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Article

Exploring Public Transportation Supply–Demand Structure of Beijing from the Perspective of Spatial Interaction Network

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Abstract: A comprehensive understanding of the relationship between public transportation supply and demand is crucial for the construction and sustainable development of urban transportation. Due to the spatial and networked nature of public transportation, revealing the spatial configuration and structural disparities between public transportation supply and demand networks (TSN and TDN) can provide significant insights into complex urban systems. In this study, we explored the spatial configuration and structural disparities between TSN and TDN in the complex urban environment of Beijing. By constructing subdistrict-scale TSN and TDN using urban public transportation operation data and mobile phone data, we analyzed the spatial characteristics and structural disparities of these networks from various dimensions, including global indicators, three centralities, and community structure, and measured the current public transportation supply and demand matching pattern in Beijing. Our findings revealed strong structural and geographic heterogeneities of TSN and TDN, with significant traffic supply–demand mismatch being observed in urban areas within the Sixth Ring Road. Moreover, based on the percentage results of supply–demand matching patterns, we identified that the current public transportation supply–demand balance in Beijing is approximately 64%, with around 18% of both excess and shortage of traffic supply. These results provide valuable insights into the structure and functioning of public transportation supply–demand networks for policymakers and urban planners; these can be used to facilitate the development of a sustainable urban transportation system.

Keywords: public transportation network; supply–demand structure; spatial network; Beijing

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1. Introduction

Transportation plays a vital role in urban development and spatial evolution. It provides the necessary support system for the movement of people, goods, and information, all of which are critical elements of a city's growth and sustainability. Changes in transportation modes and improvements in traffic accessibility have a profound effect on the spatial evolution and structural adjustment of cities [1–3]. Given the significant impact of transportation on urban development and spatial evolution, it is essential to explore and understand the patterns and trends of urban transportation. Researchers from multiple disciplines such as geography, urban planning, and transportation have carried out a series of scientific explorations around urban transportation over the past few decades [4,5]. Some of these explorations have been effectively applied in urban management [6–8]. For example, optimizing the urban spatial structure and improving operational efficiency can be achieved by rationally and efficiently planning public transportation infrastructure construction based on supply–demand relationships [9,10]. This initiative is recognized by urban planners and policymakers. Although the relationship between public transportation supply and demand is essential for urban traffic planning and management, the complexity and variability of traffic flow make it difficult to grasp the urban public transportation supply and demand [11]. Traditional traffic surveys are time-consuming and expensive, providing limited information to reflect actual traffic demand for large cities. Consequently, early urban transportation studies had a relatively limited understanding of the relationship between public transportation supply and demand.

Recently, globalization and informatization have led to a dramatic increase in the mobility of urban elements, including the population, traffic, and goods, profoundly impacting urban development and spatial structures [12]. The traditional research perspective based on the static "space of place" has been challenged, and the dynamic view of the "space of flow" has become increasingly crucial in human mobility and urban studies [13–15]. Under the paradigm of the "space of flow", a city is regarded as a complex system composed of networks and flows [14]. As the primary component of the urban complex system, urban traffic promotes interactions between different urban spaces and affects the flow of various elements, contributing to the formation of a complex network with spaces as nodes and to the flow of elements as connections [16–18]. In this context, the traditional study of urban traffic structure based on a static perspective inevitably has certain limitations in the current complex urban environment, with increasingly rapid dynamic changes underway.

The big data era offers an excellent opportunity to overcome the above challenges of studying urban traffic. Advances in "flow" data acquisition and processing technologies provide a rich database and technical methods for use in dynamic network analysis of urban traffic [19,20]. Traffic flow reflects the mobility status and interaction characteristics of traffic elements and is vital to understanding the network structure of urban spaces [21,22]. By leveraging traffic flow data and complex network analytics, we can construct a spatial interaction network of urban public transportation. This network perspective facilitates a better understanding of the global and local properties of the network, providing insights into complex urban systems [23]. Thus, analyzing the spatial structure of urban traffic from a network perspective can lead to the development of a more scientific understanding of urban systems.

As an affordable and effective method, network analysis has been widely used to examine the structures and functions of urban traffic networks (UTNs) and aid urban and transportation planners [24]. By applying network science to UTNs, we can better understand the reasons for urban form variation and identify potential areas for future development [25]. Determining the static and dynamic structural characteristics of UTNs can also provide relevant information for urban transportation planning, design, optimization, and sustainable development and maintenance [15,26]. Despite the widespread use of graph theory and complex network methods to analyze real-world complex traffic systems, there has been limited attention paid to the structural characteristics and disparities between public transportation supply and demand networks within cities. The importance of applying TSN and TDN to urban economic and social development is self-evident. Given the stability of urban development and the difficulty of changing land use patterns, more attention should be given to research and demonstrate the structural characteristics and spatial disparities between TSN and TDN [24,27].

In this study, we conducted a comprehensive comparative analysis of TSN and TDN in Beijing, China, using complex network analysis and spatial analysis methods. We collected urban public transportation operation data and mobile phone data to construct weighted, directed, and geospatially embedded TSN and TDN, and analyzed their macroscopic characteristics. We also analyzed the spatial distribution of node centrality from the perspective of individual nodes, i.e., subdistrict units, to assess their connectivity, accessibility, and impact, and to reveal public transportation supply and demand matching patterns. Additionally, we explored the spatial characteristics of different communities in TSN and TDN from the view of community structure. Ultimately, the study aims to reveal the spatial characteristics and structural disparities between TSN and TDN and measure the matching patterns of the urban traffic supply–demand structure. The findings can be used to optimize the spatial configuration of the urban public transportation infrastructure, mitigate the contradiction between traffic supply and demand, and promote the performance of the urban spatial structure.

The remainder of this paper is organized as follows. Related and previous studies are described in detail in Section 2. Section 3 describes the study area and data, including urban public transportation data and mobile phone signaling data. Section 4 explains the methodological framework, and the corresponding methods are described in detail. In Section 5, we present the results of our analyses, which is followed by a comparison between TSN and TDN. The final section discusses the implications of this study results and concludes this work.

2. Related Work

Public transportation systems form a vital part of our infrastructure that permits the movement of large numbers of people within and between cities. As urban mobility increases, public transportation networks have to keep up with the demand to reduce travel time and expand coverage. However, public transportation networks are facing numerous challenges, including accommodating growing passenger volumes, achieving long-term sustainability, and improving service quality. These challenges are encountered at various operational levels, from infrastructure deployment to optimal route planning. To address these issues, diverse methodologies have been adopted in various disciplines to represent, perceive and analyze the complex dynamics of transport systems, including geographic information systems, complex network theory, mathematical programming, and agent-based modeling [23].

Complex network theory is a multidisciplinary branch of complexity science. Motivated by the notable contributions of network theory [28,29], the application of complex network analytics in modern urban and transportation science has attracted significant attention. By representing urban traffic systems as complex networks and adopting concepts from statistical physics, nonlinear and dynamic urban traffic structures can be modeled and analyzed more effectively [14,23,24,30]. Today, this approach has become one of the most widely used to understand the nature of UTNs. The related studies are abundant and mainly concentrate on the following aspects: the representation methods of traffic networks [31,32]; traffic hub and center detection [33]; structural characteristics and dynamics [34,35]; mining of traffic communities and groups [36,37]; robustness and vulnerability of traffic network [38,39]; and multilayer or multi-modal traffic network [40,41].

These studies mentioned above can be categorized into two main groups based on their research perspectives. The first group explores the spatial configuration of transportation infrastructure networks from the supply perspective. Many studies have investigated the relationships between network shape and the layout of transportation systems, including road networks [42,43], bus networks [36], and metro networks [44,45] within cities. Some of these studies have examined the connections between the structural topology of traffic networks and performance. For example, Wang et al. (2020) proposed a methodological framework for geospatial network analysis that combines spatial and network analysis to analyze the spatial configuration of urban bus networks in Hangzhou [36]. Other studies have explored the structural properties of UTNs based on actual urban road connections or traffic operation routes and schedule data to seek reasonable traffic planning strategies and spatial structure improvement solutions [46–48]. These studies have shown that rational planning and efficient management of urban public transportation systems can effectively alleviate many urban problems such as traffic congestion, environmental pollution, and over-commuting. They also provide meaningful insights for policy makers and planners seeking to optimize transportation infrastructure configuration [36,49,50].

