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Revealing Characteristics of the Spatial Structure of Megacities at Multiple Scales with Jobs-Housing Big Data: A Case Study of Tianjin, China

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Abstract: Urban spatial structure reflects the organization of urban land use and is closely related to the travel patterns of residents. The characteristics of urban spatial structure include both static and dynamic aspects. The static characteristics of urban spatial structure reflect the morphological features of space, and the dynamic characteristics of urban spatial structure reflect intra-city functional linkages. With the continuous agglomeration of population and industries; megacities have become the core spatial carriers leading China's social and economic development; and their urban spatial structure has also been reconstructed. However; there is still a certain lack of understanding of the characteristics of the spatial structure of China's megacities. This study aimed to reveal characteristics of the spatial structure of Chinese megacities at different scales using jobs-housing big data. To achieve this goal, spatial autocorrelation and a geographically weighted regression (GWR) model were applied to reveal static polycentricity, and community detection was used to reveal dynamic commuting communities. The distribution of jobs in urban space and jobs–housing balance levels in commuting communities were further analyzed. Experiments were conducted in Tianjin, China. We found that: (1) the static characteristics of the spatial structure of megacities presented the coexistence of polycentricity and a high degree of dispersion at macro- and meso-scales; (2) the dynamic characteristics of the spatial structure of megacities revealed two types of commuting communities at macro- and meso-scales and most commuting communities had a good jobs-housing balance. These findings can be referenced by urban managers and planners to formulate relevant policies for spatial distribution optimization of urban functions and transportation development at different spatial scales.

Keywords: megacity; spatial structure; polycentricity; commuting communities; Tianjin

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1. Introduction

In recent decades, the agglomeration of population and industries in metropolitan areas has become a common phenomenon of urbanization worldwide [1–3], which is particularly obvious in China [4,5]. Since China's reform and opening-up, the country has achieved the fastest urbanization rate in the world. The share of Chinese people living in urban areas has increased significantly from 17.9% in 1978 to 63.9% in 2020. According to China's criteria for urban scale, cities with more than five million residents in an urban area are classified as megacities. At present, there are twenty-one megacities in China, seven of which have more than ten million residents within their urban area. Megacities, as well as dense urban areas with megacities as the core, have undoubtedly become the core spatial carriers leading China's social and economic development. With urban expansion, the spatial structure of megacities has also been reconstructed [6], leading to changes in the distribution of different types of urban land use, and changes in travel patterns of residents. These changes have led to a series of problems in the sustainable development of megacities, including jobs–housing segregation [7], excess commuting [8], air pollution [9], and a decline in the quality of life [10]. Therefore, an investigation of the characteristics of the spatial structure of megacities would help to understand the current spatial development of Chinese cities, and provide corresponding urban transport and land use policies.

By looking at the case of Tianjin, this paper aimed to reveal the characteristics of the spatial structure of Chinese megacities at different scales, including static urban morphology and dynamic functional linkages. Previous studies on Chinese cities mostly rely on demographic data to detect urban spatial structure at a single spatial scale. This cannot take into account the impact of employment on the formation of the spatial structure and lacks the commuting connections between home and workplaces. In addition, the results of urban studies are also dependent on the spatial scale, but little research has examined spatial structure at multiple scales. Therefore, we used jobs–housing big data obtained from Baidu, which can simultaneously reflect a large-scale spatial distribution of employment and population, as well as the commuting flows connecting them. Besides, we examined the characteristics of urban spatial structure at both macro-scale and meso-scale. Spatial autocorrelation and a geographically weighted regression (GWR) model were used to identify static polycentricity, and community detection was used to identify dynamic commuting communities. We found that: (1) the static characteristics of the spatial structure of megacities presented the coexistence of polycentricity and a high degree of dispersion at macro- and meso-scales; (2) the dynamic characteristics of the spatial structure of megacities revealed two types of commuting communities at macro- and meso-scales, and most commuting communities had a good jobs–housing balance. This study makes up for the limitation of lack of an employment distribution perspective and dynamic functional connections in previous research. The multi-scale analysis results also contribute to help urban managers and planners formulate relevant policies for spatial distribution optimization of urban functions and transportation development at different spatial levels.

The rest of this paper is organized as follows. Section 2 briefly reviews the literature related to this study. Section 3 introduces the study area, data and methods. Section 4 presents the research results. Section 5 discusses our findings. Section 6 concludes and discusses the potential policy implications.

2. Literature Review

2.1. Sustainable Urban Development and Spatial Structure

The focus on sustainable development issues originated in the Brundtland Commission report in 1987. This concept is defined as development that can meet the needs of the present without compromising the ability to meet those of the future generations [11]. The connotation of sustainable development is multidimensional, and its three pillars are environmental, social and economic sustainability [12]. From the perspective of sustainable development, cities, as consumers of energy and producers of waste, are regarded as practical places that cause unsustainable problems [13]. Therefore, in the face of swelling urban populations, promoting the sustainable development of large urban areas is the key to achieving the global sustainable development goals [14]. In fact, the World Commission on Environment and Development (WCED) emphasized the challenges of sustainable urban development when the concept was first proposed [11]. In recent years, the topic of sustainable urban development has changed from whether the city can realize sustainability to how the city can achieve sustainable development [15,16]. For the design of sustainable cities, scholars have proposed a variety of sustainable urbanism models, including compact cities [17], eco-cities [18], low-carbon cities [19], resilient cities [20], and new urbanism [21]. While these models describe the vision of sustainable urban development, they also emphasize the connection between urban form, that is, urban spatial structure and sustainability. The term urban spatial structure refers to discernible patterns in the distribution of human activity in cities [22]. It reflects the organization of urban land use and is closely related to the travel patterns of residents. A sustainable urban spatial structure contributes to control the size of the city and population, reduce the traffic distance and the use of vehicles, and achieve the efficient use of land resources, thus promoting urban sustainability [17,23].

