

Article

Urban Traffic Dominance: A Dynamic Assessment Using Multi-Source Data in Shanghai

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Abstract: This study redefines the evaluation of urban traffic dominance by integrating complex network theory with multi-source spatiotemporal trajectory data, addressing the dynamic nature of various transportation modes, including public transit and shared mobility. Traditional traffic studies, which focus predominantly on static road traffic characteristics, overlook the fluid dynamics integral to urban transport systems. We introduce Relative Weighted Centrality (RWC) as a novel metric for quantifying dynamic traffic dominance, combining it with traditional static metrics to forge a comprehensive traffic dominance evaluation system. The results show the following: (1) Both static and dynamic traffic dominance display core-periphery structures centered around Huangpu District. (2) Dynamically, distinct variations in RWC emerge across different times and transport modes; during the early hours (0:00–6:00), shared bicycles show unique spatial distributions, the subway network experiences a notable decrease in RWC yet maintains its spatial pattern, and taxis exhibit intermediate characteristics. Conversely, the RWC for all modes generally increases during morning (6:00–12:00) and evening (18:00–24:00) peaks, with a pronounced decrease in subway RWC in the latter period. (3) The integration of dynamic evaluations significantly modifies conventional static results, emphasizing the impact of population movements on traffic dominance. This comprehensive analysis provides crucial insights into the strategic management and development of urban traffic infrastructure in Shanghai.

Keywords: traffic dominance; dynamic assessment; multi-source data; complex network theory



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1. Introduction

In urban infrastructure, the city transportation network is complex and intricate, serving as a necessary prerequisite and crucial support for regional socio-economic development [1,2]. It is the precursor and core of regional development and urban structure shaping [3], determining residents' quality of life and the sustainable development of the city. Traffic dominance is an integrated indicator for assessing regional transportation, reflecting the supporting capability and security level of regional transportation infrastructure [4]. It also serves as the fundamental basis for the spatial layout of regional economic activities. The study of traffic dominance has always been a focal point in the fields of transportation geography and urban planning, with higher levels often indicating good development potential [5]. The traffic dominance of a city can effectively measure the level of regional infrastructure and reveal trends in regional spatial development, which is of great importance for city management and planning.

Jin et al. introduced the concept of “traffic dominance”, indicating it as the level and state of economic and social activities supported by the transportation infrastructure network of an area, referencing the entire system including that area, or comparing regions

and ideal targets [6]. They elaborated its mathematical model, assessing regional transportation conditions through three static indicators: Network density, trunk influence, and locational advantage. This research has been referenced and applied by many scholars to different scales of regional development, including national [7], provincial [8], urban agglomerations [9], and counties [10]. Advances in this research include enriching the choice of static indicators, such as considering the shortest road distance [3], population density weighting [4], road traffic volume [11], and spatial distribution hot and cold patterns [12], making the evaluation system more scientific and precise; considering more elements such as ports [13], airports [14], and high-speed transport combinations [15], enhancing calculation accuracy. However, current methods for assessing traffic dominance mainly focus on traditional evaluation models based on static indicators, intended to depict a region's "quality", "quantity", and "advantage" of transportation conditions [6]. Although urban development's rapid pace has made urban traffic's spatial structure increasingly complex, with high-frequency interactions between people and the traffic system causing short-term changes in traffic dominance within limited areas, these studies often only focus on specific moments or periods, unable to fully reflect the complexity and dynamic changes of urban traffic systems. The limitations of static indicators make these methods less flexible and comprehensive in dealing with increasingly complex urban transportation demands. The requirements for urban transportation infrastructure construction are no longer limited to accessibility [16]. To some extent, traditional traffic dominance assessment models have become insufficient to meet new evaluation requirements and development connotations, presenting new challenges in defining the connotations of traffic dominance. To better meet the needs of urban traffic planning and management, researchers have begun to focus on comprehensive evaluation methods using multi-source spatiotemporal data [17].

People encounter different environments in everyday life while working, studying, shopping, exercising, or engaging in other activities, constantly moving. Thus, many scholars have considered human mobility an important factor, with multi-source spatiotemporal data widely used in related dynamic evaluation studies [18–20]. With the increasing availability of massive spatiotemporal trajectory data and the urgent need for intelligent transportation systems, evaluating a region's traffic dominance requires decision-makers to have a deeper understanding of human spatiotemporal behavior dynamics, and multi-source spatiotemporal data can meet this need. In evaluating traffic dominance using multi-source spatiotemporal data, not only the static characteristics of road traffic need to be considered, but also the dynamic changes of various transportation modes such as public transportation and shared mobility, requiring origin-destination data (OD) data [21–23]. Such data records the movements or flows of people, goods, or information from one location (origin) to another (destination). In past research, people often focused on traffic flow [11], road speed [3], and traffic congestion [24] to assess traffic dominance, overlooking the importance of OD data. These data include road traffic flow, public transportation passenger movement, shared mobility trajectories, etc., and their application is becoming a new trend in the field of transportation research. The use of OD spatiotemporal data has enriched the content of transportation research, but a comprehensive evaluation method that fully utilizes this information has not yet been widely adopted in the field of traffic dominance.

In this study, we aim to effectively integrate OD data to assess regional traffic dominance. The transportation network exhibits complex network dynamics [25], spatiotemporal characteristics [26], and structural properties [27]. Previous studies have introduced complex network theory to reveal the complex structure and dynamic evolution of urban transportation systems [28–31]. In terms of network characteristics, scholars both domestic and international have studied the basic network characteristics (centrality, clustering coefficient, etc.) of different cities' road and public transportation networks. For example, Seaton and Hackett [32] calculated various metrics such as clustering coefficients, path lengths, and average degree vertices for the Boston and Vienna rail systems; Derrible analyzed the betweenness centrality indices of various global subway systems, finding a

negative correlation between betweenness share and network size [33]; similarly, Wang et al. studied the centrality of Baton Rouge, Louisiana's streets, and further compared the centrality indices with urban land use intensity [34]. The importance of a node within the network depends on its connectivity with other nodes, which influences the transportation advantage of urban development [35,36]. Thus, the study of rail transit network structure and characteristics is of great practical significance for assessing traffic dominance.

In this context, traditional methods of evaluating traffic dominance show certain limitations when facing the dynamic changes of urban traffic systems. The widespread use of spatiotemporal data provides a richer information foundation for traffic dominance research but lacks an effective method to fully utilize these data. As a potential solution, complex network theory has achieved some results in the transportation field, but its application in multi-source spatiotemporal data evaluation still needs further research. Therefore, this study aims to combine complex network theory and multi-source spatiotemporal data to construct a more dynamic and comprehensive traffic dominance evaluation framework.

This study on traffic dominance within the Shanghai region underscores a strong link to sustainability, highlighting the importance of considering dynamic factors in urban transportation planning. Adopting such a comprehensive perspective is essential for developing the emergence of resilient, flexible urban landscapes poised to confront forthcoming urbanization and sustainability challenges adeptly. The overarching objective is to create cities that are not only environmentally sustainable but also socially inclusive and economically viable in the long run. The remaining parts of this paper are organized as follows. Section 2 briefly introduces the study area and selected data set. Methods and results are provided in detail in Section 3. We discuss the impacts and main findings in Section 4 and provide our conclusions in Section 5.

2. Materials and Methods

2.1. Study Area

Shanghai, as one of China's important economic engines, has a traffic system that plays a vital role. Its developed economic system and constantly growing population make traffic mobility a key challenge for urban planning and management. Shanghai's transportation network is vast, including a developed road network, an efficient subway system, and a busy public transportation network. In Shanghai, the acquisition of multi-source spatiotemporal data is becoming increasingly convenient. Various data sources are widely used, including GPS trajectory data, public transportation IC card data, and shared mobility platform data. This provides a rich information base for an in-depth understanding of urban transportation behavior and traffic dominance evaluation. Therefore, this study chooses Shanghai as the empirical research area (Figure 1).

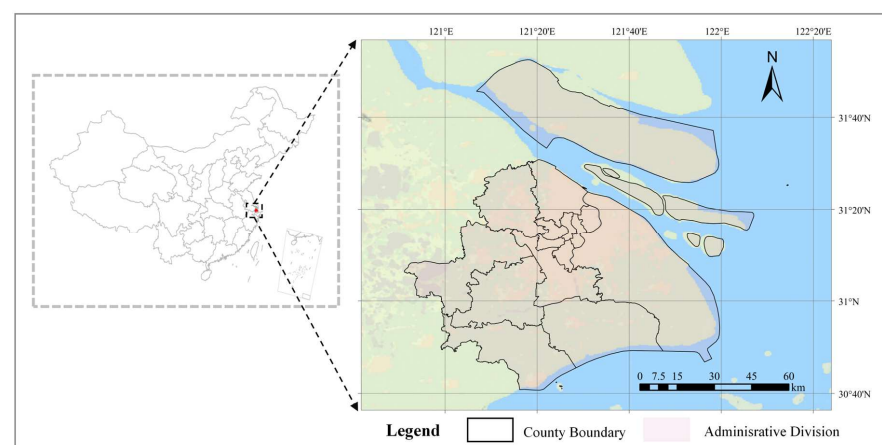


Figure 1. Map of the study area in Shanghai.