Recently, researchers have taken a novel approach to studying UTNs by leveraging traffic flow datasets and spatial interaction network methods. Unlike previous studies that focused on the relationship between network topology and performance, this approach considers UTNs and travel structure from the perspective of traffic demand. With the increasing availability of urban mobility data, obtained through the development of information and communication and mobile positioning technologies, researchers can gain rich and detailed real-time information on various traffic flows, such as population, cars, and goods [51–53]. Using various traffic flow data and spatial network approaches, researchers have extensively explored urban travel patterns and traffic networks from the perspective of traffic demand [54–56]. By leveraging big data, including mobile phone, smart card, floating vehicle, and social media data, researchers can analyze user movement data as traffic flows on networks, thereby creating weighted networks that reveal the structure and related properties of UTNs [57–59]. Some studies have shown that complex network analysis based on various types of emerging traffic flow data can effectively reveal urban traffic demand and its dynamics [11,60]. For instance, Zhong et al. (2014) constructed a weighted directed network of Singapore based on smart card datasets and identified the spatial structure of urban hubs, centers, and boundaries by integrating network and spatial analysis methods [33]. With the combination of complex network methods and various types of emerging traffic big data, studies of UTNs have been further developed. As a result, big data-based research has become an important paradigm among researchers investigating urban transportation system [24].

Overall, the studies discussed above offer valuable insights into the characteristics and patterns of urban public transportation networks from both the supply and demand perspectives. These findings demonstrate that the development of public transportation networks is essential for sustained urban economic growth, and that optimizing traffic supply–demand structure can facilitate the continuation of urban activities [61]. Despite the multitude of studies examining different aspects of public transportation supply or demand structure, there remains a lack of a comprehensive and integrated approach that considers the public transportation supply–demand structure from a network perspective. Additionally, the current literature overlooks the structural disparities between public transportation supply and demand networks. Therefore, this study aims to provide a comprehensive methodological framework and empirical evidence to enhance our understanding of these issues and improve urban public transportation supply–demand structures.

3. Study Area and Data

3.1. Study Area

Beijing, the political and cultural center of China, is one of the largest cities globally, comprising 16 districts, 327 subdistricts, and a permanent population of 21.87 million in 2021 [62]. However, the city's high population density and limited spatial resources pose a significant challenge to its development as a bustling international metropolis. To tackle this issue, the Beijing Municipal Government is decentralizing the population and non-capital functions of the central urban district in order to optimize the urban spatial structure and reduce the humanity–land conflict [63]. Transportation is essential for the smooth functioning and orderly development of cities, and it profoundly impacts urban development and spatial evolution. Therefore, examining Beijing's urban structure through the lens of traffic supply–demand network is crucial, both theoretically and practically. Additionally, as subdistricts are the fundamental administrative units in Chinese cities and play a vital role in implementing urban planning and management policies, this study focuses on 327 subdistricts as the primary research units (Figure 1).

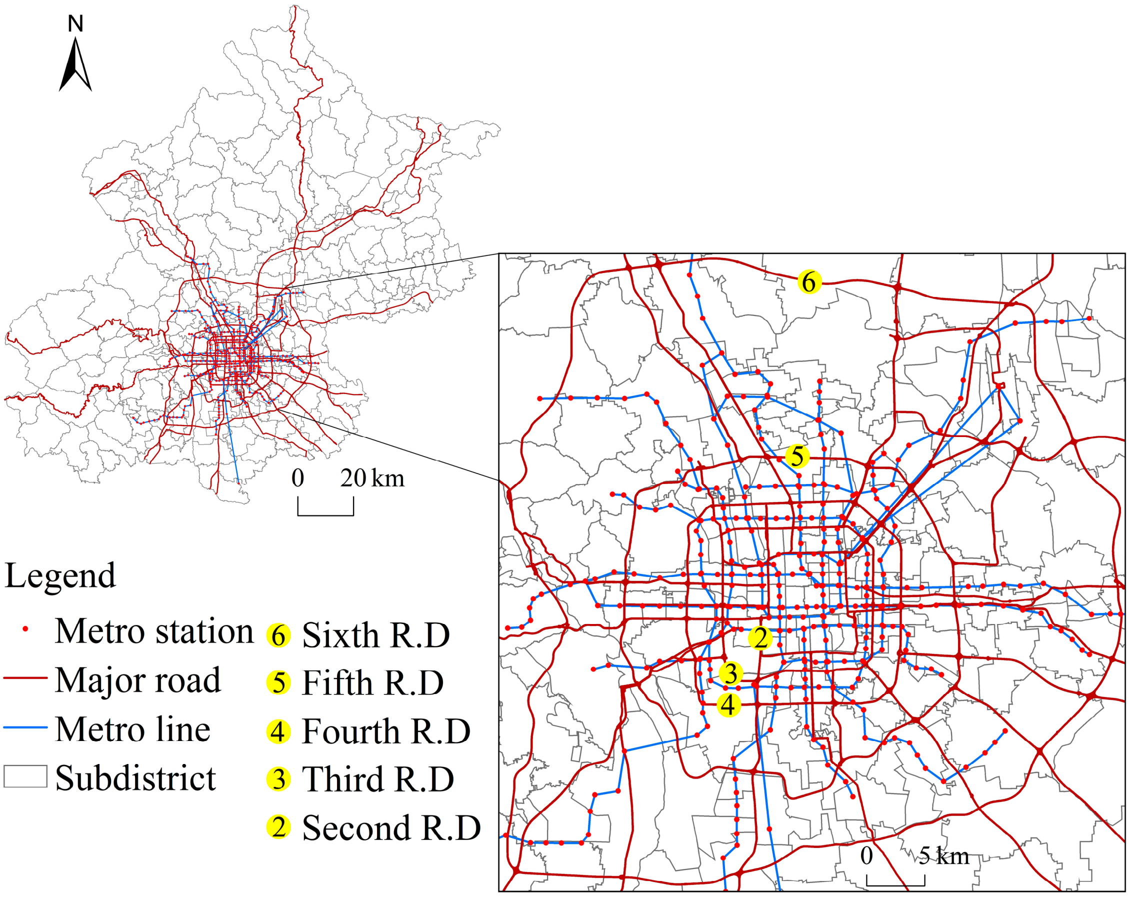


Figure 1. Study area: Beijing, China. Note: R.D: Ring Road.

3.2. Data

In this study, public transportation operation data and residents' travel data, both extracted from mobile phone data, were utilized to represent traffic supply and demand in Beijing. Specifically, the public transportation operation data used in this study referred to the information related to the functioning and management of public transportation systems such as buses and metros, including information on bus and metro stations, codes of bus and metro routes, schedules, and the direction of operation. The original data were obtained from the Beijing Municipal Commission of Transport (http://jtw.beijing.gov.cn/ (accessed on 13 August 2022)), and the data were dated December 2019 for 1134 bus lines, 8059 bus stops, 24 subway lines and 342 metro stations in Beijing. According to the Beijing Transport Development Annual Report 2020 [64], public transportation accounted for nearly 90% of the total urban passengers in 2019, making it an appropriate proxy for the characterization urban traffic supply.

The residents' travel data were obtained from mobile phone data provided by Unicom Smartsteps (http://www.smartsteps.com (accessed on 24 July 2022)), the second largest telecom operator in China with 300 million daily active users. With the high density of its base stations in Beijing, user location data can be generated in a 100 m grid. The mobile phone data used in this study covered approximately 7.89 million mobile phone users within a span of one month (May 2019). This data for each user included the following: a user ID, the grid's longitude and latitude, timestamp of stay, and personal information that correlates with the user's ID (e.g., gender and age, the longitude and latitude of their residential and workplace locations). Notably, the stay data included the location data of the first location in the morning and the last location in the evening, and stay data for the rest of the time were recorded when multiple signals were triggered at the same grid. Additionally, the starting and ending intervals were more than 30 min. Changes from one stay location to another were considered travel or movement [65]. Moreover, the validity of the mobile phone dataset was verified by counting the identified homes of local users in each subdistrict and comparing them with the populations of each subdistrict in the Gazette of the Seventh National Population Census for the Beijing Municipality. The highly representative nature of the mobile phone dataset used in the study was confirmed by the Pearson correlation coefficient between the mobile phone data and statistics, which was 0.873 ($R^2 = 0.763$, $p < 0.001$).

The combination of these two datasets provides a comprehensive representation of traffic supply and demand in urban areas. By using proxy datasets, it is possible to analyze and understand public transportation supply–demand patterns, identify problems, and improve transportation systems.

4. Methodology

Our study is based on an analytical framework consisting of three parts: dataset collection and preprocessing, traffic supply–demand flow extraction and network construction, and network structure analysis (Figure 2). Specifically, we first collected public transportation data and mobile phone data through various platforms and approaches, and pre-processed them to eliminate noise and outliers. Next, the traffic connections between stations were mapped into subdistricts by spatial join, and the travel flows were linked into subdistricts as well. With these steps, we established TSN and TDN, where 327 subdistricts served as nodes and traffic supply and demand flows functioned as edges. Finally, we applied spatial analysis and complex network analytics to compare the two networks based on macroscopic characteristics, node centrality, and community structure.