2.2. Identification and Characteristics of Urban Spatial Structure

Researchers believe that the characteristics of urban spatial structure include both static and dynamic aspects [24,25]. The static characteristics reflect the morphological features of space [26]. Workplaces and residences are the two most important functions affecting urban development and residential living conditions. Therefore, using the spatial distribution of employment and population to describe the morphological features of urban spatial structure is a common method in existing research [27–30]. Besides, studies on US metro areas have dominated related works [31]. Burgess abstracted the monocentric city model based on the relationship between land uses and social classes in Chicago [32]. This model indicates that, in the early development of megacities, all or most jobs were concentrated in the urban core, while residences were arranged in concentric circles around the core area [33–35]. With changes to the economic development mode and the evolution of transportation technology, a suburbanization process had taken place in big cities, in developed countries, by the 1960s [36]. The city center maintained its dominance for tertiary industry, while office space, research and development institutions, university campuses, logistics parks, and residential areas gradually spread to the urban fringe [37]. The concept of edge city [38] and employment subcenter [39] have proved the emergence of polycentric morphology in the process of suburbanization in the United States. Since then, empirical studies on large cities in other countries have also confirmed the existence of polycentricity [40–42], and polycentric development has also been considered as an effective planning tool to combat unorganized urban sprawl [43,44]. However, another perspective emphasizes that the suburbanization process will not necessarily form a polycentric urban spatial structure, but will further promote the decentralization of jobs and people [45]. This makes megacities form a pattern of generalized dispersion, and some recent studies in the United States and other developed countries present evidence consistent with this view [46–49].

The dynamic characteristics of urban spatial structure reflect intra-city functional linkages, which are manifested as dense functional urban regions [50]. Existing studies have used a variety of flows to measure the functional connections, among which the traffic flow generated by human daily activities is the most frequent [51–54]. The traditional approach to obtaining travel data is that of a household travel survey, which is costly, error-prone, and not easily updated. Moreover, the sample size limitation makes it difficult to provide comprehensive evidence of human mobility [55]. Thus, although Berry tried to reveal the spatial structure via complex flow systems in the 1960s [56], related studies have still concentrated on the nodal regions, such as those organized by various interactions between urban core nodes and their hinterlands [57]. The updating of research data and methods in recent years has triggered a renaissance of dynamic urban structure studies. The development of information and communication technologies (ICT) and location-aware technology has provided new data sources for detecting the dynamics of urban structure, including Global Positioning System (GPS) log data, smart card data, mobile phone data, and other trajectory data [58]. These new data sources have provided opportunities to track human movements and obtain socio-demographic information [59,60]. On the other hand, researchers have discovered that the statistical characteristics of travel behavior follow a power law and have a truncated heavy-tailed distribution, meaning that people are more likely to travel repeatedly in familiar areas and/or close to their place of residence [61–63]. These findings have resulted in the introduction of complex network theory and methods into the field of urban studies, and researchers have started to explore dynamic functional areas from large-scale trajectory data [50,55,64–67].

As the most populous country in the world, China's urban development has had a significant impact on the global urbanization process and environmental issues [4]. However, due to the limitations of data, previous studies have certain deficiencies in the understanding of the spatial structure of Chinese megacities. First, from the perspective of the static characteristics of urban spatial structure, previous datasets used in these studies mostly rely on statistical sources, which are usually renewed once every five or ten years [68]. For example, some recent studies still rely on the population census for 2010 and economic census for 2008 [6,69,70]. Besides, due to the difficulty of obtaining the spatial distribution of job statistics from public sources, Chinese scholars have had to measure urban patterns based on resident population data for a long time [70]. However, usually employment, not population, is considered to be the key to shaping the urban form and determining economic development [28]. Therefore, there needs to be more empirical research to explore the morphological features of Chinese megacities from the perspective of employment distribution. Second, from the perspective of the dynamic characteristics of urban spatial structure, scholars have revealed the functional urban regions formed by population flows and spatial interactions in the inner city based on different sources of trajectory data in recent years. However, it should be noted that most studies used trajectory data generated by specific types of vehicles, such as taxi trajectory data [50,67], rather than commuting flows. In fact, the commuting flows that connect workplaces and residences is the specific representation of dynamic spatial structure [49]. In addition, compared with statistical data used in urban form research, the new trajectory data differs greatly in methods, scope and time in which statistics are gathered. Therefore, few studies can analyze the static and dynamic characteristics of the urban structure at the same time, because different sources of data reflect the spatial development in different periods. Third, urban studies are scale-dependent. This means that the characteristics of the urban spatial structure may be different at different research scales, and that policy making at different spatial levels will also be affected [71]. Urban planning of Chinese megacities usually involves two spatial scales, the metropolitan area as the macro-scale, and the central area as the meso-scale. Correspondingly, planners will study the spatial structure and make policies for land use and transportation development at these two spatial scales. However, most previous studies have focused on exploring the characteristics of urban spatial structure at a single spatial scale, and there is limited research examining spatial structure at multiple scales [70].

3. Materials and Methods

3.1. Study Area

Tianjin (116°43′–118°04′ E, 38°34′–40°15′) is located in the Bohai Rim Region of China. It is one of the central cities in the Beijing-Tianjin-Hebei Urban Agglomeration and one of the four municipalities directly under the Central Government of China. By the end of 2019, the residential population of Tianjin was 15.6 million, and the urbanization level had reached 83.5%. We investigated the characteristics of urban spatial structure at two spatial scales: the metropolitan area as the macro-scale and the central area as the meso-scale (Figure 1). The Tianjin metropolitan area is a dense built-up area within the administrative region, with an area of 4351 km^2. The administrative divisions are divided into three circles: Heping, Nankai, Hexi, Hedong, Hebei, and Hongqiao in the center circle; Dongli, Xiqing, Beichen, and Jinnan in the suburban circle; and Binhai New District in the peripheral circle. Tianjin central area is the political, economic, and cultural center of the city, as well as its most densely populated area. It is within the outer ring expressway, covering an area of 475 km^2.