2.2. Data Sources

2.2.1. Static Geographic Data

Current research indicates that traffic networks and transportation nodes have a significant impact on traffic dominance; therefore, the following data were collected:

- Road network data: Sourced from <https://www.openstreetmap.org/> (accessed on 15 April 2023)
- POI data for ports, airports, buses, and railways: Sourced from the Amap API
- Administrative division data: Sourced from the National Geographic Conditions Monitoring Cloud Platform

2.2.2. Dynamic Trajectory Data

- Subway data: Comes from the Shanghai Public Transportation Card Data provided by the “Youzu Cup” Shanghai Open Data Application Competition. The dataset contains a total of 15,772,842 samples, each with 7 attributes (Table 1):

Table 1. Smart card data attributes and descriptions.

Attributes	Descriptions
Cardholder	User identifier
Card swiping date	Public transport card swiping date
Card swiping time	Public transport card swiping time
Public transport information	Bus routes, rail transit lines, taxi, and ferry information
Mode of transport	Bus, subway, taxi, ferry, P + R parking
Price	Public transport price
Discount	Whether there is a discount on commercial transport card transactions

- Taxi GPS data: Comes from a dataset of nearly 100,000 entries shared by the Smart City Research Group at the Hong Kong University of Science and Technology (<https://cse.hkust.edu.hk> (accessed on 1 May 2023)), features include: taxi ID, time, longitude, latitude, angle, instantaneous speed of the taxi, and taxi occupancy status.
- Shared bicycle data: Comes from over 100,000 entries provided by Mo-bike.

2.3. Research Methods

As illustrated in Figure 2, the methodological framework devised in this paper comprises three main components. The first segment, the static model for traffic dominance, encompasses three dimensions labeled influence degree of trunk lines, spatial accessibility, and traffic network density. The second segment, the dynamic indicator model for evaluating traffic dominance, employs complex network theory and community modularity weighted calculation to assess the traffic dominance of subways, taxis, and bike-sharing. Finally, the third segment, the comprehensive model, integrates the aforementioned models to evaluate traffic dominance across various times.

2.3.1. Static Model for Evaluating Traffic Dominance

The traffic dominance of a city is inextricably linked to locational conditions and the density of the traffic network. Therefore, the static index evaluation system for traffic dominance constructed in this article is shown in Table 2.

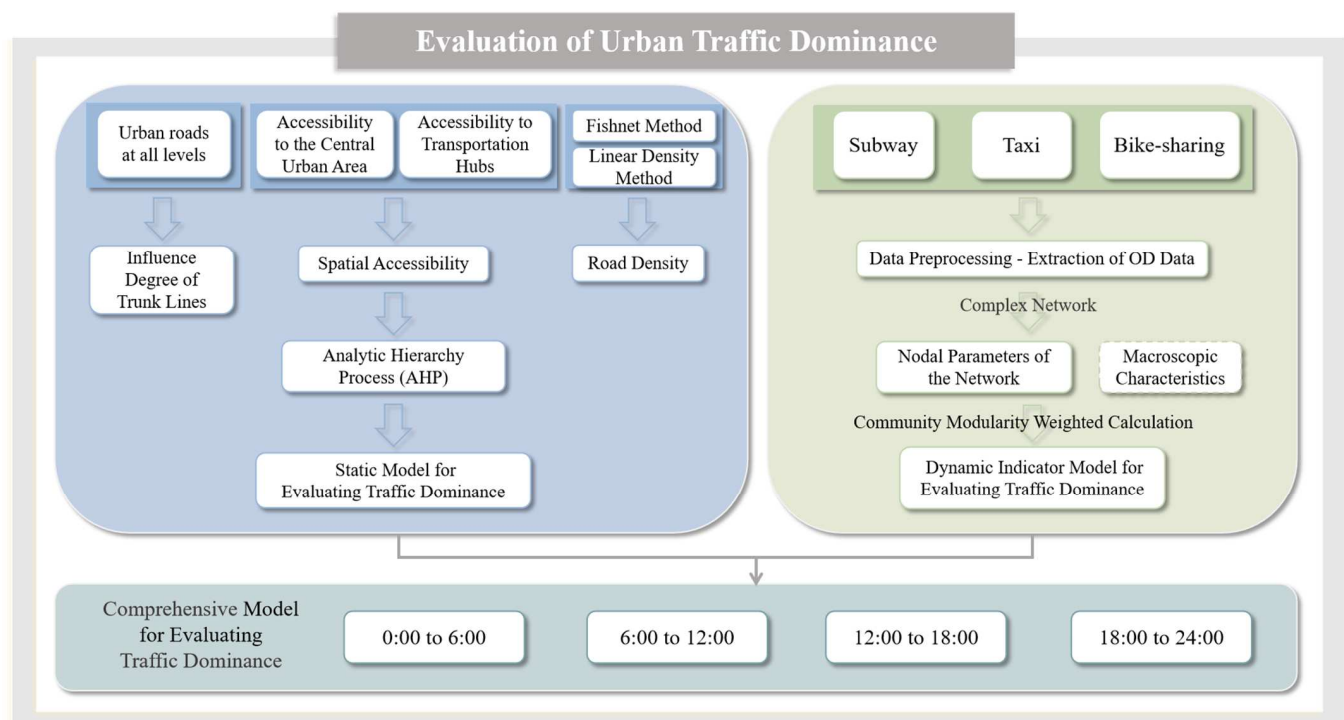


Figure 2. Methodological framework.

Table 2. Evaluation system for urban traffic dominance.

Primary Indicator	Secondary Indicator	Tertiary Indicators
Static traffic dominance	Influence degree of trunk lines	Elevated and express roads Main urban roads Secondary urban roads Internal roads
	Spatial accessibility	Accessibility to the central urban area Accessibility to transportation hubs
	Traffic network density	-

1. Influence Degree of Trunk Lines

The influence degree of trunk lines reflects the proximity of the study area to major traffic arteries or important transportation infrastructure (including expressways, fast tracks, primary, secondary, and tertiary roads, and internal roads). This indicator is a key factor in assessing the region's connectivity to a broader transportation network. The shorter the distance, the higher the degree of influence of the trunk line, indicating more favorable traffic conditions in the region. Combining existing literature [37], we use a classification assignment method to assess the degree of influence of traffic dominance.

2. Spatial Accessibility

Spatial accessibility reflects the ease of travel from a study unit to a specific destination through a certain transportation system [9], which can indicate the accessibility between two places. This paper considers two types of spatial accessibility: The central urban area and transportation hubs. Accessibility to the central urban area reflects the spatial connection cost between grid units and the central urban area. Accessibility to transportation hubs (railroads, highways, etc.) reflects the potential for block development along hub cities under the trend of network development. Hubs with higher accessibility can attract more passenger flow and can improve the level of urban traffic development [38]. This paper measures these two types of accessibility based on the time distance between nodes, scoring

from 0 to 5 based on the transportation time distance to the central urban area and different types of transportation hubs.

3. Road Density

Traffic network density is an important indicator for evaluating the level of support of regional transportation infrastructure, reflecting to a certain extent the regional development support capability and a manifestation of traffic supply capacity. It is defined as the absolute ratio of the length of transportation routes to the land area of the region. The higher the traffic network density, the stronger the region's reliance on social economy and external connections, the stronger the economic guarantee capability of the region, meaning the better the traffic facility conditions of the area [39–41].

Let the traffic network density of the region be D , the total length of road routes be L , and the land area of the region be A , then the traffic network density formula, taking the road network as the main subject of the traffic network density evaluation, is:

$$D = L / A \quad (1)$$

where D is the traffic network density (km/km²), L is the total mileage of road routes within the grid unit (km), and A is the neighborhood area of the grid unit (km²).

The calculation of traffic dominance needs to integrate the results of the calculations for the influence degree of trunk lines, spatial accessibility, and traffic network density to obtain a composite evaluation value as follows:

$$S = \sum_{i=1}^n B_i W_i \quad (2)$$

where S is the composite evaluation value for the evaluation unit, B_i are the normalized values for the influence degree of trunk lines, spatial accessibility, and traffic network density, and W_i are the weight values of the three indicators.