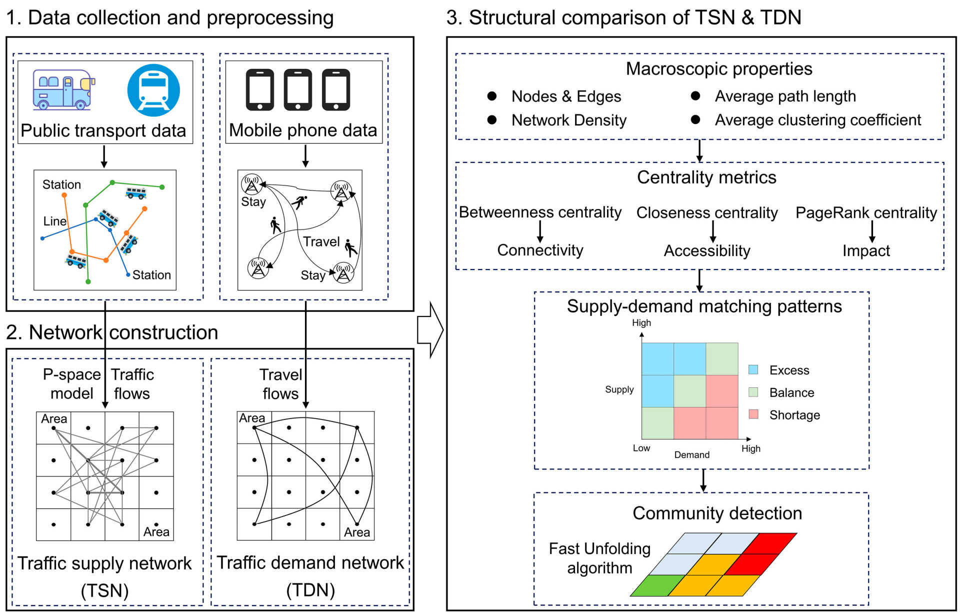


Figure 2. Analytical framework of this study. (Note: the grid is a brief representation of the spatial unit, not the actual subdistrict).

4.1. Network Construction

Generally, there are two prevalent approaches for the construction of public traffic networks: the L-space model and the P-space model [26,36]. The L-space model only recognizes the direct connections between traffic stations. Thus, only nearby stations for a single traffic route line are considered to have edge connections. In contrast, the P-space model is a new abstract rule which states that if any two traffic stations in the public traffic network can be connected by a single traffic route, those two stations are considered to have an edge connection. The degree k of each node and the distance between nodes based on the P-space model have definite physical meanings, in which the degree represents the number of traffic stations reachable from this station without having to transfer traffic routes. The distance between traffic stations can be explained by the line distance or the number of traffic routes from one station to another. Thus, the P-space model is more suitable and scalable for use building connections between traffic stations in a traffic route for geospatial network research. Therefore, the P-space model was chosen to construct the traffic supply network in our study. Figure 3 illustrates the network construction process. First, we integrated public transportation route data and station data and added spatial unit attributes to each station. Second, the links between stations were transformed into connections between spatial units. Finally, we constructed the TSN by regarding spatial units as network nodes, connections between spatial units as edges, and the number of connections as edge weights. Similarly, by integrating the travel flows between spatial units, TDN was constructed. Notably, when aggregating the trip flow data, since the original mobile phone data was generated based on a 100 m grid, we conducted a spatial join between the 100 m grid cells and the subdistrict boundaries and calculated the proportion of each subdistrict covered by the grid cells. We then aggregated the grid cells at the subdistrict level using these proportions. The detailed network construction process is illustrated in Figure 3.

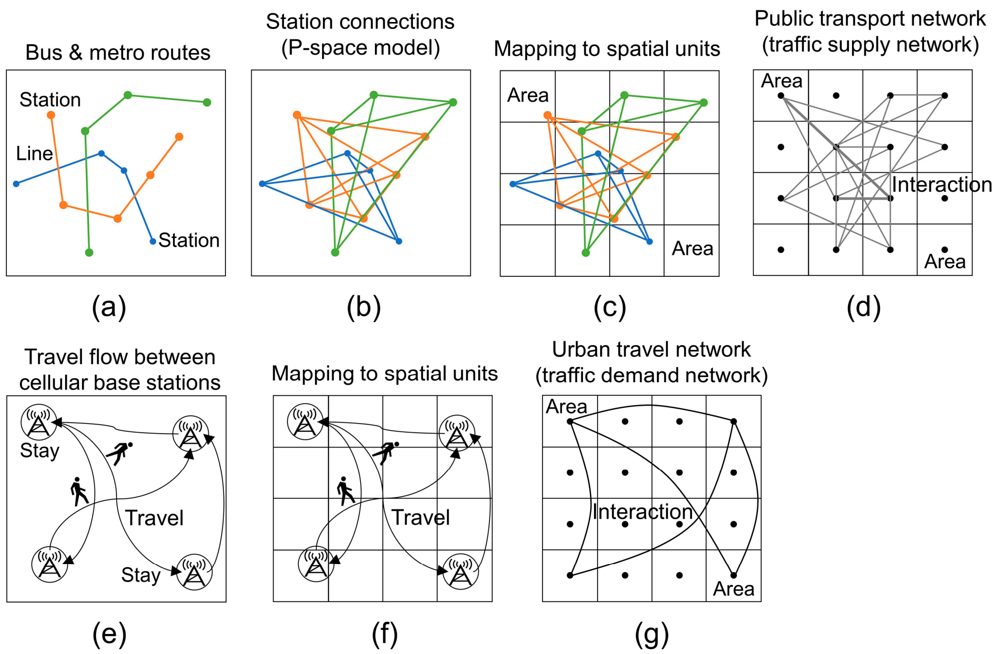


Figure 3. An illustration of the network construction: (**a**) three bus/metro routes, (**b**) bus/metro station connections under the P-space model, (**c**) superposition of the bus/metro station connections and spatial units, (**d**) public traffic network (traffic supply network) construction based on spatial units. (**e**) travel flows extraction based on cellular base stations, (**f**) superposition of the travel flows and spatial units and (**g**) urban travel network (traffic demand network) construction based on spatial units.

4.2. Macroscopic Properties

We constructed the TSN and TDN of Beijing using the geospatial network construction method described above. Both networks are complex networks with spatial embedding, meaning that they exhibit complex network characteristics as well as general spatial constraint characteristics [36]. By analyzing the macroscopic statistical properties of the networks, we can gain insights into their spatial interactions and overall structure. Therefore, we analyzed the TSN and TDN from a macroscopic statistical perspective using three indicators: *network density*, *average path length*, and *clustering coefficient*.

The *network density* represents the overall connectivity within the network and is defined as the ratio of the actual number of edges to the maximum number of possible edges.

$$D = \frac{l}{n(n-1)} \tag{1}$$

where l is the actual number of edges, and n is the number of nodes in the network.

The *average path length* is defined as the average number of steps along the shortest paths for all possible pairs of network nodes [66], which can be used to describe the degree of separation between nodes in a network.

$$AL = \frac{1}{n(n-1)} \sum_{i,j \in N} dist(i,j) \tag{2}$$

where $dist(i,j)$ denotes the shortest distance between i and j and N is the node set of the network.

The *clustering coefficient* quantitatively measures the degree to which nodes in the networks tend to cluster together and shows how well the neighbors of a node are connected to each other. The local clustering coefficient of node i for a directed network is defined as follows [67]:

$$C_i = \frac{1}{2\left[k_i(k_i-1) - 2k_i^{\leftrightarrow}\right]} \sum_h \sum_j (a_{ij} + a_{ji})\left(a_{jh} + a_{hj}\right)(a_{hi} + a_{ih}) \tag{3}$$

where k_i is the degree of node i and $k_i^{\leftrightarrow} = \sum_{i \neq j} a_{ij} a_{ji}$. a_{ij} is a binary variable which denotes the state of connection between node i and node j, a_{ij} is equal to 1 if node i and node j connect to each other; otherwise, it is equal to 0. The *average clustering coefficient* is defined as follows:

$$ACC = \frac{1}{n} \sum_i C_i \tag{4}$$

4.3. Centrality Metrics: Betweenness, Closeness and PageRank Centrality

Centrality is one of the main measurements of network modeling and can reflect the influence and importance of every node in a network [68]. By measuring centrality, we can identify critical traffic nodes in both human mobility networks and UTNs that can help describe the urban structure [40]. In this study, we adopted three kinds of centrality: betweenness centrality (BC), closeness centrality (CC), and PageRank centrality (PC).