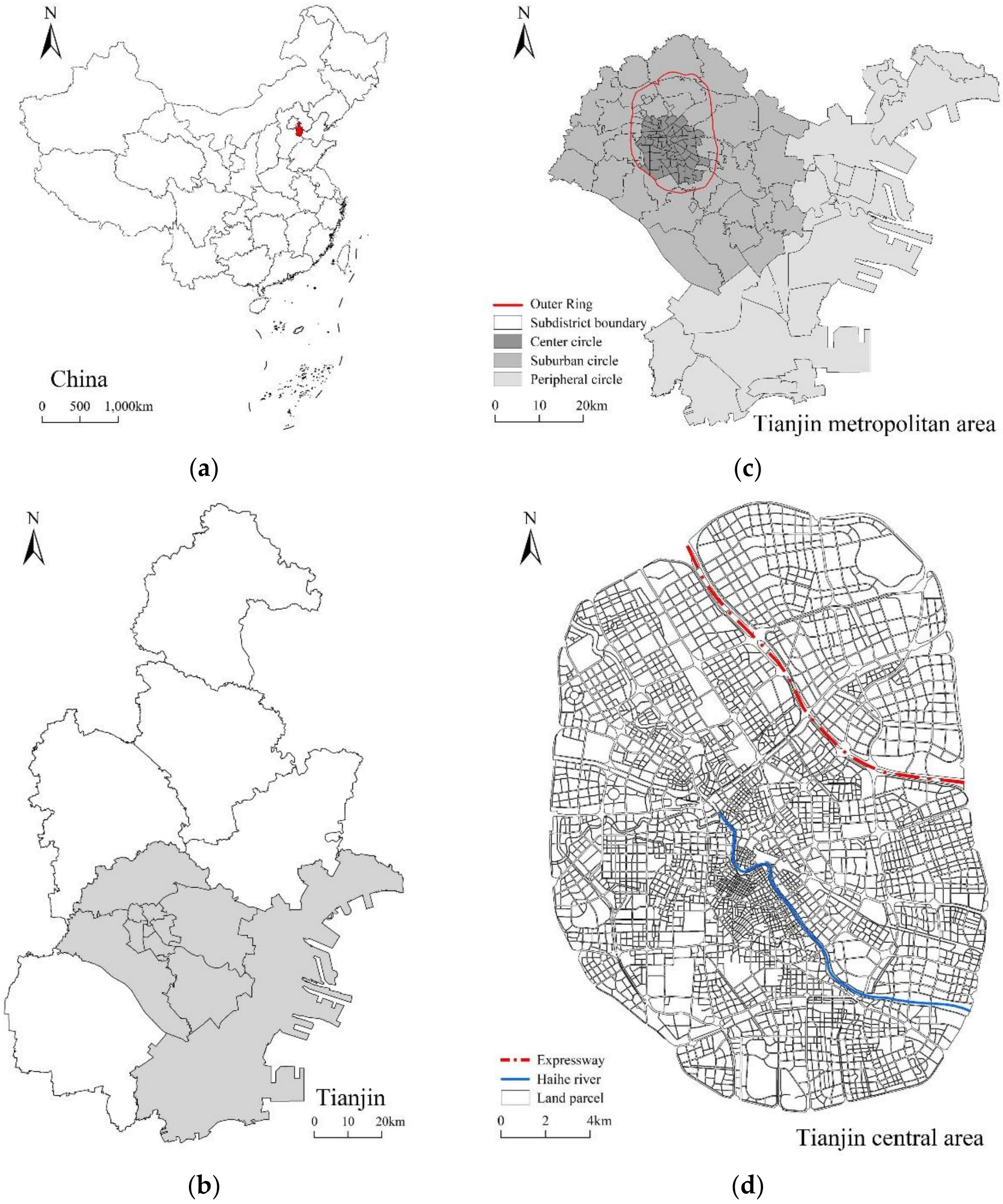
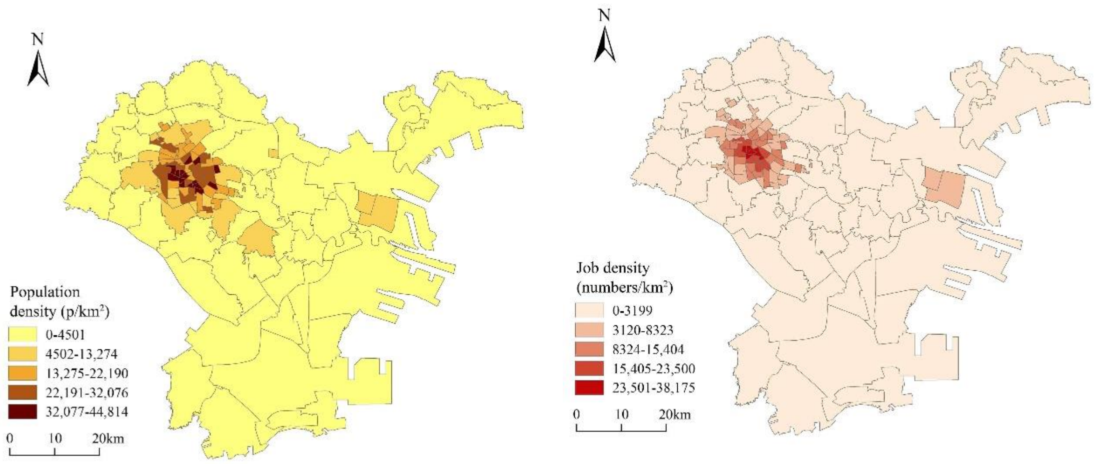


Figure 1. (**a**) Tianjin's location in China; (**b**) The study area in Tianjin; (**c**) The macro-scale: Tianjin metropolitan area; (**d**) The meso-scale: Tianjin central area.

3.2. Data

This study relies on two sets of data. The first is the jobs-housing big data obtained from Baidu. Baidu gathers geographical information data from users from smartphones and other apps using its Location-Based Service (LBS). Records are generated whenever users stay, call, send or receive messages, use related apps, and connect to positioning systems (such as GPS, Wi-Fi, or cellular base stations). Baidu identifies the home and workplace of a single user based on his/her daily stay locations. Then, Baidu calculates the number of residents and jobs in given areas (such as grids, land parcels, traffic analysis zones, subdistricts, cities, etc.), and produces commuting flows connecting them. The final statistical result of a given area is a monthly average, considering that there would be differences in the number of residents and jobs identified every day. We obtained Tianjin metropolitan area data from Baidu in June 2019 and Tianjin central area data in November 2019, respectively. At that time there were approximately 11.3 million residents and 5.3 million jobs in Tianjin metropolitan area, and 5.5 million residents and 2.3 million jobs in Tianjin central area. The second set of data is the vector file of administrative boundaries of subdistricts in Tianjin metropolitan area and the vector file of land parcel boundaries in Tianjin central area provided by Tianjin Planning and Design Institute. We created research units for metropolitan area and central area based on subdistricts and land parcels, respectively. It should be pointed out that due to the insufficient precision of the data we obtained, we merged some land parcels during the analysis. Figures 2–4 show the population density, job density, and commuting flows in Tianjin metropolitan area and Tianjin central area.