4. Weight Allocation

The analytic hierarchy process (AHP) is a decision analysis method that combines quantitative and qualitative analyses. Using the AHP method, complex problems can be decomposed into several levels and factors. The relevance and membership relationship of the factors involved in the evaluation are calculated. Through pairwise comparisons, a comparison matrix is constructed to determine the relative importance of each factor within the hierarchy structure. Then a judgment matrix is built to determine the weights of various elements, thus providing a basis for the selection of decision-making schemes.

Therefore, using the AHP, this paper builds a static traffic volume dominance evaluation model by classifying and assigning values to the above-mentioned indicators (Figure 3).

2.3.2. Dynamic Indicator Model of Complex Network

If all trips within a city are abstracted as connections between origins and destinations, an abstract network can be constructed. By analyzing this network, we can obtain information on the spatial connection structure of the entire city and the macro travel characteristics of the population. Therefore, this paper establishes three types of transportation networks for bike-sharing, taxis, and subways, which include nodes (bike-sharing points, taxi stands, subway stations) and the edges that connect them (each trip). If there is a link between two nodes, they are defined as neighbors. This paper abstracts the three transportation networks into a connected network graph $G = (N, E)$, N is the set of nodes, E is the set of edges, which is necessary for computing the macroscopic and nodal parameters of the network, as described below (Figure 4).

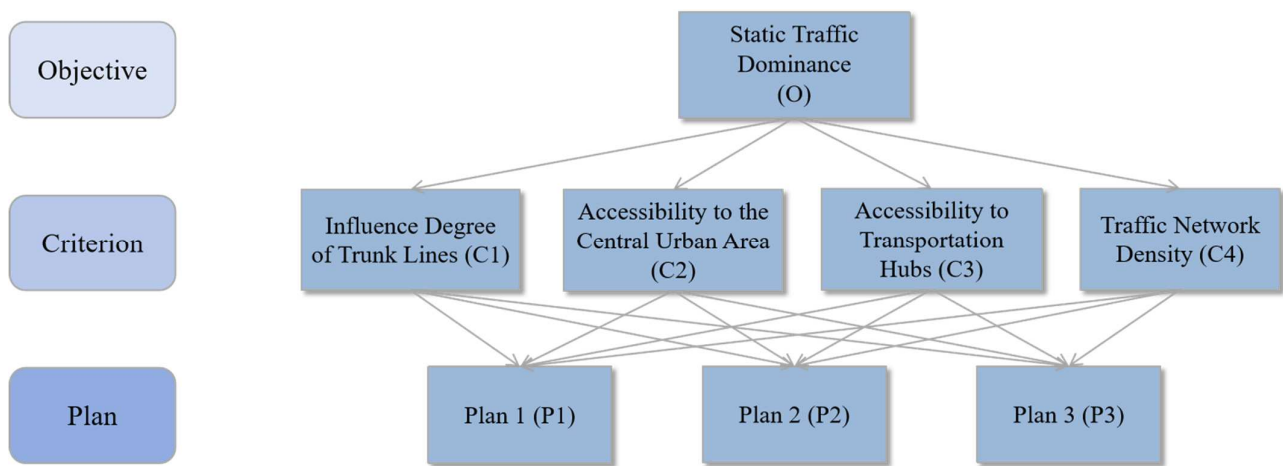


Figure 3. Analytic hierarchy process modeling process.

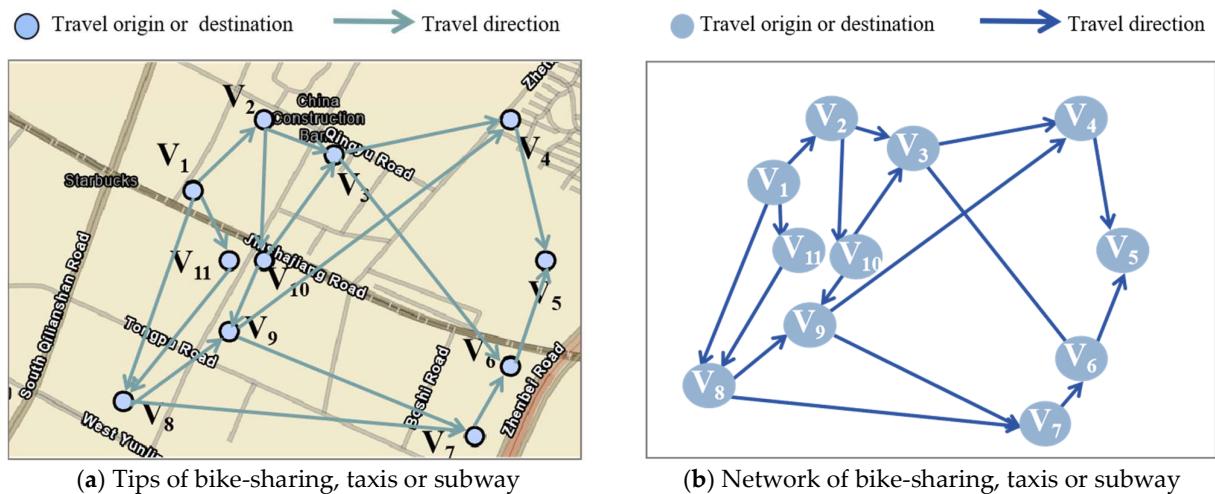


Figure 4. Constructions of transportation network.

1. Macroscopic Characteristics of the Traffic Network

The dynamic indicators reflecting traffic dominance are extracted from the constructed transportation network, thus bearing the characteristics of complex networks and general spatial constraints [42]. In this section, we analyze the traffic network from a macroscopic statistical perspective, mainly to analyze the topological structure characteristics of the network. Specific indicators are as follows:

(1) The number of nodes (N) and the number of edges (E).

(2) Degree: The degree of a node represents the number of nodes connected to that node, indicating how many regions are directly connected to any given region. The degree reflects the topological importance of the node in the network. It can be classified as out degree (k_i^{out}) and in degree (k_i^{in}). The degree of the network is $k_i = k_i^{in} + k_i^{out}$.

This paper uses two indicators: average degree (AD) and average weighted degree (AWD).

(3) Network density (ND): The ratio of the actual number of edges in the network (n) to the maximum possible number of edges (e), used to indicate the overall connectivity within the network.

$$ND = \frac{n}{e} \quad (3)$$

(4) Average clustering coefficient (C): A fraction value obtained by dividing the actual number of edges by the maximum possible number of edges, defined as the clustering

coefficient of this node. It measures the tendency of nodes in the network to cluster together [43]. The calculation formula for C is as follows:

$$C = \frac{2E_i}{k_i(k_i - 1)} \quad (4)$$

where k_i is the number of the directed neighbors of node i , and E_i is the number of actual connections among these k_i nodes.

(5) Average path length (AL): A concept in network topology, defined as the average number of steps along the shortest path for all possible pairs of network nodes. The calculation formula for AL is as follows:

$$AL = \frac{1}{N(N-1)} \sum_{i \neq j} d_{ij} \quad (5)$$

where N represents the number of the nodes, $\sum_{i \neq j} d_{ij}$ is the minimum number of edges from node i to node j .

2. Nodal Parameters of the Network: Indicators of Dynamic Traffic Dominance

To further study the dynamic characteristics of the network, this section considers related network nodal parameters. Nodes with high centrality are often traffic hubs bearing more daily travel activities, which is beneficial for us to dissect the characteristics of urban flow and urban structure [44].

Betweenness centrality (BC), which has been a key indicator in network analysis to assess the importance of edges in the network [45–47], is a measure of centrality in a graph based on shortest paths and is used in transportation networks to reflect transitivity [48]. The road segments with high betweenness centrality have a greater impact on the volume of traffic. Therefore, betweenness centrality is considered an important indicator for understanding traffic patterns and inferring traffic volumes [49]. To measure the mediating role of paths in the traffic network, considering the variability and directionality of travel flows in different segments due to geographical location and mode of transport, we use this indicator. The higher the betweenness centrality, the more important the role of the node in connecting the shortest paths between other nodes. For directed graphs, it is defined as:

$$BC(i) = \sum_{j \neq i \neq k \in N} \frac{\sigma_{jk}(i)}{\sigma_{jk}} \quad (6)$$

where $BC(i)$ is the betweenness centrality of node i , σ_{jk} represents the number of shortest paths from source node j to target node k , $\sigma_{jk}(i)$ represents the number of those paths passing through node v_i , and N is the number of nodes in the network.