First, BC is a metric that measures a node's information transfer capability in a network, quantifying the extent to which a node acts as a bridge between any other nodes in a network [33]. The shorter the paths that traverse a node, the higher its BC. Therefore, we used BC as the connectivity index for traffic nodes in our study. The equation is shown as follows:

$$BC_i = \sum_{s \neq j \neq t} \frac{\delta_{st}(i)}{\delta_{st}} \forall s, t \epsilon N \tag{5}$$

where δ_{st} is the total number of shortest paths between s and t, and $\delta_{st}(i)$ denotes the number of such paths which pass through i.

Second, CC is an index used to describe the nearness of a node to all other nodes in a network. It is calculated as the inverse of the sum of the distances from a node to all the other nodes in the network [36]. Nodes with higher CC have better accessibility and are easier to reach, making it a useful accessibility index. The equation of CC is shown below:

$$CC_i = \frac{1}{\sum_{j \epsilon N} dist(i,j)} \tag{6}$$

Third, PC measures a node's impact on attracting flows from all nodes in the network, taking into account all direct and indirect links, weights, and directions [33]. It simulates the behavior of random surfers within a webpage network connected by hyperlinks and assumes that node importance is determined by both the quantity and quality of the nodes linked to it. In the urban traffic context, this metric reflects how a location attracts outbound interactions with other locations, which can then be used to identify the key nodes in a transportation system and to simulate traffic to find important nodes that have a high impact on transportation efficiency [40]. In our study, PC was regarded as an impact index. The PC of node i is defined by:

$$PC_i = (1-d)\frac{1}{n} + d\sum_{j \in M} a_{ij}\frac{PC_j}{k_j} \tag{7}$$

where PC_i reflects the contribution of node i to the mutual connection. The parameter d is a damping factor, which can be set between 0 and 1; it is generally assumed that the damping factor should be set around 0.85, which we use in this application [69]. If a node does not connect to any other nodes, its PC value would be $\frac{(1-d)}{n}$ [70].

4.4. Traffic Supply and Demand Matching Patterns

To assess the degree of coordination between public transportation supply and demand in different regions, we compared the structural disparity and spatial heterogeneity between TSN and TDN. This comparison helped us to take targeted measures to optimize the public transportation supply–demand structure and alleviate the imbalance of traffic supply and demand. To begin, we classified the connectivity, accessibility, and impact of each node in TSN and TDN into three levels: low, medium, and high, using the natural breaks classification scheme. Then, we combined these three indicators for each node in TSN and TDN to form three supply and demand matching patterns: excess, balance, and shortage, as shown in Figure 4. For instance, if the connectivity level of area A in TSN was low, and the corresponding connectivity level of area A in TDN was high, we defined area A as a traffic supply shortage pattern, and vice versa as an excess pattern. Conversely, if the connectivity level of area A was at the same level in TSN and TDN, we considered the traffic supply and demand levels in the area to be approximately equal and categorized it as a balanced pattern. Finally, we mapped the supply and demand matching patterns of each node onto the geographic space to explore the spatial heterogeneity characteristics of public transportation supply and demand coordination.

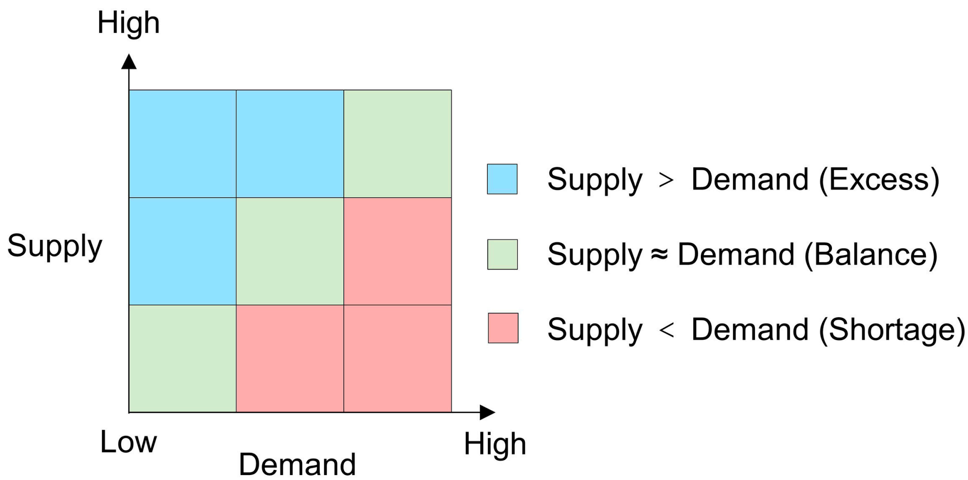


Figure 4. Public transportation supply–demand matching patterns.

4.5. Community Detection

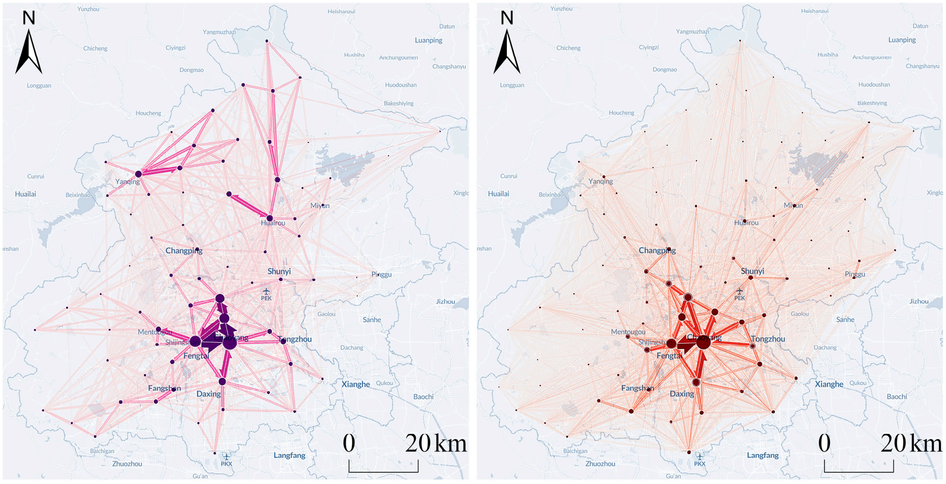
Community structures reflect an organizational pattern of nodes clustered into tight groups (with a high density of within-group edges and a low density of between-group edges) [36]. Detecting community structures in UTNs is crucial for revealing well-connected groups and their spatial patterns, which can help us to understand the connectivity level of spatial units and their similarity to the administrative spatial divisions of a city. This information can indicate whether each community forms an independent functional area [71]. In the context of public transportation networks, community detection can help to identify groups of subdistricts that have similar transportation supply and demand characteristics. By identifying these groups, researchers can gain insights into the spatial structure and characteristics of the public transportation network and potentially develop more targeted and effective transportation planning and management strategies. In our study, we used the 'Fast Unfolding algorithm', based on modularity optimization proposed by Blondel et al. (2008), to reveal the community structures and geospatial patterns of TSN and TDN [72]. This algorithm uses a bottom-up hierarchical clustering approach to aggregate and determine the community structure of neighboring nodes with the objective of maximizing network modularity. It has good accuracy and efficiency and has been widely used in relevant studies [73]. Thus, this algorithm was introduced in this study to detect the community structures of TSN and TDN.

5. Results

5.1. Macroscopic Characteristics of TSN and TDN

As shown in Figure 5, we constructed the TSN and TDN of Beijing using the network construction method from our proposed methodological framework. The edges between subdistricts represent network connections between corresponding spatial units. The thickness of the edges corresponds to the weights of connectivity level, and the edge gradient from thin to coarse represents a change in weight from weak to strong. Figure 5 visually demonstrates the heterogeneous spatial distribution of edges in the TSN and TDN, with the presence of spatial hotspots. The overall structure of the TSN and TDN exhibits certain hierarchical distribution characteristics, with higher traffic connections present in the central city and lower connections in the suburbs. In contrast, the TDN has more network connections distributed in urban centers, whereas the TSN has network connections distributed in both urban and suburban centers. According to the Beijing Transport Development Annual Report 2020 [64], the urban areas within the Sixth Ring Road account for 79% and 78% of the residential population and jobs in Beijing, respectively, in 2019. As a result, the urban center area has a richer and more complete public transportation infrastructure configuration and a higher demand for traffic travel, leading to high-intensity spatial connections in both the TSN and TDN in the city center area. Conversely, some suburban areas far from urban centers have relatively small populations and traffic travel demand. Nevertheless, public transportation facilities between suburban areas are still well-developed enough to guarantee inter-regional connectivity and meet basic public transportation needs. Consequently, there are some relatively strong spatial connections between some suburbs seen in TSN.