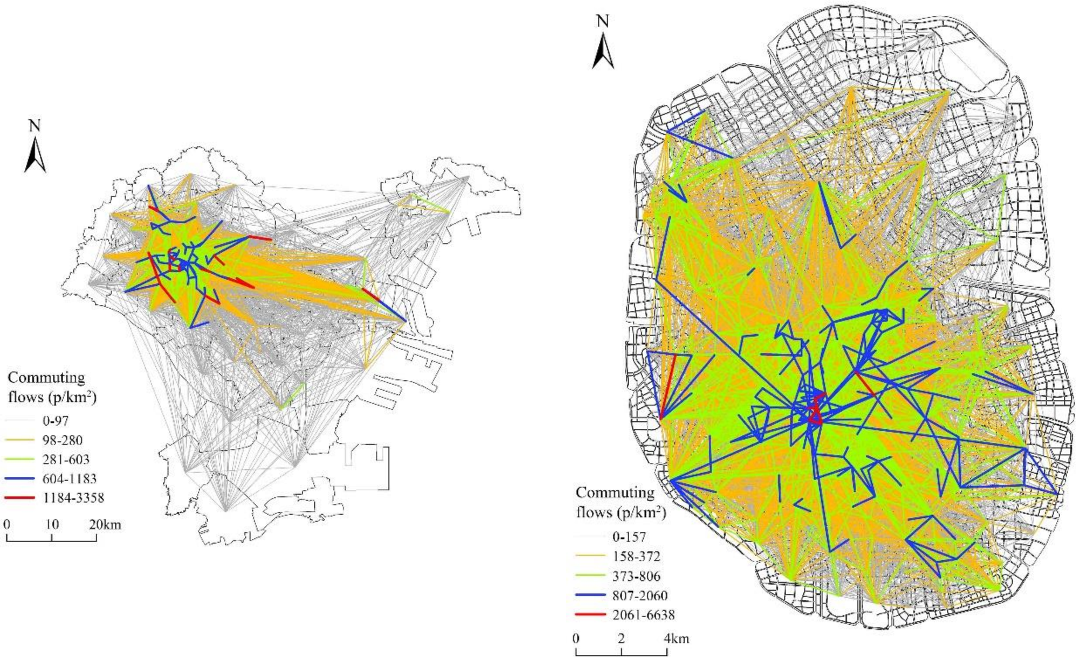


(**a**) (**b**)

Figure 2. (**a**) Population density in Tianjin metropolitan area; (**b**) Job density in Tianjin metropolitan area.

(**a**) (**b**)

Figure 3. (**a**) Population density in Tianjin central area; (**b**) Job density in Tianjin central area.



(**a**) (**b**)

Figure 4. (**a**) Commuting flows in Tianjin metropolitan area; (**b**) Commuting flows in Tianjin central area.

3.3. Methods

3.3.1. Identification of Static Characteristics

Understanding the static characteristics of urban spatial structure requires the identification of spatial polycentricity, including the main center and subcenters. It is generally believed that monocentric morphology is the starting point of urban form studies [72]. Thus, the definition and identification of subcenters would result in differences in the understanding of urban spatial polycentricity. A widely accepted definition is that a subcenter is an area where significantly higher employment agglomeration has remarkable effects on the overall spatial distribution of urban functions [73]. However, recent studies have reported that the share of jobs in centers is relatively low and most jobs are dispersed outside the main center and subcenters [49]. This means that the reality is that the centers, especially the subcenters, might only have local effects on the spatial distribution of employment and population.

A two-step workflow was applied to identify the main center and subcenters in this study. Spatial autocorrelation was used to locate the main center, and GWR was used to locate subcenters. Spatial autocorrelation is based on objective spatial statistical techniques, which can identify the center by discovering the inherent structure of spatial data [74]. Therefore, there is no need for subjective threshold selections and local planning knowledge in the identification process [68,72]. The modeling tool of GWR only uses nearby observations when analyzing spatial data [75], thus the area with local high value of employment density would be represented as positive residuals. To determine the location and scale of subcenters through the selection of positive residuals might be more in line with the actual employment distribution.

Step 1: identification of the main center.

A main center can be defined as an area with high job density in the study area, and which also has the characteristics of a spatial cluster [68]. Therefore, spatial autocorrelation methods were applied to locate the main center, including the Global Moran's I (GMI) and Anselin Local Moran's I (LMI_i) [76]. The GMI and LMI_i were calculated using the following Equations (1) and (2), respectively:

$$\mathrm{GMI} = \frac{\sum_{i=1}^{n}\sum_{j\neq i}^{n} W_{ij} z_i z_j}{\sigma^2 \sum_{i=1}^{n}\sum_{j\neq i}^{n} W_{ij}} \tag{1}$$

$$\mathrm{LMI}_i = z_i \sum_{j\neq i}^{n} W'_{ij} z_j \tag{2}$$

where:

$$z_i = \frac{x_i - \overline{x}}{\sigma} \tag{3}$$

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{4}$$

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n} (x_i - \overline{x})^2 \tag{5}$$

where W_{ij} is the spatial weight matrix based on distance function; i and j represent two research units, respectively; n is the total number of research units; x_i is the job density of unit i; z_i and z_j are the standardized transformations of x_i and x_j, respectively; and $\overline{x}$ is the mean job density of the whole area.

First, the GMI was used to assess the pattern of job density and determine whether it was dispersed, clustered, or random. Meanwhile, the z-score and the p-value were introduced to examine statistical significance. The range of the GMI lies between −1 and +1. A positive value for GMI indicates that the job density observed is clustered spatially, and a negative value for GMI indicates that the job density observed is dispersed spatially. If the GMI is equal to zero, it suggests that the job density presents a random distribution pattern in the city. When the calculation results of the GMI showed that the job density presented a spatial agglomeration pattern, the LMI_i was used to locate the main center. A high positive z-score (larger than 1.96) for a research unit indicates that it is a statistically significant (0.05 level) spatial outlier. Research units with high positive z-score values surrounded by others with high values (HH) were defined as a main center.

Step 2: identification of the subcenter.

A subcenter was defined as an area with a local high job density within the study area. The GWR was applied to locate the subcenter. First, we defined the weighted centroid of the main center as the main center point of the city, and calculated the Euclidean distance between the centroid of each research unit and the main center point of the city. Then, we selected the square root of job density as the dependent variable and the Euclidean distance as the explanatory variable, and used GWR to model the relationship between them for each unit. The GWR was calculated using the following formula:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) d_{ik} + \varepsilon_i \tag{6}$$

where y_i is the square root of the job density for unit i; d_{ik} is the independent variable of unit i; (u_i, v_i) is the coordinates of unit i; $\beta_0(u_i, v_i)$ is the intercept; $\beta_k(u_i, v_i)$ is the kth regression coefficient for unit i; and ε_i is the residual error.

Planning districts containing research units with standard residuals >1.96 were defined as subcenters. Thus, the job density values of these subcenters were significantly higher than average at the local scale [68], and the continuity of planning works can be guaranteed.

3.3.2. Identification of Dynamic Characteristics

Understanding the dynamic characteristics of urban spatial structure requires the spatial identification of functional regions. Commuting flows of residents within a city connect discrete home and work locations into a complex system. By treating residences and workplaces as nodes, and commuting flows as edges, we were able to construct a commuting complex network. The spatial mapping of the sub-network structure of the commuting complex network indicated the location and scale of dynamic functional regions. We defined these dynamic functional regions as commuting communities. Thus, a commuting community was a sub-network structure of the commuting complex network, which contained locations with a higher number of internal commuting links compared to the outward commuting links toward it. Therefore, community detection was applied to locate the commuting communities.