Considering the characteristics of the spatial interaction network formed by daily travel flows, as well as the variability and directionality of travel flows between spatial units, we use Degree Centrality to quantify the importance of different traffic network nodes [50]. The higher the degree of centrality, the more routes pass through the station, and the more trips the station has [51]. The calculation formula for degree centrality is as follows:

$$DC(i) = \sum_{j=1}^N a_{ij} \quad (7)$$

where $DC(i)$ is the degree centrality of node i , a_{ij} represents the number of edges connecting node i to node j , and N represents the total number of nodes contained in the network.

However, due to the vast differences between different travel flows, the network patterns of different transportation modes will vary. Betweenness centrality focuses on the intermediary status and transmission efficiency of nodes in the network, while degree centrality is more concerned with the degree of direct connections of nodes and the structural

features of the network. Therefore, the relative importance between nodes cannot be fully reflected by absolute betweenness centrality and degree centrality. To solve this problem, we use the entropy weight method to weigh the two, resulting in relative weighted centrality (RWC), which enables meaningful comparisons of the relative importance of nodes in different transportation networks. The calculation formula for RWC is as follows:

$$RWC(i) = \alpha BC(i) + \beta DC(i) \quad (8)$$

where $RWC(i)$ is the relative weighted centrality of node i , α represents the weight of betweenness centrality of node i , and β represents the weight of degree centrality of node i .

RWC stands as a weighted nodal metric that uniquely incorporates the dynamic fluctuations in traffic patterns, a facet often overlooked in conventional static traffic dominance models. By integrating both betweenness centrality and degree centrality, it offers insights into the varying degrees of traffic dominance across different times, reflecting the mobility inherent in travel behavior. This nuanced perspective enables clearer observations of temporal shifts in traffic dynamics, thereby offering valuable insights for the strategic planning of infrastructure layouts, promoting the sustainable development of urban transportation systems.

3. Community Modularity Weighted Calculation for Community Structure Detection

Community detection is the identification of community structures within a network through algorithms, i.e., collections of nodes with close connections, to discover the travel characteristics and needs of different communities in the city, providing support for refined traffic management and services. Modularity refers to the proportion of edges within the community structure in the network, minus the expected value of randomly connecting the two nodes within the same community structure [52]. The goal of community partitioning is to make the connections within the divided community tight while the connections between communities are sparse. Modularity can depict the quality of such divisions; the larger the modularity, the better the community partitioning effect. In this paper, the result of this algorithm is many communities, each containing similar bike-sharing/taxi/subway travel OD flow data. Therefore, for our network, modularity can be calculated as follows:

$$\Delta Q = \left[\frac{\sum_{in} + 2k_{i,in}}{2m} - \left(\frac{\sum_{tot} + 2k_i}{2m} \right)^2 \right] - \left[\frac{\sum_{in}}{2m} - \left(\frac{\sum_{tot}}{2m} \right)^2 - \left(\frac{k_i}{2m} \right)^2 \right] \quad (9)$$

where $\sum_{in}$ represents the sum of all edge weights within community C (the inverse of the average distance in the network), $\sum_{tot}$ is the sum of the weights of edges connected to the nodes in C , k_i represents the total weight of edges connected to node i , $k_{i,in}$ is the total weight of edges from i to the nodes in C , and m is the total weight of the network.

3. Results

3.1. Evaluation and Analysis of Static Traffic Dominance

The road network is meticulously crafted through the cleaning and classification of OpenStreetMap (OSM) data, tailored to the specific circumstances of Shanghai's road infrastructure. This requires discerning and organizing the data to create an accurate representation of the road network. Subsequently, utilizing the traffic condition impact assessment model established by this study, the degree of influence of major roadways and spatial accessibility is determined, which includes the accessibility of central urban areas (Figure 5a) and transportation hubs (Figure 5b–f).

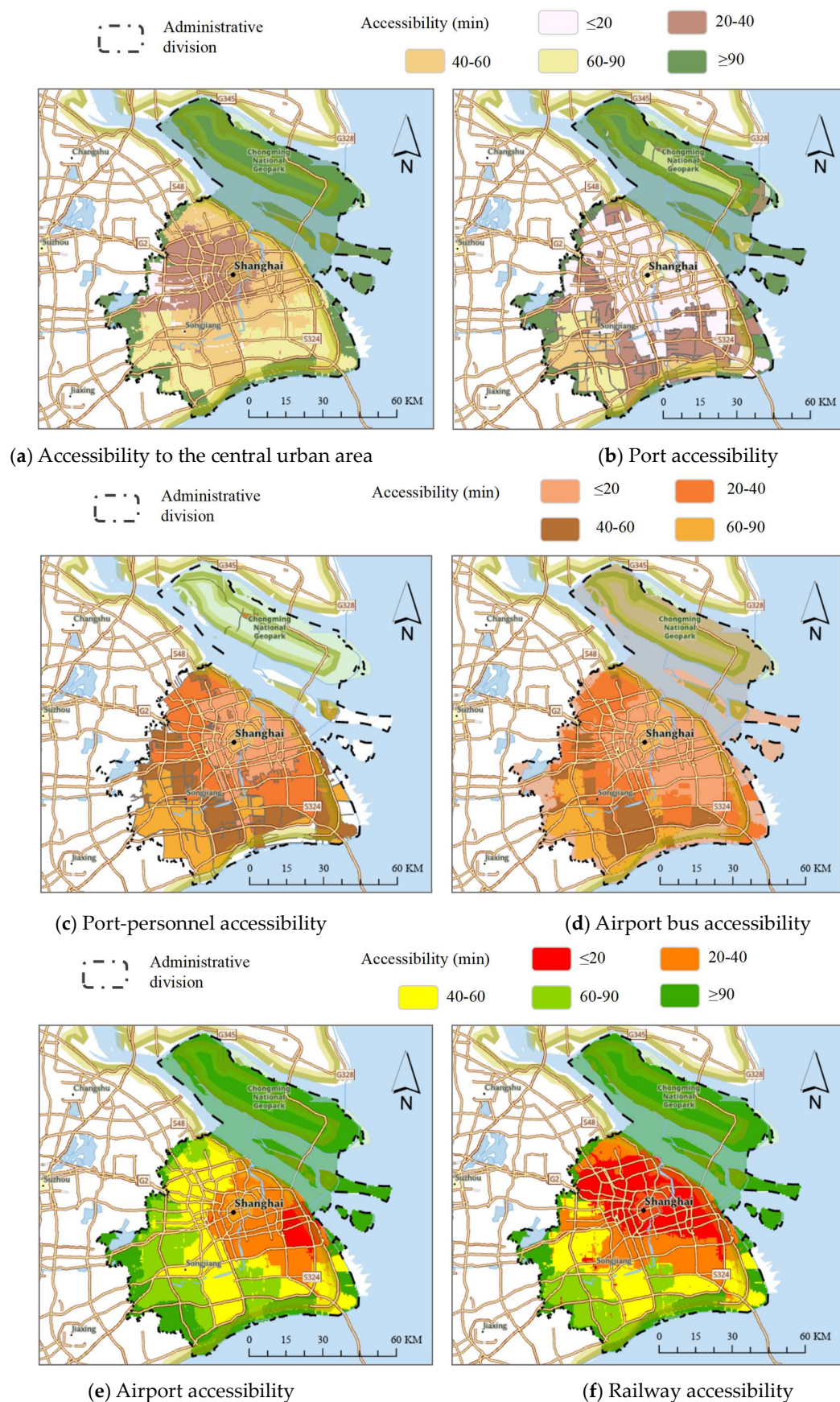


Figure 5. Calculated results of accessibility.

Shanghai has two central urban districts according to the “Shanghai City Master Plan (2017–2035)”: the main urban district and the new urban district. The main urban district encompasses Shanghai’s core functions and population, while the new urban district is an emerging area in the city’s development requiring more transportation and infrastructure support. The new urban district covers areas such as Nanhui, Fengxian, Songjiang, Qingpu, and Jiading, whose accessibility directly relates to the ease of transit in the city’s future planning of core functional areas. Most regions are within 60 min of reach, but there are still a few districts where the transit time exceeds 60 min, and in some cases, even 90 min. Therefore, ensuring optimal accessibility in these areas is essential for future urban planning, particularly to enhance the convenience of transportation in Shanghai’s core functional areas.

Figure 5b–f vividly depicts the accessibility of transportation hubs, detailing the spatial distribution of accessibility for ports, port-passenger traffic, airport buses, airports, and railways. Here, port-personnel refers to docks and ferry stations related to personnel at the ports; airport-bus refers to the bus stations served by airport buses. As observed from Figure 5c,d, these two types of accessibility are spatially dispersed. These transportation hubs hold strategic importance for the overall development of the city, and their accessibility plays a crucial role in facilitating the growth of logistics, tourism, and business.