Table 1 provides an overview of the global indicators of TSN and TDN, highlighting significant differences between the two networks. Firstly, all spatial units are included in TDN, whereas TSN excludes 23 spatial units, indicating that TDN has greater completeness. Secondly, TDN has over five times more edges and a higher network density than TSN, implying that TDN has a greater degree of connectivity. Additionally, both TSN and TDN show high clustering coefficients and low characteristic path lengths, suggesting small-world behavior. However, TDN exhibits higher clustering coefficients and shorter average path lengths than TSN, indicating that TDN has greater connectivity and closeness.



(a) TSN (b) TDN

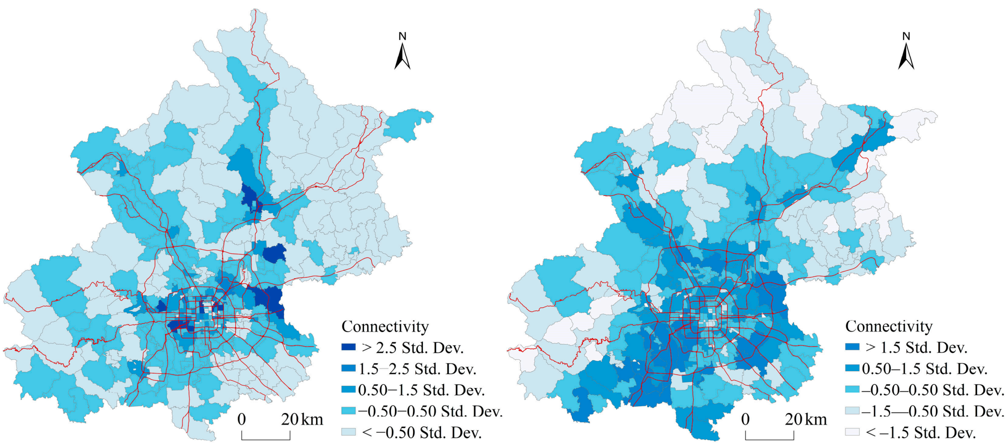
Figure 5. TSN and TDN at the subdistrict level in Beijing.

Table 1. Global indicators of TSN and TDN.

Parameters	TSN	TDN
Node number	304	327
Edges number	16,082	94,180
Network density	0.175	0.883
Average path length	2.009	1.12
Average clustering coefficient	0.61	0.902

5.2. Comparison of the Spatial Distribution Characteristics of Various Centrality of Nodes in TSN and TDN

Node centrality in complex networks represents the heterogeneous nature of individual nodes that play roles in structure and function [36]. In geospatial networks, the spatial distribution of node centrality also presents spatially heterogeneous and special characteristics. Therefore, this study employed three centralities (BC, CC, PC) to analyze their spatial distribution and physical significance (connectivity, accessibility, and impact), as described in the methodology section. We conducted a spatial analysis using standard deviation classification to visualize the results on maps, and Figures 6–8 presents the various centrality levels of subdistricts in TSN and TDN.



(a) TSN (b) TDN

Figure 6. Spatial distribution of traffic node connectivity in TSN and TDN.

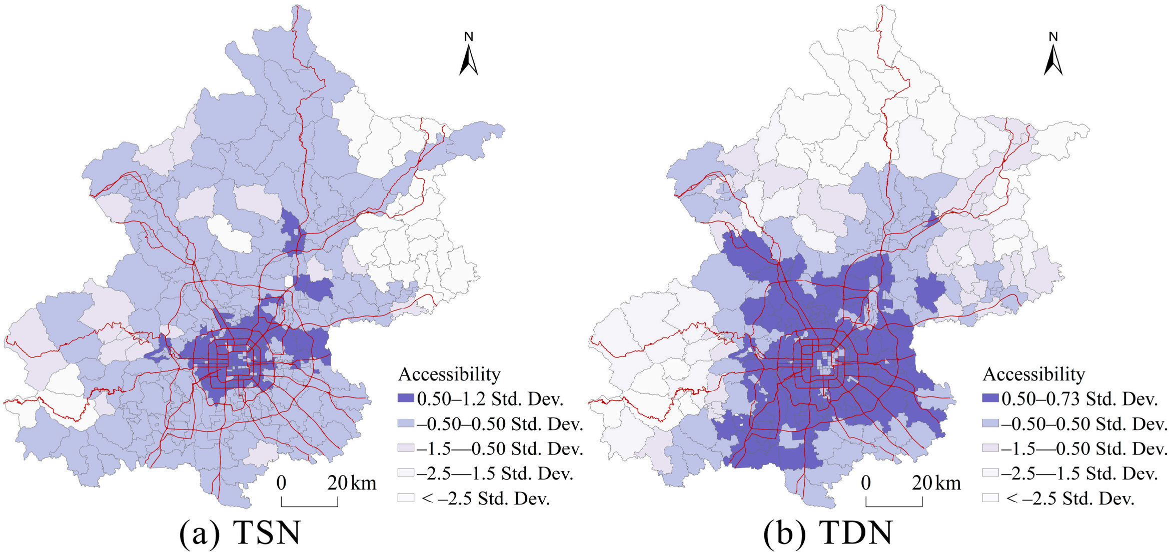


Figure 7. Spatial distribution of traffic node accessibility in TSN and TDN.

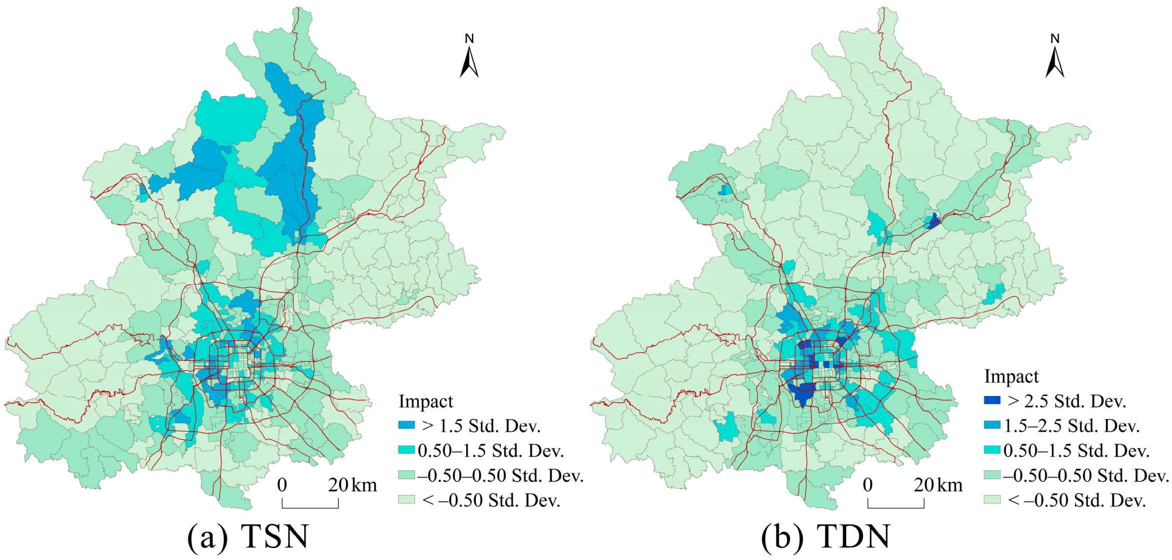


Figure 8. Spatial distribution of traffic node impact in TSN and TDN.

5.2.1. Comparison of the Spatial Distribution of Node Connectivity in TSN and TDN

Figure 6 illustrates the connectivity levels of subdistricts in TSN and TDN. Both networks exhibit a similar spatial distribution of node connectivity, with high-connectivity subdistricts located in urban centers and lower-connectivity subdistricts in suburban areas. Moreover, subdistricts situated along major roads or intersections also tend to have higher connectivity. However, there are differences between the two networks in terms of statistical and spatial disparities. TSN displays a more pronounced hierarchical and heterogeneous structure, with only a few high-connectivity nodes mainly located in urban areas between the Second and Fifth ring roads, as well as in some suburban centers. Most other nodes have a low level of connectivity. On the other hand, TDN shows less pronounced hierarchical features, with a higher number of nodes with relatively high connectivity levels being mainly located between the Fifth and Sixth ring roads, and with relatively average connectivity levels in other areas.