To build a commuting network from the commuting flows of the city, we need to determine the nodes, edges, and weights of the edges. The weighted centroid of each research unit i was denoted as the node D_i. Commuting trips originating from unit i and ending in unit j indicated the existence of an edge T_{ij}. The weight of edge T_{ij} was calculated using the following formula:

$$Weight_{ij} = \frac{h}{S_i} \tag{7}$$

where h is the number of the trips originating from D_i and ending in D_j; and S_i is the area of unit i, considering the changes in the number of commuters caused by the size of each unit.

Then, a smart local moving (SLM) algorithm was applied to partition the commuting network into sub-networks. Compared with some previous classical algorithms, SLM algorithm has been proved to be able to find local optimal solutions with respect to both communities merging and individual node movements, and to identify better community structures with fewer iterations, especially for medium, large and very large networks [77]. Based on the idea of modularity optimization [78], the SLM algorithm uses the local moving heuristic [79] to obtain the community structure of network. It is composed of three steps (for the pseudo-code and more details, please refer to Waltman and van Eck [77]):

(1) By treating every node as a single community, the SLM algorithm uses the local moving heuristic to repeatedly move individual nodes from one community to another. Then, it calculates the modularity change caused by node movements, and moves the node to the community with the maximum modularity increase. Repeat this process until stable community partition result is obtained. The modularity is calculated using the following formula:

$$Q = \frac{1}{2m} \sum_{i,j} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta\left(c_i, c_j\right) \tag{8}$$

where Q is the network modularity, m is the total edge weight, c_i is a community of D_i, $\delta\left(c_i, c_j\right)$ indicates whether two nodes belong to the same community, A_{ij} denotes whether there is an edge between node D_i and D_j, and k_i is the degree of node D_i.

(2) The SLM algorithm iterates all the communities partitioned in step (1) to construct a subnetwork for each community. Then, it runs the local moving heuristic again in each subnetwork. In this way, a subnetwork may be merged into one community or split into multiple communities.

(3) The SLM algorithm constructs a reduced network by taking the communities obtained in step (2) as a new node. Then, local moving heuristic is used to assign nodes to communities in the reduced network. Repeat the above steps until the network cannot be reduced further.

4. Results

4.1. Static Polycentricity

4.1.1. Polycentricity in the Metropolitan Area

In Tianjin metropolitan area, the GMI value obtained by job density was 0.56, when the obtained p-value was less than 0.05 ($p < 0.05$), and the obtained z-score was greater than 2.58 (z-score > 2.58). These indexes suggested that the spatial distribution of jobs formed a clustered pattern. Then, the LMIi was used to explore the main center, and high value subdistricts that were geographically contiguous and surrounded by other subdistricts with high values (HH) were selected as the main center of Tianjin metropolitan area (Figure 5). The main center contained 32 subdistricts located in the central circle of Tianjin metropolitan area. After defining the main center, the GWR was used to explore the subcenters. Areas with standard residuals > 1.96 were regarded as subcenters of Tianjin metropolitan area. As shown in Figure 5, there was only one subcenter containing one subdistrict located in the peripheral circle of Tianjin metropolitan area. The number of jobs and job density of the main center and subcenter are displayed in Table 1.

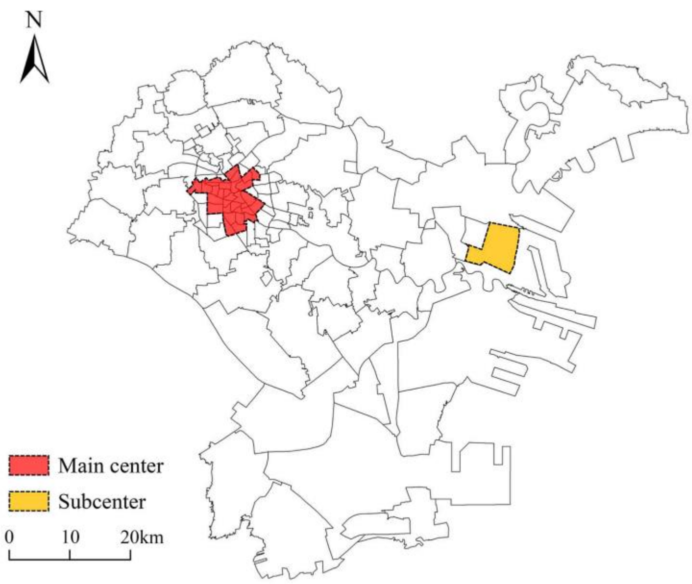


Figure 5. The main center and subcenter in Tianjin metropolitan area.

Table 1. The number of jobs and job density of centers in Tianjin metropolitan area.

Centers	Number of Jobs	Job Density
Main center	1,222,316	17,167/km^2
Subcenter	267,183	5951/km^2

4.1.2. Polycentricity in the Central Area

In Tianjin central area, the GMI value obtained by job density was 0.33, when the obtained p-value was less than 0.05 ($p < 0.05$), and the obtained z-score was greater than 2.58 (z-score > 2.58). These indexes suggested that the spatial distribution of jobs also formed a clustered pattern. Then, the LMIi was used to explore the main center, and the final main center of Tianjin central area and its location are shown in Figure 6. The main center, located in the downtown, covered the CBD, Haihe River International Business Center, and the Tianjin Railway Station and surrounding areas. After defining the main center, the GWR was applied to explore the subcenters. Planning districts containing land parcels with standard residuals > 1.96 were considered to be the subcenters of Tianjin central area. We identified five subcenters at the Tianjin central scale (Figure 6). According to their locations, these five subcenters were named Beicang (BC) subcenter, Dahutong (DH) subcenter, Huayuan (HY) subcenter, Tianta (TT) subcenter, and Wenhua (WH) subcenter. The number of jobs and job density of the main center and five subcenters are displayed in Table 2.