According to the traffic network density model established in this paper, by employing a grid unit of $1 \text{ km} \times 1 \text{ km}$ for statistical and visualization purposes, the traffic network density of Shanghai is presented as shown in Figure 6. It exhibits the distribution of traffic network density across different districts and counties of Shanghai. The core areas display a high density of the traffic network, reflecting their busy traffic activities and efficient transportation system. Meanwhile, the peripheral areas have relatively lower traffic network density, showing a clear spatial gradient. Multiple factors, including land use structure, urban planning, and population distribution, influence this distribution characteristic. The core areas, due to the concentration of various functions such as economic and cultural activities, have a large traffic demand, thereby forming a high-density traffic network. In contrast, the peripheral areas have fewer functional zones, lower population density, and consequently, a lower traffic network density.



Figure 6. Calculated results of road density.

The static traffic dominance of Shanghai has been evaluated using the analytic hierarchy process (AHP). The results (Figure 7) indicate an uneven spatial distribution of static traffic dominance levels across the city’s districts, presenting a “core-periphery” spatial pattern. This distribution reflects the uneven development of Shanghai’s transportation system in different regions, with the central urban area and key commercial districts possessing relatively higher traffic dominance, while peripheral areas exhibit relatively lower levels.

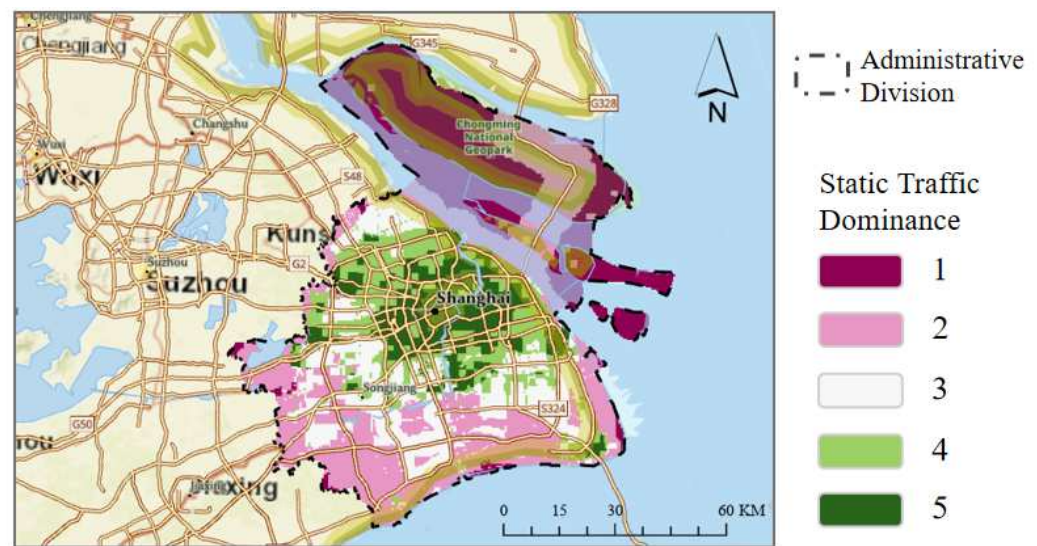


Figure 7. Evaluation of static dominance.

3.2. Evaluation and Analysis of Dynamic Traffic Dominance

3.2.1. Analysis of Network Macroscopic Parameters

In this section, we systematically analyze the macroscopic characteristic parameters of networks formed by three modes of travel (bicycles, subways, and taxis) to gain an in-depth understanding of their operational characteristics and network performance across different periods. Table 3 lists seven macroscopic characteristic parameters for these modes of travel, including the number of nodes (N), the number of edges (E), average degree (AD), average weighted degree (AWD), network density (ND), clustering coefficient (C), and average path length (AL). Our results show that for network connectivity, the subway indicators (except for the number of nodes N) are higher than those for bike-sharing and taxis. This indicates that Shanghai's subway transit system is more developed and complete, with more residents using this mode of travel. Taxis come next, followed by bike-sharing.

Table 3. Traffic network parameter calculations.

Period	N (Nodes)	E (Edges)	AD (Avg Degree)	AWD (Weighted Avg Degree)	ND (Network Density)	C (Clustering Coefficient)	AL (Avg Path Length)
Bike network parameters							
0:00–6:00	50	45	1.800	0.037	0.018	0.030	0.323
6:00–12:00	116	294	5.069	0.044	0.022	0.108	0.363
12:00–18:00	121	314	5.190	0.043	0.022	0.105	0.427
18:00–24:00	135	416	6.163	0.046	0.023	0.116	0.320
Subway network parameters							
0:00–6:00	169	7663	90.686	0.540	0.270	0.484	1.717
6:00–12:00	169	25,040	296.331	1.764	0.882	0.912	1.124
12:00–18:00	169	24,741	292.793	1.743	0.871	0.909	1.134
18:00–24:00	169	21,096	249.657	1.486	0.743	0.849	1.263
Taxi network parameters							
0:00–6:00	365	2702	14.805	0.041	0.020	0.185	0.630
6:00–12:00	558	6420	23.011	0.049	0.025	0.206	0.797
12:00–18:00	527	6793	25.780	0.049	0.025	0.263	0.657
18:00–24:00	495	6747	27.261	0.056	0.028	0.282	0.610

In the bike-sharing network, nearly all indicators (except for average path length AL) show an increasing trend throughout the day and reach their highest values from 18:00–24:00. Conversely, the average path length AL shows the lowest value of the day in

this time slot, at 0.320, indicating that during this period, people use bike-sharing most frequently, and the commuting distances are the shortest. Observing the subway network's macroscopic parameters, ND values are highest during 6:00–12:00 and 12:00–18:00, which correlates significantly with the number of subway trips. However, from 0:00–6:00, the ND value is the lowest at 0.270, suggesting poor connectivity between subway nodes during this period: When the subway is not operational, the subway traffic network's connectivity significantly drops. The taxi network's AWD and ND values remain unchanged from 6:00–12:00 and 12:00–18:00, at 0.049 and 0.025, respectively, indicating a certain symmetry in residents' travel activities during these periods. At night, the values of AD, AWD, ND, and C all peak from 18:00–24:00, reflecting an increase in residents' travel activities.

Comparing the three modes of transport, the subway has the highest clustering coefficient, with values above 0.8 except during the early morning non-operational hours. This indicates a high degree of connectivity and clustering among most nodes in the subway network, outperforming bike-sharing and taxis. The subway's AL value is the longest, above 1.0, meaning that the spatial distribution of nodes in the subway network is more dispersed, and residents need a transfer node to reach their destination, often facilitated by using bike-sharing or taxis. We found that although most indicators for these two modes show clear differences during the 0:00–6:00 time slot compared to the other three, the AL values do not change much, suggesting that certain modes of travel correspond to specific commuting lengths, typically unaffected by time. By analyzing network macroscopic parameters, we can gain a deeper understanding of the operational characteristics and network structures of different modes of travel, thereby providing a comprehensive view for subsequent assessments of dynamic traffic dominance.

3.2.2. Analysis of the Importance of Network Nodes

Using the degree centrality and betweenness centrality discussed in Section 2.3.2, weighted by the entropy weight method, we calculate the importance of Shanghai's traffic network nodes, represented by the relative weighted centrality (RWC). Here, we believe that the importance of traffic network nodes can largely define the traffic dominance of that area. We use Jenks natural breaks method to categorize RWC into five levels, 1–5, and the importance of traffic network nodes and traffic dominance increasing correspondingly. The spatial distribution of RWC for bike-sharing, subways, and taxis during the four-time slots of 0:00–6:00, 6:00–12:00, 12:00–18:00, and 18:00–24:00 is shown in Figures 8 and 9. Overall, we can observe from the figures that the importance of different traffic nodes presents a significant polycentric hierarchical pattern. At the same time, there are several high-level important nodes in the network of each transport mode, but as the importance increases, their number gradually decreases, with most network nodes being of low importance (level 3 and below). All three have similar spatial distribution characteristics, exhibiting a core-periphery structure.

From Figures 8–10, the importance distribution of bike-sharing network nodes is relatively small, concentrated in the center of Shanghai. This is because the use of bike-sharing is mainly influenced by the spatial distribution of corresponding facilities (such as bike parking spots), so its transportation network exhibits strong spatial dependency. Moreover, the node importance from 0:00–6:00 is noticeably lower than the other three time slots, and with the progression of time within the day, the overall value of RWC shows an initial increase followed by a decrease. From 12:00–18:00, the number of highly important nodes within the central city is the most, indicating that the bike-sharing network has formed high-level clusters.