5.2.2. Comparison of the Spatial Distribution of Node Accessibility in TSN and TDN

Figure 7 shows the accessibility levels of subdistricts in TSN and TDN, with a clear concentric zone structure observed in both networks. This pattern is more pronounced in TDN, where accessibility gradually decreases from the city center towards the periphery. Within TSN, subdistricts with high accessibility are mostly concentrated in the city center within the Fourth Ring Road, with suburban centers and subdistricts located along major roads also exhibiting higher accessibility levels. In contrast, within TDN, subdistricts within the Sixth Ring Road and along its roads have high accessibility levels, while areas outside of the Sixth Ring Road experience a decrease in accessibility with distance from the city center. Overall, the spatial distribution patterns of accessibility in both TSN and TDN conform to the traditional Beijing urban spatial structure and are closely linked to the spatial distribution of urban location advantages, population density, and transportation resource allocation.

5.2.3. Comparison of the Spatial Distribution of Node Impact in TSN and TDN

Figure 8 illustrates the spatial distribution of PC in TSN and TDN, reflecting the impact of traffic nodes in the two networks. Specifically, TSN has a relatively large number of subdistricts with high impact. These are more widely dispersed and include urban and suburban centers and major roads. Conversely, TDN has fewer subdistricts with high impact, and these are instead mainly concentrated in the central urban areas within the Fifth Ring Road. Moreover, the hierarchical distribution of node impact is more pronounced in TDN, with a clear bifurcation where the number of high-level nodes is small, and most of them have low impact. In contrast, the distribution of node impact is relatively balanced in TSN. It is worth noting that the distribution patterns of node impact differ significantly from those of connectivity and accessibility. For instance, while the accessibility and connectivity of subdistricts in the central urban areas are high, their impact is relatively low. Conversely, subdistricts in certain suburban areas have relatively low accessibility and connectivity, but their impact is relatively high. This result indicates that even though some areas may lack apparent location advantages or public transportation resources, they are in crucial positions in TSN or TDN, their status in the networks is high, and they exert significant influence on the entire network. Therefore, such influential areas deserve greater attention in actual UTN management, as their disruption (due to traffic accidents or congestion) can cause significant damage to the entire UTN.

5.3. Traffic Supply–Demand Matching Patterns from Various Centrality Perspectives

Table 2 presents the statistical results of public transportation supply and demand matching patterns based on three centrality metrics. Matching patterns were categorized into three types: excess, balance, and shortage. Figure 9 provides a visual representation of the geographic distribution of matching patterns across subdistricts. Specifically, the results indicate that public transportation supply–demand matching patterns are similar across the three centrality measures. From the perspective of connectivity, 208 subdistricts demonstrated a balanced traffic supply–demand pattern, accounting for 63.61% of the analyzed subdistricts. Excess and shortage were found in 17.43% and 18.96% of subdistricts, respectively. From the accessibility perspective, 204 subdistricts displayed a balanced traffic supply–demand pattern, accounting for 62.39% of the analyzed subdistricts. Excess and shortage were found in 19.27% and 18.35% of subdistricts, respectively. From the impact perspective, 215 subdistricts demonstrated a balanced traffic supply–demand pattern, accounting for 65.75% of the analyzed subdistricts. Excess and shortage were found in 16.21% and 18.04% of subdistricts, respectively. Overall, the results suggest that the current public transportation supply–demand is balanced in Beijing in approximately 64% of subdistricts, while the degree of excess and shortage of traffic supply is considerable in around 18% of areas both cases.

Table 2. Statistical results of traffic supply–demand matching patterns.

Patterns \ Index	Connectivity		Accessibility		Impact	
	Number	**Ratio**	**Number**	**Ratio**	**Number**	**Ratio**
Supply > demand (Excess)	57	17.43%	63	19.27%	53	16.21%
Supply ≈ demand (Balance)	208	63.61%	204	62.39%	215	65.75%
Supply < demand (Shortage)	62	18.96%	60	18.35%	59	18.04%

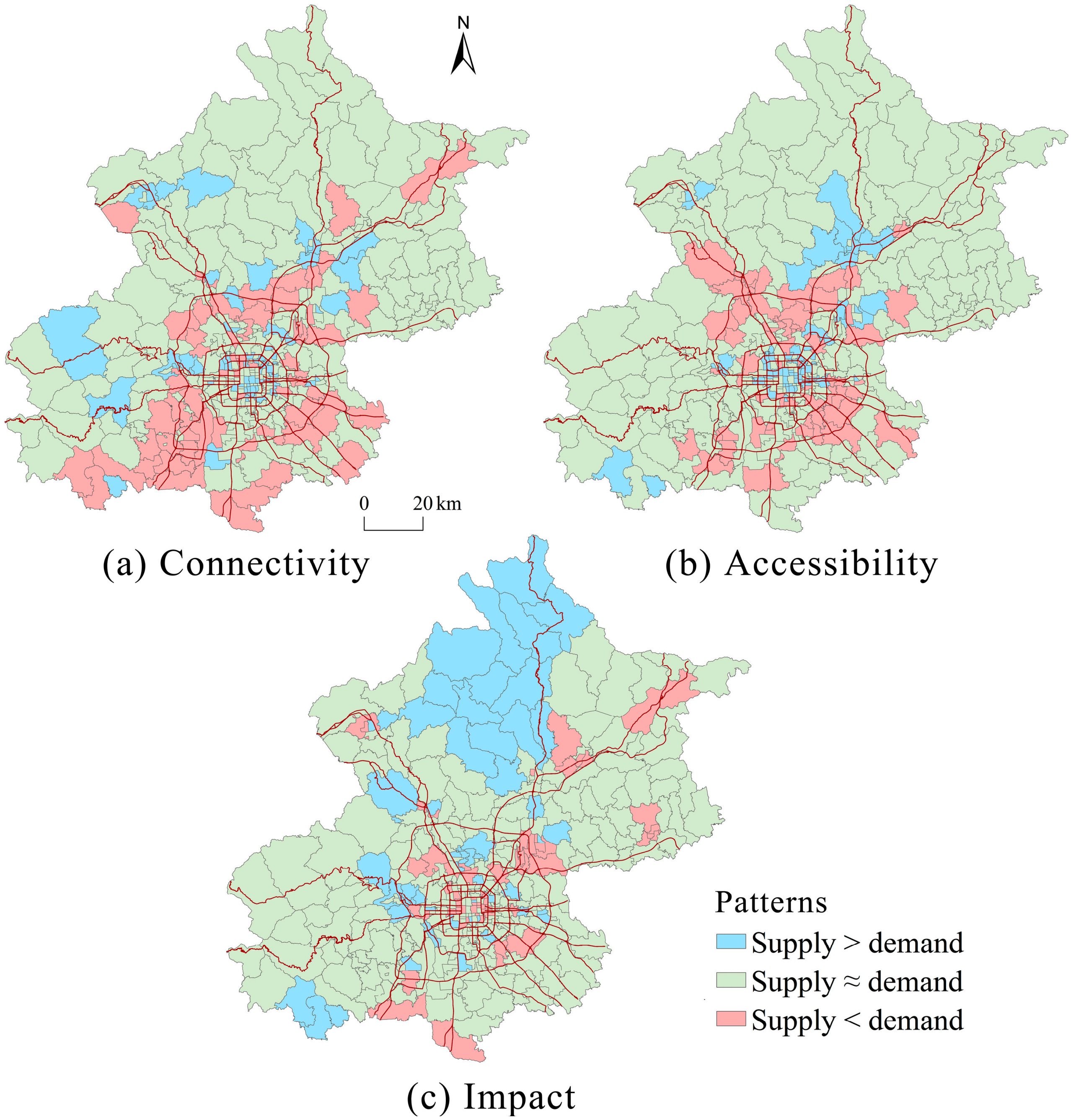


Figure 9. Public transportation supply–demand matching patterns from various centrality view.

Furthermore, the matching patterns showed consistent spatial characteristics across the three indicators. The areas with a shortage of traffic supply were mainly concentrated between the Fifth and Sixth ring roads and certain suburbs, while the areas with excess supply were primarily located within the inner-city areas enclosed by the Second Ring Road and in some suburbs intersected by major roads outside the Sixth Ring Road, particularly in the northern suburbs. Most of the central city between the Second and Fifth rings, as well as the majority of areas outside the Sixth ring, exhibited a balanced pattern of supply and demand.

To identify regions with extreme public transportation supply imbalances, we utilized the three indicators of connectivity, accessibility, and impact. Specifically, we defined a subdistrict as having an extreme shortage of traffic supply if its levels of all three indicators in TSN were lower than the corresponding levels in TDN. Conversely, a subdistrict was deemed to have an extreme excess of traffic supply if its levels of all three indicators in TSN were higher than the corresponding levels in TDN. A subdistrict was classified as traffic supply–demand balanced if the levels of all three indicators in TSN were equal to the corresponding levels in TDN. For subdistricts with no extreme imbalances between traffic supply and demand, we defined them as a insignificant pattern. According to our analysis (Table 3), nine subdistricts exhibited an extreme excess pattern, while eight subdistricts exhibited an extreme shortage pattern. The spatial distribution of these subdistricts (Figure 10) indicated that areas with an extreme shortage of traffic supply were mainly located between the Fifth and Sixth ring roads, as well as along the Sixth Ring Road. In contrast, subdistricts with an extreme excess of traffic supply were primarily located in the inner-city areas within the Second Ring Road and some suburban areas. Overall, these 17 subdistricts with extreme imbalances between supply and demand require key attention.