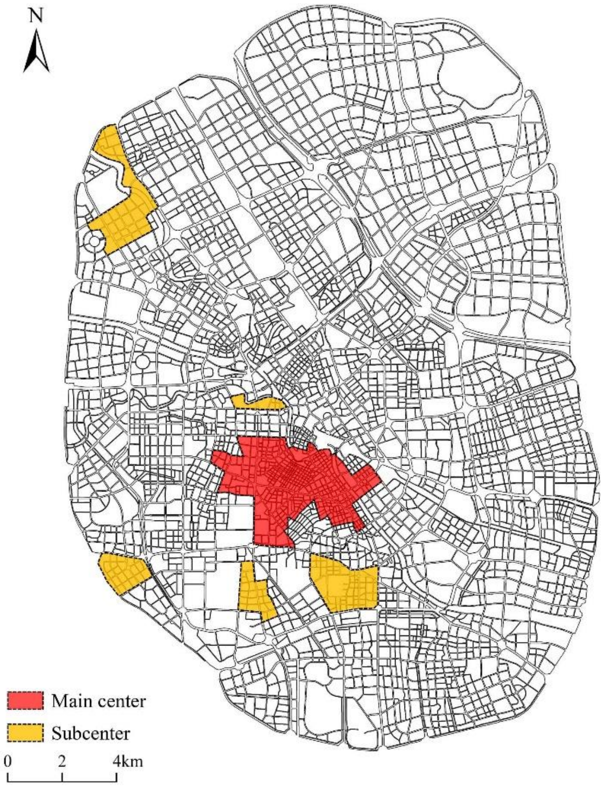


Figure 6. The main center and subcenter in Tianjin central area.

Table 2. The number of jobs and job density of centers in Tianjin central area.

Centers	Number of Jobs	Job Density
Main center	384,461	27,659/km^2
BC subcenter	31,985	6462/km^2
DH subcenter	18,012	24,674/km^2
HY subcenter	46,000	21,596/km^2
TT subcenter	29,211	16,319/km^2
WH subcenter	49,613	12,497/km^2

4.2. Dynamic Commuting Communities

4.2.1. Commuting Communities in the Metropolitan Area

In Tianjin metropolitan area, five spatially continuous commuting communities were identified based on commuting linkages. From the perspective of the commuters, these five commuting communities could be divided into two types: core and periphery. The core type contained four commuting communities which were named MC1, MC2, MC3, and MC4. The periphery type contained one commuting community named MP1. The final commuting communities and their locations are displayed in Figure 7. The number of residents and jobs of commuting communities are displayed in Table 3.

Table 3. The number of residents and jobs of commuting communities in Tianjin metropolitan area.

Commuting Communities	Number of Residents	Number of Jobs
MC1	2,099,700	825,203
MC2	2,467,886	1,185,182
MC3	1,694,100	941,802
MC4	1,971,600	830,969
MP1	3,113,505	1,513,038

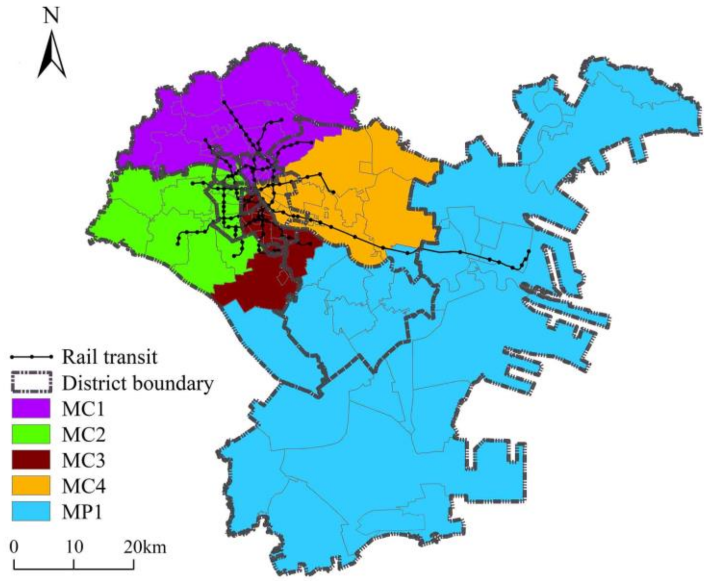


Figure 7. The commuting communities in Tianjin metropolitan area.

For the core type, these four commuting communities contained all the subdistricts located in the central circle and most of the subdistricts located in the suburban circle. During the expansion of the megacities, the outward movement of the population and industries from downtown formed new residential and industrial areas at the fringes of the city. Thus, compared with the subdistricts in the peripheral circle, the subdistricts in the central circle and suburban circle are more connected by commuting trips. The radial rail traffic lines also enable these connections. Therefore, the core type of commuting communities formed a sectorial spatial pattern spreading from the center outwards, with community delineations that were spatially coupled with rail traffic lines. For the MP1 of the periphery type, it contained all the subdistricts located in the peripheral circle and a small number of subdistricts located in the suburban circle. These subdistricts are located far from the downtown area, and thus their development is more dependent on the local population and industries rather than the decentralization of the population and industries from downtown. In addition, there is a lack of public transport facilities in MP1, with only one rail line and seven stations, which also reduces the possibility of long-distance commuting for local residents. Its internal commuting connections are mainly between adjacent subdistricts. Therefore, MP1 presented a large, ribbon shaped structure that extended along the coast.

4.2.2. Commuting Communities in the Central Area

As shown in Figure 8, seven commuting communities were identified based on commuting linkages in the inner Tianjin central area. However, different from the results in Tianjin metropolitan area and some existing studies [80], there were a very small number of enclaves in Tianjin central scale. This implied that when choosing land parcels as much finer and independent research units, some land parcels would not have close commuting connections with surrounding units due to specific commuting flows, such as rail transit or company shuttles. However, these enclaves accounted for a small proportion in terms of numbers, commuters and jobs, and had little impact on the division of commuting communities. Therefore, these seven commuting communities could also be divided into two types, core and periphery, from the perspective of the commuters. The core type contained two commuting communities named CC1 and CC2. The periphery type contained five commuting communities which are named CP1, CP2, CP3, CP4 and CP5. The number of residents and jobs of commuting communities are displayed in Table 4.

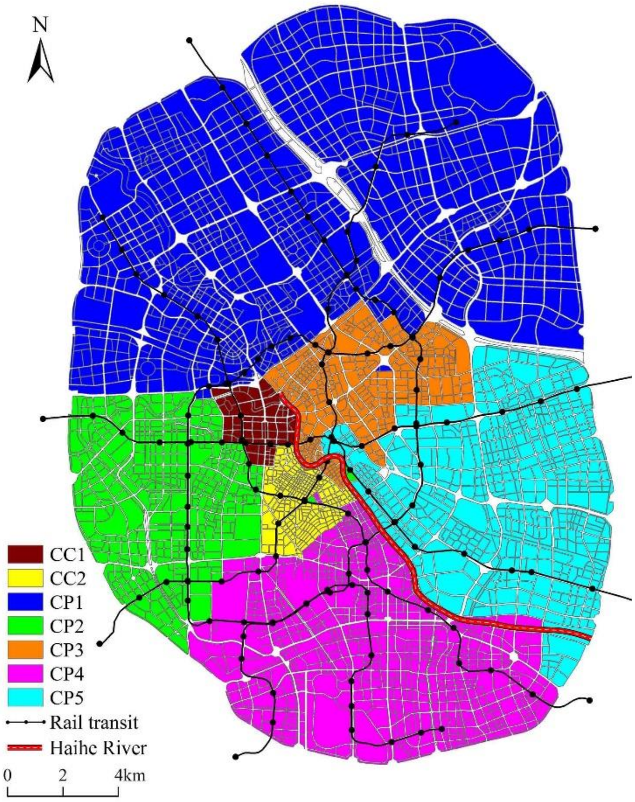


Figure 8. The commuting communities in Tianjin central area.