The subway transportation network's node distribution shows a high degree of concentration in the center of Shanghai and radiates towards the suburbs, becoming more dispersed towards the city outskirts. From 0:00–6:00, the importance of nodes in peripheral areas is almost zero, but the central area still has a few important nodes. This is because the subway's operational times differ between areas based on passenger flow and travel demand, with subways in the city center generally operating longer hours than those in the

suburbs. From 6:00–12:00 and 12:00–18:00, apart from the characteristic of a higher number of high-importance nodes, the shape, and values of subway node importance distribution are very similar, indicating a strong symmetry in the use of this transport system during these periods.

The distribution of taxi RWC is characterized by a large area with low importance overall. It spreads outwards in concentric circles to the edges of Shanghai and is the only type among the three modes of transportation, with a small number of nodes distributed in the Chongming area. From 6:00–12:00, the node distribution is the widest and the degree of importance is higher. By 12:00–18:00, the distribution range does not change much, but the degree of importance decreases. During the 18:00–24:00 period, the central city compared to peripheral areas experiences more human activity, producing a certain polarization effect, enhancing the importance of nodes as they cluster towards the center.

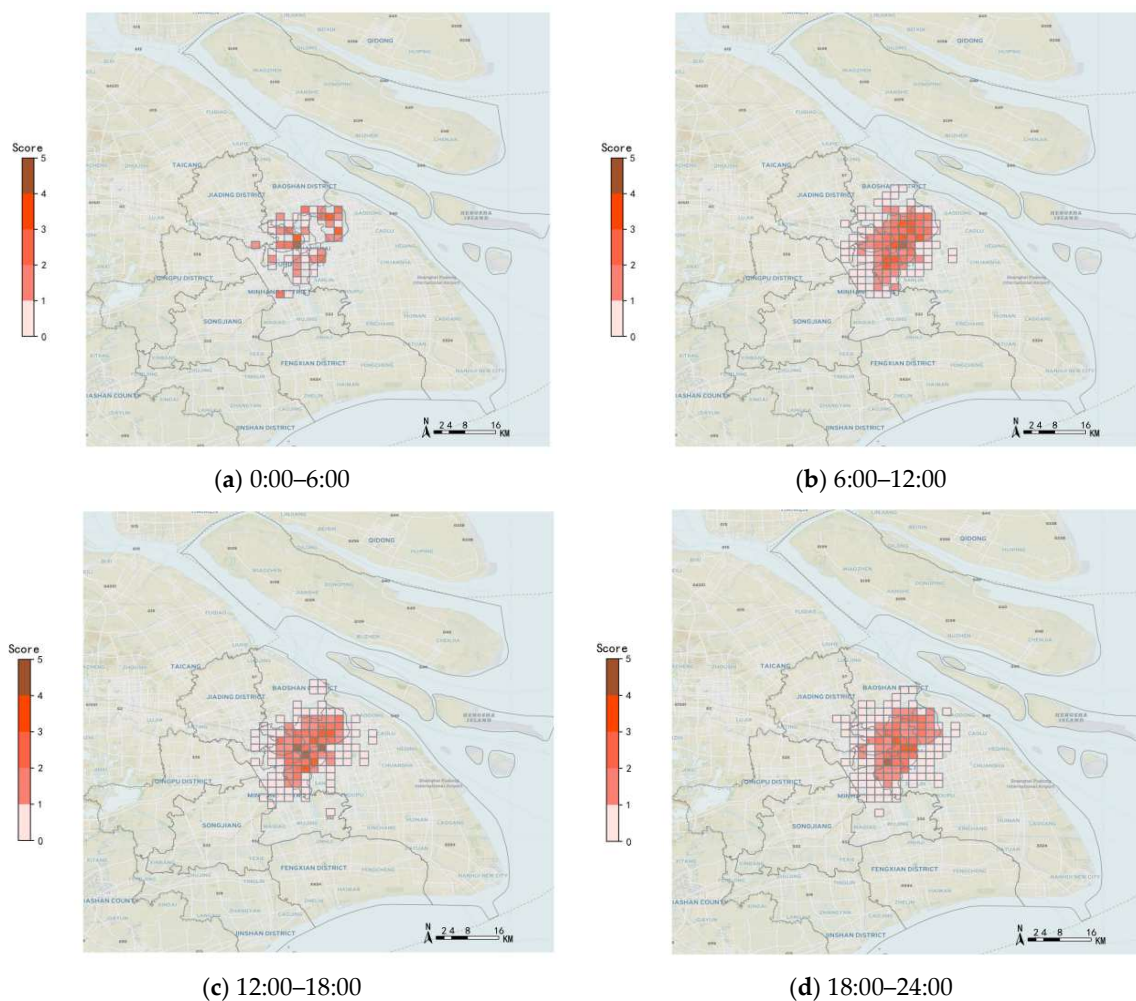


Figure 8. Bike-sharing.

During the 0:00–6:00 period, the RWC distribution pattern for bikes differs greatly from other periods, with significant changes in the quantity of traffic dominance and spatial shape; for the subway network, the RWC value during this period decreases significantly, but the spatial shape remains almost unchanged. Meanwhile, taxis change between bikes and subways. From 6:00–12:00, the node importance of all three modes of transportation rises to a considerable degree, and the spatial shapes of taxis and bicycles significantly expand. By 12:00–18:00, the spatial patterns and node importance of the three modes of transportation remain nearly consistent with the previous period. During the evening period of 18:00–24:00, the spatial shape of the taxi network slightly contracts compared to bike-sharing and subways, and the importance of subway nodes decreases more notice-

ably. These changes effectively demonstrate the characteristics and temporal evolution of Shanghai's dynamic traffic dominance patterns.

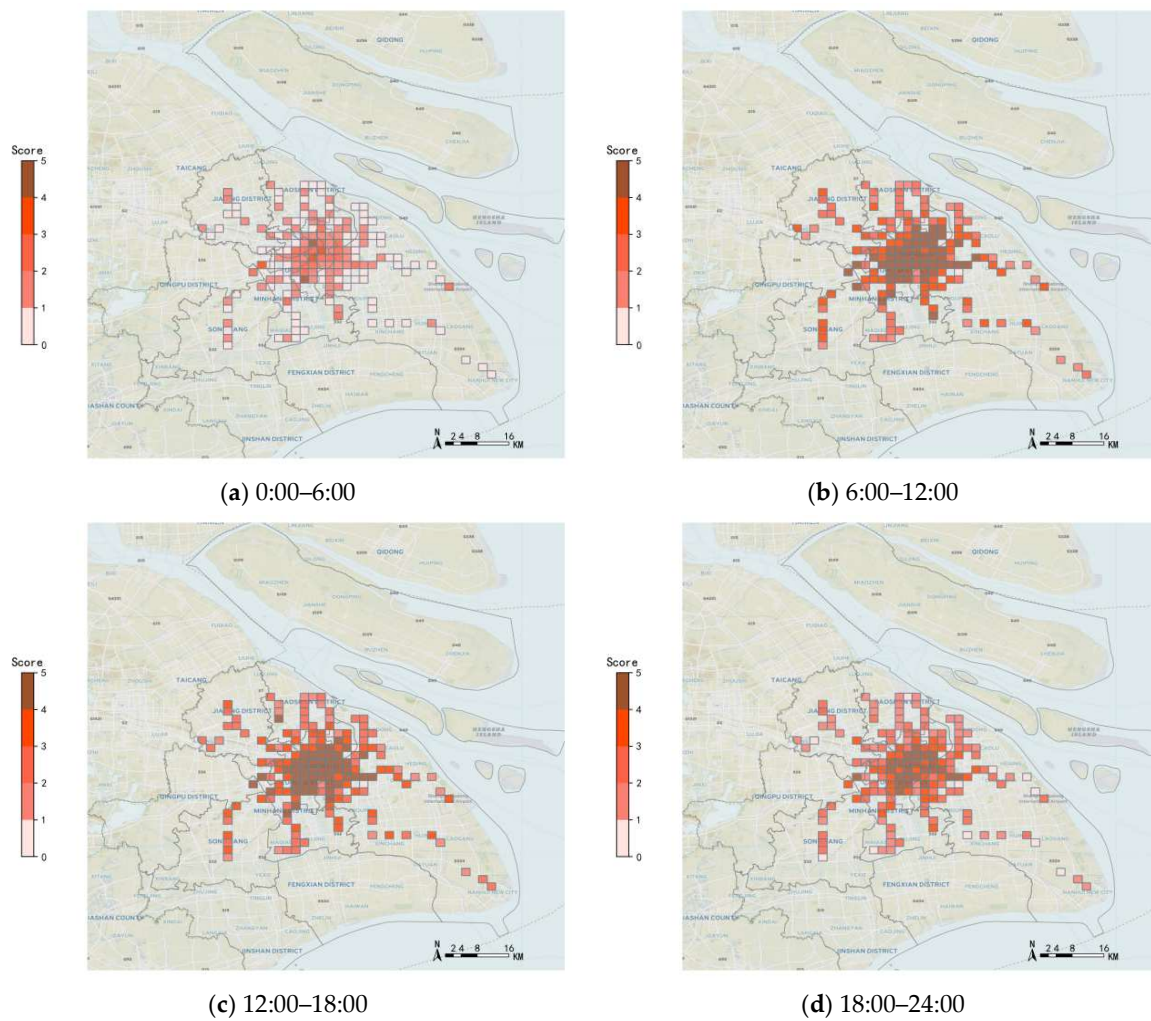


Figure 9. Subway.