Table 3. Subdistricts with extreme imbalance between traffic supply and demand.

Subdistricts with Extreme Excess of Traffic Supply	Subdistricts with Extreme Shortage of Traffic Supply
Guangming Street	Chengnan Street
Maizidian Street	Liqiao Town
Nancai Town	Liangxiang District
Shenjiaying Town	Sanmafang District
Gymnasium Road Street	Taihu Town
Tianqiao Street	Wangquan Street
Wulituo Street	Wenquan District
Perfume Garden Street	Youanmen Street
Changgou Town	

5.4. Community Structure of TSN and TDN

We used a community detection algorithm to explore the community structures of TSN and TDN, dividing both networks into nine communities. Since several community boundaries overlap with Beijing's administrative boundaries, we labelled these communities based on their administrative names, and the results are shown in Table 4. The size of the communities varies, with the Shunyi–Miyun–Huairou, Changping–Haidian, Chaoyang–Tongzhou, and Mentougou–Shijingshan–Fengtai communities being larger in size, while the Pinggu, Fangshan, and Yanqing communities in the distant suburbs are relatively small. In terms of community agglomeration, the average clustering coefficient (ACC) of TDN is 0.91, which is much higher than that of TSN (ACC of 0.55). In addition, TSN also forms a larger community—the Inner City; conversely, the Shunyi–Miyun-Huairou community is split into Shunyi and Miyun–Huairou communities in TDN.

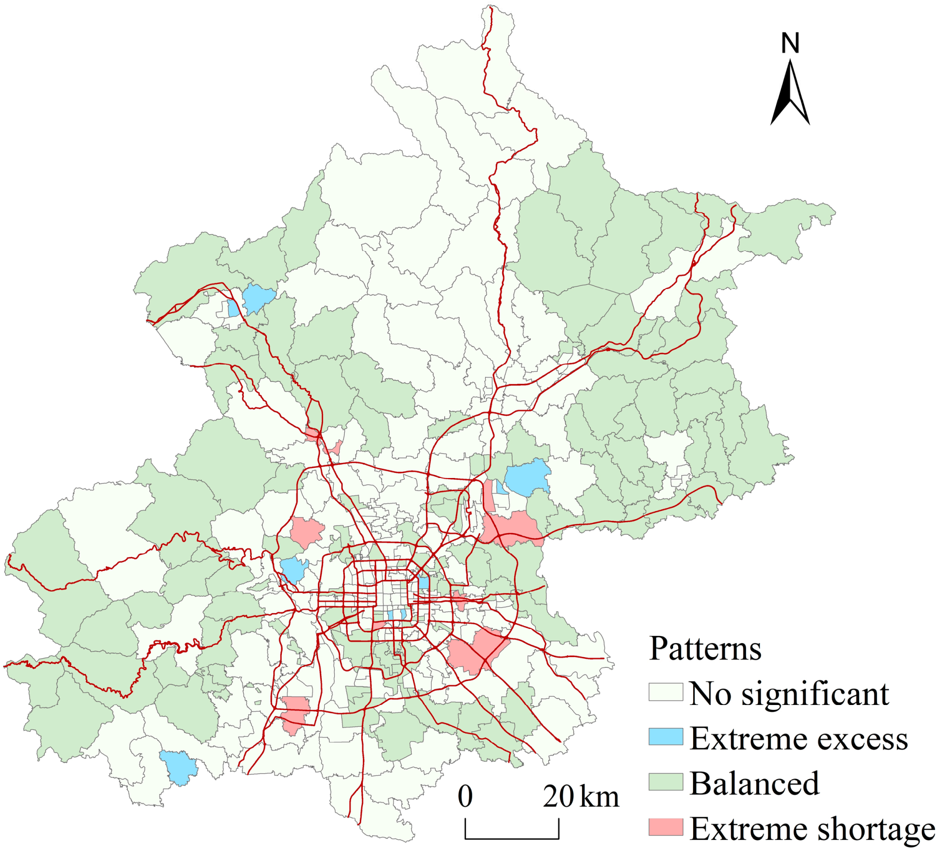


Figure 10. Spatial distribution of subdistricts with extreme imbalance between traffic supply and demand.

Table 4. Community detection statistics for TSN and TDN.

Communities	ID	TSN			TDN		
		PNN *	PLS *	ACC *	PNN	PLS	ACC
Chaoyang–Tongzhou	1	13.82%	15.59%	0.57	16.21%	20.34%	0.89
Changping–Haidian	2	15.46%	18.49%	0.6	14.98%	23.70%	0.89
Daxing–Fengtai	3	12.17%	11.61%	0.63	8.56%	11.54%	0.89
Mentougou–Shijingshan–Fengtai	4	12.17%	13.04%	0.62	16.82%	22.01%	0.89
Fangshan	5	7.24%	4.49%	0.64	8.56%	4.69%	0.91
Yanqing	6	5.92%	10.11%	0.63	5.50%	1.18%	0.93
Pinggu	7	0.33%	0.0011%	0	5.50%	1.50%	0.93
Shunyi–Miyun–Huairou	8	19.74%	15.18%	0.62	/		/
Inner City	9	13.16%	11.49%	0.61	/		/
Shunyi	10	/	/	/	12.84%	11.42%	0.90
Miyun–Huairou	11	/	/	/	11.01%	3.63%	0.92

* Note: percentage of node counts: PNN; percentage of link strength: PLS; average clustering coefficient: ACC.

Figure 11 depicts the spatial distribution pattern of community structures in TSN and TDN, indicating a notable trend of spatial agglomeration. Notably, the community detection algorithm does not incorporate geospatial location as a parameter. However, the results demonstrate a high degree of geographic proximity, with neighboring subdistricts tending to belong to the same community. Moreover, in the suburban regions, several community boundaries somewhat align with the administrative boundaries, particularly in TDN. For example, the Yanqing, Fangshan, and Pinggu communities in TDN correspond to their respective administrative districts, and the Yanqing community in TSN is identical to its administrative district. Additionally, the Miyun–Huairou community used in TDN merges these two administrative districts. Nonetheless, there are disparities in the distribution of communities between TSN and TDN. Specifically, upon comparing the communities of each subdistrict in TSN and TDN, we identified that 179 subdistricts are in the same community in both networks, while 148 subdistricts belong to inconsistent communities in TSN and TDN. In TSN, the Inner City community comprises the eastern and western districts of Beijing, whereas these two districts are combined with other communities in TDN. This result reveals that the current configuration of public transportation infrastructure in the central urban area of Beijing does not align with the actual traffic demand.

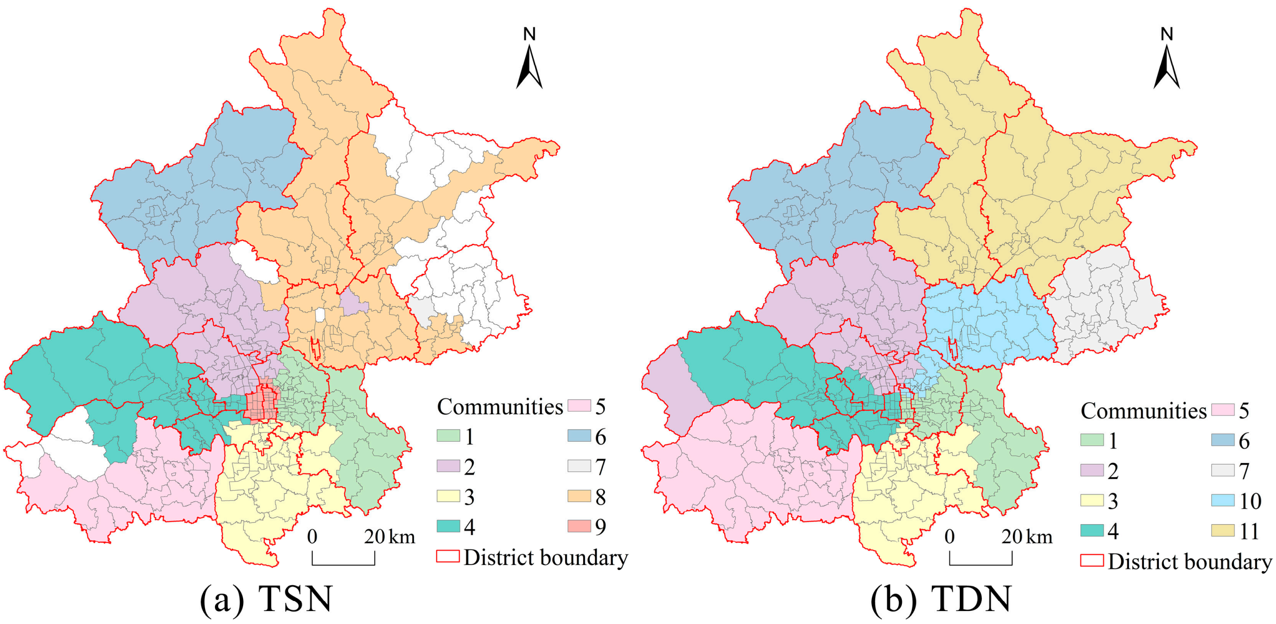


Figure 11. Spatial distribution of the communities of TSN and TDN.