Table 4. The number of residents and jobs of commuting communities in Tianjin central area.

Commuting Communities	Number of Residents	Number of Jobs
CC1	158,370	90,899
CC2	266,677	229,683
CP1	1,288,781	445,169
CP2	894,811	394,929
CP3	608,605	232,616
CP4	1,147,716	551,986
CP5	1,155,372	381,729

Some empirical studies of commuting have indicated that commuters tend to maintain or reduce their commuting distance and time by periodically changing their residence and workplace, and choosing reasonable travel modes. This has resulted in urban expansion not significantly increasing commuting distance and time, which is referred to as the co-location hypothesis [81]. This hypothesis implies that short-distance commuting trips account for a large proportion of the trips made within cities. The above two types of community reflect differences in commuting behavior of residents in different regions. For the core type, the two communities have access to a higher proportion of commercial and business facilities, and better traffic accessibility due to their location within the city. Therefore, they are more likely to attract a large number of commuters from other areas, with a relatively high proportion of long-distance commuting trips. For example, residents on the fringe of the city take the subway to work in the downtown. Compared with the core type of commuting communities, the periphery type has access to a more balanced proportion of land uses and most residents mainly undertake short-distance commuting trips. The spatial division of commuting communities also supports the argument in a previous study [67], which assumes that short trips would dominate the local spatial interactions.

In addition, several other interesting findings were apparent. First, as a natural barrier, rivers play a role in the formation of commuting communities. Commuting communities on both sides of the Haihe River had clear boundaries that extended along the river. Only in the downtown area were there strong commuting connections across the river. Second, there was a large amount of industrial land distributed on both sides of the expressway in the north of the city. This resulted in CP1 covering a large region across the expressway. Third, metro lines also played an important role in forming the commuting structure at the meso-scale. The boundaries of the periphery type of communities extended outward alongside the radiating subway lines.

5. Discussion

5.1. Does Polycentricity Explain the Distribution of Jobs in Cities?

This study used the spatial distribution of jobs to describe the static characteristics of urban spatial structure. Through an empirical study of Tianjin, we found that the megacity presented polycentricity at both the metropolitan and central scales. However, the polycentric model did not provide an accurate explanation of the spatial distribution of jobs in the city. This was apparent from the proportion of jobs located in the main center and subcenters. In the Tianjin metropolitan area, the proportion of jobs located in the main center was 23.1%, while the figure was 5.0% in the subcenter. In the Tianjin central area, the proportion of jobs located in the main center was 16.5%, while the figure was 7.5% in the five subcenters. These statistics indicated that 71.9% of all jobs were dispersed outside the main center and subcenter at the macro-scale, and 76.0% of all jobs were dispersed outside the main center and subcenters at the meso-scale. Therefore, it can be argued that the polycentric city model does not describe the spatial distribution of jobs in a modern megacity because it assumes that all or most of the jobs in the city are concentrated in the main center and subcenters. The reality is that the main center and subcenters do not attract more than 30% of all jobs at different urban scales. Within the urban spatial structure there is a coexistence of polycentricity and a high degree of dispersion.

Our empirical results are to some extent similar to those of other studies focusing on metropolises in the United States. Angel and Blei reported that, on average, only $10.8 \pm 3.1\%$ of all jobs were located in the main urban center and an average of $13.8 \pm 2.0\%$ of all jobs were located in subcenters [49]. The majority of jobs are dispersed outside the main center and subcenters in a modern megacity and, therefore, the urban spatial structure has moved beyond polycentricity [45]. However, the main centers of Chinese megacities still maintain a relatively high proportion of jobs, while some main centers in U.S. metropolitan areas have a lower proportion of jobs than the subcenters. This difference could be attributed to the expansion process of urban spaces in Chinese and American cities. American metropolitan areas have generally formed by a group of cities of varying size gradually expanding toward each other [49], while Chinese megacities have generally formed through the sprawl process of traditional monocentric old cities. Therefore, unlike American cities, Chinese megacities often have a central area with a high concentration of population and functions. Our empirical results even differ to some extent from some related studies focusing on Chinese cities. Li has indicated that Chinese megacities have become more polycentric and less dispersed (e.g., Beijing, Shanghai, and Tianjin) [72]. However, these differences might be attributed to the data used in studies. Due to the difficulty of obtaining job statistics, most existing studies of Chinese cities have measured urban spatial structure based on resident population data. However, as megacities in China have expanded, the decentralization of employment and population have generally occurred separately. Before the 1980s, the development of Chinese cities was concentrated in the urban centers. Danwei, a Chinese socialist workplace with its specific range of practices [82], can provide workplaces, housing and various public facilities for its employees. Therefore, the urban space formed a highly mixed land use pattern, with the danwei as the basic unit [83]. After China's reform and opening-up, the market-oriented reform of the land and housing systems have promoted suburbanization in Chinese cities [84]. During this process, the decentralization of the residential population caused by the regeneration of the old city and suburban housing construction was the main feature of China's suburbanization, whereas employment decentralization has been a gradual process [85].

5.2. Jobs–Housing Balance Levels in Commuting Communities

The commuting network is a complex network of residences and workplaces, together with the commuting flows between them. In a complex network, the connections between nodes are not random, but present a clustered pattern. Therefore, a complex network can be divided into sub-networks, with dense internal connections. The commuting communities were identified in this study by the spatial mapping of the sub-networks of the commuting network. That is to say, a commuting community containing areas that are more densely commuting linked to each other than to the rest of the city. From the perspective of commuters, short-distance commuting trips account for the largest proportion of trips in cities and, therefore, most areas in cities only maintain strong commuting links with the surrounding local areas, with weak commuting links to distant areas.