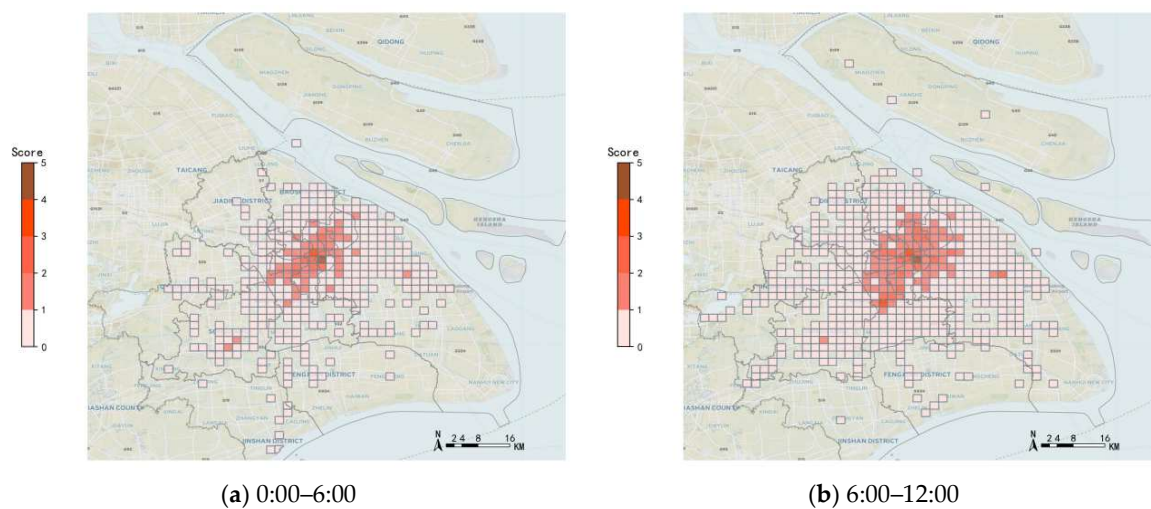


Figure 10. Cont.

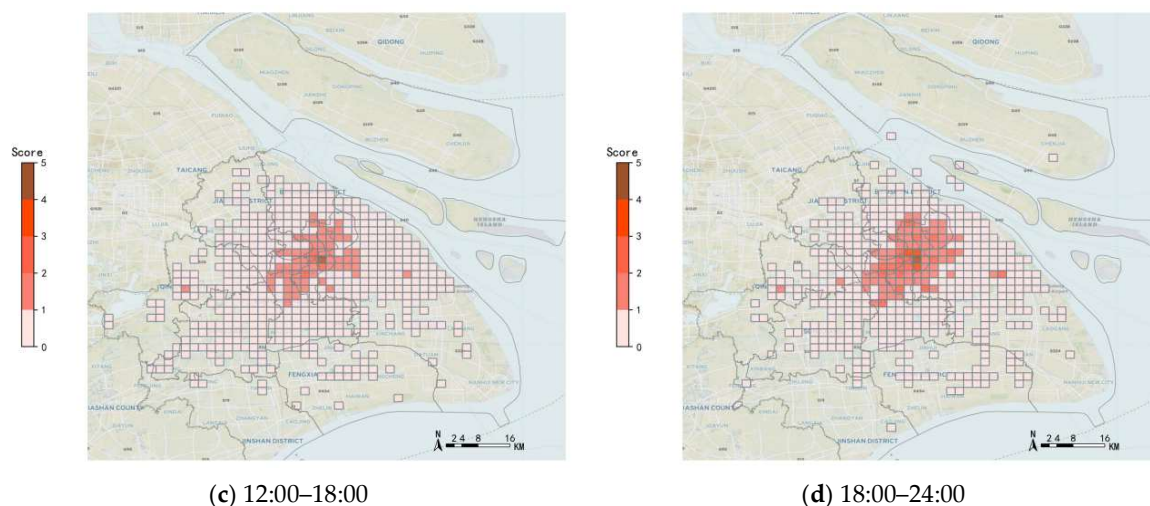


Figure 10. Taxis.

Figures 8–10 Distribution of network node importance for bike-sharing, subway, and taxis across different periods.

3.2.3. Community Modularity Weighted Calculation Analysis

Urban traffic networks possess community structure characteristics, and the detection of these community structures is crucial for deeply understanding the characteristics of subway, taxi, and bike-sharing networks. We can identify and delineate communities within these networks through relevant algorithms in complex networks, thereby revealing the interactions and relationships between different modes of transportation.

Overall, the community modularity of bike-sharing traffic is greater than that of taxi traffic, which is greater than that of subway traffic. The subway network exhibits the highest clustering coefficient but the lowest modularity value. These indices suggest that the community structure in the subway network is not prominent, with relatively weak internal community connections. However, this also indicates relatively strong connections between different communities, possibly due to Shanghai's uneven distribution of office areas and residential areas and the need for long-distance commuting. In contrast, the bike-sharing network shows the lowest average clustering coefficient and the highest modularity, indicating better community connectivity. This means that bike-sharing is most efficient when distances between nodes are short. The taxi network falls between these two, with relatively close connections between nodes. From a temporal perspective (Table 4), the community modularity values for all three types of transport are highest from 0:00–6:00, attributed to the predominance of short-distance commuting behaviors during early morning hours, which strongly feature community structure characteristics. From 6:00–12:00 and 12:00–18:00, which are daytime hours, the community modularity of the same type of transportation often appears very similar due to the symmetric nature of morning and afternoon commuting behaviors. The modularity values for bike-sharing and taxi networks from 18:00–24:00 do not show significant changes compared to the daytime, indicating that human activities are also quite active in Shanghai at night.

Table 4. Network community modularity calculations.

Period	Bike-Sharing Network	Subway Network	Taxi Network
0:00–6:00	0.930	0.066	0.370
6:00–12:00	0.729	0.029	0.319
12:00–18:00	0.692	0.026	0.331
18:00–24:00	0.673	0.040	0.299

3.3. Analysis of Comprehensive Traffic Dominance Results

This study primarily focuses on the traffic dominance of Shanghai. In the methods described above, not only do we use a traditional traffic dominance model based on static road network data, but we also employ dynamic OD data, considering centrality as the standard for measuring the importance of traffic networks, where a higher level indicates better traffic dominance. However, using either method alone does not comprehensively assess traffic dominance in the study area. Therefore, in this section, we overlay the results obtained from the two models above on a one-to-one basis to analyze and evaluate the comprehensive transportation advantage. By doing so, we consider the distribution pattern of static transportation advantages in the traditional sense and incorporate the dynamic aspect of population mobility as an innovative element. The outcomes of the static model are illustrated in Figure 11, while the combined results are depicted in Figure 12. The results of the comprehensive transportation advantage are classified into five levels, corresponding to the lowest, lower, medium, higher, and highest degrees, respectively.

Overall, the spatial distribution pattern of comprehensive traffic dominance remains largely unchanged, primarily due to the use of static indicators by the traditional model. During the 0:00–6:00 period, comprehensive traffic dominance is the lowest among the four time periods. High-level nodes are sporadically distributed within the city center, with fewer nodes at levels 4 and 5. From 6:00–12:00, there is a noticeable increase in the number of higher-level traffic dominance nodes within the Shanghai metropolitan area, indicating an increase in population flow at this time. By 12:00–18:00, the comprehensive traffic dominance in the city area shows slight changes in spatial distribution and the number of high-level nodes compared to the morning. In the 18:00–24:00 period, the number of high-level nodes decreases compared to daytime.

It is noteworthy that areas such as Jiading, Baoshan, Pudong New Area, Minhang, Qingpu, Songjiang, Fengxian, and Jinshan exhibit strong traffic dominance in the traditional traffic dominance assessment model. However, this advantage diminishes when dynamic indicators are incorporated. Observing the four time periods of the day, we find that changes in comprehensive traffic dominance are concentrated in bustling urban areas. These areas are hubs for office, commercial, residential, and entertainment functions, where people's activities during different times.