6. Discussion and Conclusions

6.1. Discussion

Public transportation networks are critical components of modern urban systems and play essential roles in the urban development process. However, the acceleration of the spatiotemporal flow of urban elements through the development of high-speed transportation and communication technologies has made urban traffic management increasingly complex. This has created a contradiction between the speed of urban spatial evolution and transportation management capacity, which is becoming increasingly prominent. To address this issue, it is essential to plan public transportation infrastructure construction based on traffic supply and demand to achieve a balance between them, optimize the urban spatial structure, and improve operational efficiency. However, we found upon reviewing the previous literature that, although empirical evidence has been presented to understand the urban traffic structure from supply or demand perspective, little attention has been paid to the field of structural disparities between TSN and TDN. To fill this gap, we utilized public transportation operation data and mobile phone data, along with geospatial and network analytical approaches, to reveal the structural characteristics of and spatial disparities between TSN and TDN. Our study contributes new insights into the public transportation supply–demand network. In this section, we discuss several key findings and policy implications that promote the supply–demand balance and sustainability of urban transportation.

First, our visualizations and macroscopic characteristic parameters of TSN and TDN reveal the strong structural and geographic heterogeneities of the two UTNs in Beijing. These may be influenced by a range of factors including geographic location, public transportation infrastructure, and economic and demographic factors. Specifically, owing to the traditional urban structure and land use patterns, the central city of Beijing bears more important socioeconomic attributes, with a large population and urban activities being concentrated in these areas [64]. Additionally, our findings are in line with the work of Liu et al. (2021) [57]. These authors reported a high central concentration and uneven spatial distribution of resident daily travel in Beijing, leading to significant spatial heterogeneity and dependency characteristic in both TSN and TDN. The spatial distribution of network centralities in TSN and TDN, as analyzed in Section 4.2, supports these observations.

Second, as reported in Section 4.3, based on the perspective of connectivity, accessibility and impact, a significant public transportation supply–demand mismatch can be observed in urban areas within the Sixth Ring Road. In particular, there is a significant traffic supply shortage between the Fifth and Sixth ring roads and in some suburban areas. In contrast, there is a more pronounced oversupply in inner-city areas within the Second Ring Road and in certain suburban areas outside the Sixth ring road that are crossed by major roads. This phenomenon is largely caused by multiple factors. Specifically, urban centers are well known as critical regions for all urban transport infrastructure, and a certain oversupply of transportation infrastructure configuration is expected. Indeed, the UTN in an urban center should be optimized insofar as possible, and the supply–demand relationship should be reasonably adjusted to maintain it within a relatively controllable range. In addition, with the acceleration of suburbanization and urban construction, the residential and working populations in the areas between the Fifth and Sixth ring roads of Beijing have significantly increased. These factors play crucial roles in connecting urban centers with smaller towns and the countryside. However, the traffic supply cannot satisfy the growing traffic demand, presenting a challenge to the planning and operation of public transportation services. To address this issue, there is a need for new public transportation infrastructure or improvements to existing transportation structures [74]. Government and planning authorities should provide support to emerging suburban centers to ensure equitable access to public transportation services. Furthermore, diversified public transportation schemes should be implemented in order to effectively meet the needs of different subdistricts while meeting the overall goals of urban development. In particular, areas between the Fifth and Sixth ring roads should increase the coverage of traffic routes and stations in order to satisfy the requirements of traffic demand and urban development.

Finally, we take a further step to explore the community structure of TSN and TDN, which is a critical feature of real-world networks. Our study shows that most communities in TSN and TDN are geographically cohesive and densely connected by functional interaction. Moreover, our findings are consistent with those obtained using other mobility data sources (e.g., social media and smart card data), i.e., the detected communities in the geographic space generally show some correspondence with top-down administrative borders [33,75,76]. However, what is more common is the integration of multiple administrative districts into each other and the formation of more closely connected community organizations. These empirical findings may suggest to policy makers that it is necessary to rethink whether administrative planning during the wave of urban development is in fact rooted in spatial interaction patterns or is only "a forced marriage" from the top down [76].

The major contributions of this study are twofold. Firstly, the contributions proposed in this study are constructive for theoretical literature and associated with current practical issues. This study extends the existing research on urban traffic structure to urban traffic networks from a spatial network perspective, a topic which usefully complements the current research gap in urban traffic supply–demand network studies and greatly improves the scientific understanding of the urban traffic structure. This approach and perspective make finding solutions to related public transportation problems more practical and realistic. Secondly, from a spatial network perspective, in exploring the public transportation supply–demand structure in a typical metropolitan area like Beijing, the empirical findings could help to bridge the knowledge gap between existing theories and real-life applications and provide a basis for the rational and efficient planning of traffic infrastructure construction. It can also inform policies related to urban traffic supply–demand balance and the optimization of urban space structure.

6.2. Limitations and Future Work

The study has several limitations that need to be addressed. First, due to data availability constraints, we used urban public transportation operation and mobile phone data as proxies for traffic supply and demand flows, respectively. While these two datasets are crucial components of public transportation supply and demand, we cannot guarantee a perfect match between mobile phone data and public transportation data. Meanwhile, we did not consider the carrying capacity of public transportation in supply assessment due to our research emphasis. However, carrying capacity is an important consideration in assessing supply, and it should be included in future studies using more refined and dynamic traffic flow data to reveal the dynamic changes of urban traffic supply and demand networks. Furthermore, while the mobile phone data we used covered approximately 7.89 million mobile phone users within a span of one month. Future researchers should consider obtaining more comprehensive data from multiple communication operators for a comprehensive analysis in order to reduce errors and increase the representativeness of our results.

Second, although we used complex network theory and spatial analysis methods to quantify the structural characteristics between TSN and TDN in different dimensions, the analytical framework of this study is relatively simple and universal. The similarities and disparities between the two networks were still discussed based on a qualitative analysis. In the future, the analytical framework proposed in this study should be improved by incorporating state-of-the-art methods such as graph convolutional neural networks or generative adversarial networks to quantitatively measure the similarity and disparity features of various networks.

Third, there is a significant potential to further extend our study by conducting a comparative analysis of dynamic changes in traffic supply and demand structures between different cities. The current study only conducted a static analysis in Beijing based on a month's aggregated data, a decision which may have limited the diversity of our findings. Therefore, if more fine-grained relevant data could be collected for different time periods in various cities (e.g., Shanghai, Guangzhou, or Shenzhen), it would be possible to conduct a comparative analysis of dynamic changes of traffic supply and demand structures between these cities by expanding our analytical framework further. This would provide a robust methodological foundation in order to better understand the characteristics of traffic supply and demand in different cities.

6.3. Conclusions

This study conducted a comprehensive comparative analysis of TSN and TDN using complex network analysis and spatial analysis methods in Beijing. First, TSN and TDN were constructed based on public transportation operation data and mobile phone data. Next, we explored the spatial characteristics and structural disparities between these networks from various dimensions, including global indicators, three centralities, and community structure, and measured the current traffic supply and demand matching pattern in Beijing. Finally, the aim of this work was to answer the question of how to measure traffic supply–demand structure from a network perspective in the complex urban environment. Our results reported that the current traffic supply–demand balance in Beijing to be around 64%, with shortages and excess supply of approximately 18% each. We found that he areas with supply shortages are mainly located between the Fifth and Sixth ring roads and in certain suburbs, while the areas with excess supply are primarily located within the inner-city areas inside the Second Ring Road and in certain suburbs crossed by major roads outside the Sixth Ring Road. Overall, by examining the structural disparities between TSN and TDN, this study offers valuable insights into the structure and functioning of traffic supply–demand networks. These revelations have the capacity to inform urban traffic management policies and facilitate the development of a sustainable urban transportation system.

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