The commuting community might be a potential jobs–housing balance region. To measure the jobs–housing balance level, we calculated the jobs–housing ratio and the intra-travel ratio. The jobs–housing ratio is defined as the ratio of jobs and employed residents, which is determined by the size of the workforce and the number of commuters within a given region. It is generally considered that a region is balanced when this ratio lies within the range of 0.75 to 1.25 [86]. The intra-travel ratio is defined as the ratio of locally employed residents and overall employed residents, which reflects the percentage of internal commuting trips within a given region. Thus, the larger the value of the intra-travel ratio, the better the jobs–housing spatial match is in the community.

The calculated jobs–housing and intra-travel ratios of the commuting communities at the Tianjin metropolitan and central scales are shown in Tables 5 and 6, respectively. The jobs–housing ratio of each commuting community ranged from 0.86 to 1.25 at the Tianjin metropolitan scale, and it was therefore considered that these communities had reached a balanced state from the perspective of the number of jobs and commuters. They also maintained a relatively high intra-travel ratio, which indicates that most residents (more than 60%) commuted within the local community. Among them, MP1 had the most independent jobs–housing relationship, with more than 90% of residents commuting inside the community. This indicates that, for megacities, the central urban area and the new city in the peripheral circle generally formed two isolated jobs–housing regions, with a small number of people commuting between them. At the Tianjin central scale, we identified the spatial delineations of commuting communities by taking land parcels as research units. Compared to the metropolitan area, these communities were smaller. It is generally believed that the smaller a given area is, the more difficult it is to achieve a jobs-housing balance. As shown in Table 6, there were three communities in which the jobs–housing ratio was outside the range of 0.75 to 1.25. Among them, CC2 was located in the CBD, and had a high proportion of commercial and business facilities, resulting in the jobs–housing ratio being larger than 1.25. In contrast, CP1 and CP5 were located in the north and east of Tianjin central area. In these two regions, there were large areas of industrial land, with a low employment density, resulting in a small number of jobs and a jobs–housing ratio of less than 0.75. The jobs–housing ratio in the other communities was within the balanced range. In terms of the intra-travel ratio, with the exception of CC1 and CC2, which were located in the downtown area, the ratio was over 50%, indicating that more than half of the residents commuted within the local community. This indicated that most commuting communities had a good jobs–housing balance, even at a relatively small spatial scale.

Table 5. The jobs–housing ratio and the intra-travel ratio of commuting communities in Tianjin metropolitan area.

Commuting Communities	Jobs-Housing Ratio	Intra-Travel Ratio
MC1	0.86	67.6%
MC2	1.02	72.7%
MC3	1.25	68.5%
MC4	0.90	66.6%
MP1	1.01	91.1%

Table 6. The jobs–housing ratio and the intra-travel ratio of commuting communities in Tianjin central area.

Commuting Communities	Jobs-Housing Ratio	Intra-Travel Ratio
CC1	1.25	32.8%
CC2	2.66	45.1%
CP1	0.73	67.7%
CP2	0.93	65.6%
CP3	0.81	52.7%
CP4	1.05	71.4%
CP5	0.67	60.8%

6. Conclusions

This study used jobs–housing big data obtained from Baidu to explore the spatial structure characteristics of China's megacities at macro- and meso-scales. The analysis was conducted in Tianjin, China. Spatial autocorrelation and GWR were applied to identify static polycentricity, and community detection was introduced to identify dynamic commuting communities. We further analyzed the distribution of jobs in city and jobs-housing balance levels in commuting communities. The results revealed that, for the spatial structure of megacities at macro- and meso-scales, the static characteristics presented a co-existence of polycentricity and a high degree of dispersion, and the dynamic characteristic revealed two types of commuting community, most of which had a good jobs–housing balance.

There are several policy implications to be drawn from these results. First, at the metropolitan area scale, urban planning and management policies mainly focus on large-scale population and employment distribution, as well as long-distance transport modes. In recent years, Tianjin municipal government has proposed the concept of "Twin Cities", including "Jin City" and "Bin City". Jin City contains districts in its central and suburban circles, while Bin City contains Binhai New District in its peripheral circle. Our empirical research indicates that from the perspective of employment distribution, the existence of the main center and subcenter within the metropolitan area means that the urban form of "Twin Cities" has emerged. However, the industrial parks and development zones in the suburbs, especially in the inner suburbs, have not formed sufficient-scale subcenters. In fact, compared with the previous polycentric strategy, Beijing has focused more on a single subcenter in the recent urban master plan, and intends to promote the reorganization of residential and industrial distribution at the metropolitan area scale through the construction of the Tongzhou subcenter. Therefore, the recent development of Tianjin metropolitan area should also be further focused on the "Twin Cities" instead of the polycentric development pattern. Tianjin should improve the attractiveness of the subcenter to population and industries in order to expand the development scale of Bin City, making it a growth pole within the metropolitan area. In addition, the master plan intends to strengthen the connection between center circle and suburban circle. However, the commuting communities identified in this study indicate that there are weak connections in some suburban areas, from the perspective of a bottom-up jobs-housing relationship. By comparing the boundaries of commuting communities with those of administrative districts, it can be found that this mismatch mainly occurred in Jinnan District. Therefore, urban managers and planners need to focus on the future industrial development and public transport facilities in Jinnan District to promote the connection between center circle and suburban circle. Second, at the central area scale, urban planning and management policies mainly focus on the relationship between transport and land uses, as well as the allocation of public services facilities. Our empirical study indicates that current urban space has shown a polycentric urban form, but the differences in the size and location of subcenters reflect the inequality of development within the city. For example, there is only one small-scale subcenter in the north and no subcenter in the east. These two areas are also places where residents commute relatively long distances and times. Therefore, urban managers and planners should re-evaluate the implementation of the current master plan in different areas and analyze the reasons for the failure of employment agglomeration in the northern and eastern regions. Then, they can rearrange the functions, locations and scales of the subcenters in these areas. In addition, commuting communities in Tianjin central area reflect that most residents mainly undertake short-distance commuting trips. Therefore, we should support policies that give priority to short-distance local traffic, such as adjusting the structure of the secondary roads network and promoting mixed land uses. Considering that most commuting communities have a relatively good jobs-housing balance, we can arrange the quantities and spatial distribution of public service facilities with the commuting communities according to their locations and scales, so as to allow most residents to commute and carry out daily activities within their local commuting community. This could provide a feasible planning idea and method to solve the problem of traffic congestion and public facilities allocation in the megalopolis.

The main limitation of this study is that only big data for given months can be accessed from Baidu, with the value representing a monthly average. As cities develop, the mobility of the population and jobs will increase. In further studies, the results for different months or years can be compared and analyzed, enabling the operation of urban spatial structure to be more effectively monitored.

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