outlets, improving the construction environment, and creating better food access possibilities, especially in areas with poor food accessibility. When formulating policies related to adjusting the food retail environment, several factors outside urban geographic space should be taken into consideration, such as rent levels, new retail formats, and consumption habits. Multidimensional data should be integrated to support the development of optimal layout benefits.

(2) Focus on spatial and social equity of residents in peripheral areas. Based on the principle of spatial equity, urban planning departments should focus on the construction of medium- and large-scale food retail outlets in peripheral areas to compensate for the lack of spatial accessibility to these outlets. Distribution of high-quality resources should be employed to achieve a balanced regional layout and reduce the waste of resources by concentrating large-scale retail outlets in central areas. Based on the principle of social equity, urban planning departments should put more effort into low-income communities on the periphery of the city and facilitate the construction of medium- and large-scale food retail stores in these areas with policy subsidies to accelerate improved food welfare supply.

(3) Improve traffic conditions. The coupling results between each type of food retail outlet and the road network indicated that the probability of having low road network centrality and sparsely distributed food retail outlets was higher outside the Fourth Ring Road, suggesting that poor traffic conditions outside the Fourth Ring Road are directly related to fewer food retail stores. Therefore, regional geospatial differences should be emphasized in urban planning, and a resource allocation policy combining commonality and characteristics should be implemented to improve road grades and shorten travel time from marginal areas to medium- and large-scale retail stores.

(4) Incorporate spatial and inter-level coordination. Issues such as location and licensing regulations for food retail businesses can be incorporated into urban land planning to limit the phenomenon of "food deserts" in some areas, reduce inequitable access to food for residents, and prevent the emergence of problems such as suboptimal health and obesity.

(5) Construct a more resilient supply chain and encourage diversification in food provision. A more resilient supply chain can improve the ability to respond to emergency crises, such as the COVID-19 pandemic. The social contribution of more substantial and innovative small-scale production systems and digital platforms has been highlighted in the post-COVID-19 world. Therefore, in response to pandemic conditions, the government should organize an optimized point-to-point food transportation flow to avoid unnecessary difficulties caused by the intermediate process. In addition, the role of online platforms and food delivery platforms should be actively promoted to enhance the delivery system.

## 5. Conclusions

The spatial layout of food retail outlets profoundly affects the food access environment for residents and reflects the rationality of urban land planning. Using network point-of-interest data and spatial analysis models, this study explored the distribution patterns for three types of food retail outlets within the Fifth Ring Road in Beijing as well as street-centric coupling and supply-demand matching, and made five targeted policy recommendations. The main findings of the study are as follows:

(1) Spatial patterns differed among the three types of food retail outlets. Supermarkets showed an obvious "core-periphery" distribution. Produce markets displayed multi-center distribution characteristics, and small stores were relatively uniformly distributed. (2) In terms of road network centrality and food retail outlet coupling, the distribution of supermarkets was coordinated with road network centrality, although some stores had poor location conditions, whereas small stores were significantly negatively correlated with road network centrality. (3) In terms of spatial agglomeration characteristics, supermarkets had the largest range of high–high type agglomeration areas, almost all of which were distributed inside the Fourth Ring Road. The local clustering characteristics of produce markets and supermarkets showed a certain spatial similarity, while the number of high–high agglomeration areas for small stores was small and they were located close to the Fourth Ring Road. (4) The distribution of streets with extremely high LE values for supermarkets was relatively concentrated in the central area, streets with extremely high LE values for produce markets were located inside the Fourth Ring Road, and the distribution of streets with matching LE values for small stores was relatively balanced.

The findings of this study will be helpful for understanding the spatial pattern of food retail outlets in Beijing and provide a reference for scientific planning of urban public service facilities and the rational layout of food retail outlets. The development of urban food systems is not only a matter of food itself, but also involves a wide range of urban planning issues, including natural resources, transportation systems, economic development, social equity, etc. Solutions on how to redesign food systems to ensure sustainability and resilience have emerged based on the multiple innovative responses to the COVID-19 pandemic. We can now increase our resilience to future crises and mitigate them. For example, many food suppliers and retailers are shifting to online businesses (Open Food Network), and social enterprises are providing fresh, local food and backyard gardening kits to vulnerable populations. Guiding the integration of urban food and land planning systems needs to be a goal for future research.

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