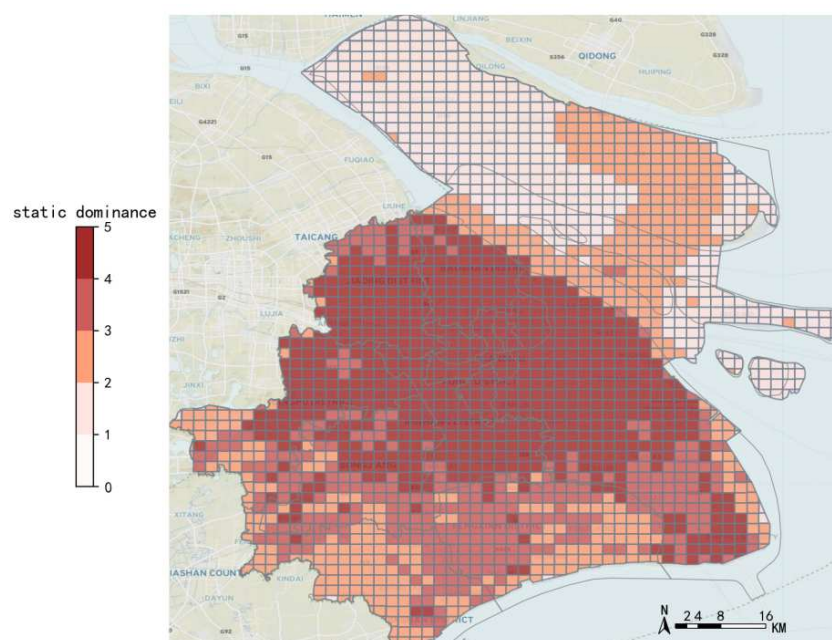


Figure 11. Static traffic dominance.

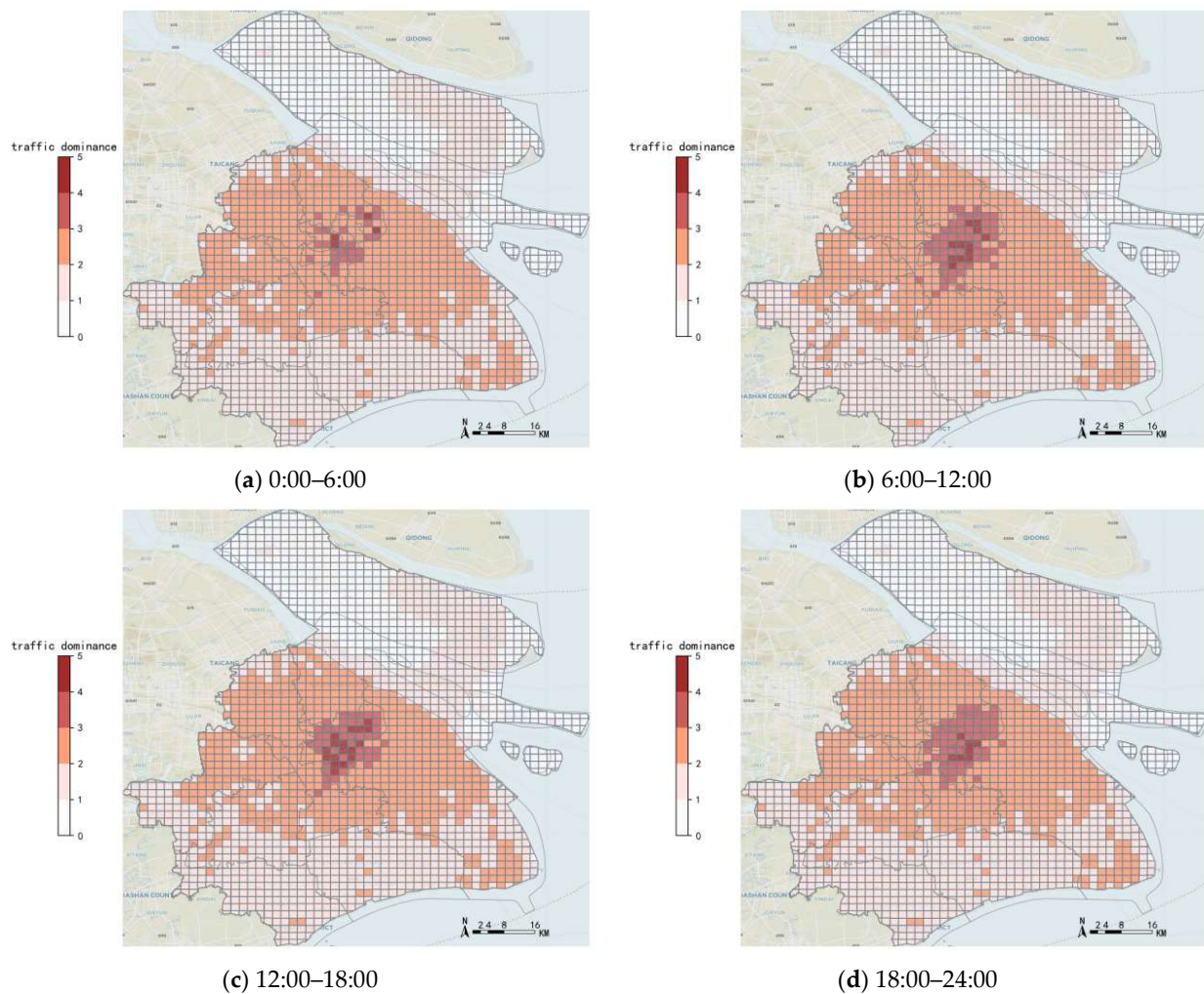


Figure 12. Comprehensive traffic dominance.

4. Discussion

4.1. Urban Traffic Dominance: Conceptual Framework, Indicator System, and Assessment Method

This study integrates static and dynamic spatiotemporal data to establish an evaluation model for urban traffic dominance, aiming to enhance our understanding of Shanghai's transportation network system. Unlike previous studies, which focused on static data to analyze the relationship between traffic dominance and its influencing factors or mechanisms in a specific area and overlooked the impact of human mobility [40,53–55], our approach uses complex network theory applied in transportation systems. We have selected nodal centrality indicators that represent the dominance of urban transportation systems, emphasizing the impact of dynamic human travel behaviors on regional traffic dominance. This conceptual framework combines traditional and dynamic models to create a comprehensive urban traffic dominance assessment framework, reflecting Shanghai's traffic dominance from different perspectives and providing a new theoretical view and analytical method for local government transportation system studies.

Previous studies at national, provincial, and urban agglomeration levels used data from Geographic Information Bureaus and Departments of Transportation to conduct studies on traffic dominance with statistically impactful multi-year traffic advantage assessments [3,12,39,56]. Recognizing the complex interplay between urban transportation structures and human mobility, previous studies faced temporal sensitivity barriers, i.e., they lacked dynamic analysis of traffic dominance at different times, making it difficult for urban planners and traffic managers to control urban traffic and devise optimal decision-

making strategies effectively. Our study uses multiple data sources, including road network data, points of interest (POI) data, and dynamic OD data, to compute macroscopic characteristics (e.g., average degree, network density, clustering coefficient, etc.) and nodal parameters (degree centrality and betweenness centrality) of the network, effectively depicting the spatiotemporal variations, distribution characteristics, and patterns of traffic dominance in Shanghai.

4.2. Spatiotemporal Changes, Distribution Characteristics, and Patterns of Traffic Dominance in Shanghai

Over a 24 h period, Shanghai's static, dynamic, and comprehensive traffic dominance all exhibit a "core-periphery" spatial structure. Our empirical study in the international metropolis of Shanghai reinforces the importance of networks formed by human activity trajectories in assessing local traffic dominance.

Related studies have assessed regional static traffic dominance [7–10], but our research integrates multisource spatiotemporal big data to establish a traffic dominance evaluation model considering population flow impacts at different times of the day, thus enhancing our understanding of the daily variations in Shanghai's traffic dominance. We found that the city center's functional areas show the most significant changes in dynamic dominance throughout the day, also being the areas with the highest values of dominance. Indeed, Shanghai's city center, particularly around Huangpu District and extending to the periphery, such as Xuhui, Jing'an, and Hongkou districts, has a high population density and is a major hub for logistics, information, capital, and technology flows, carrying significant economic, political, and cultural functions for the city. This area is economically advanced, has better infrastructure resources compared to peripheral areas, and features the most representative landscapes and vibrant commercial districts. Important nodes are more likely to overlap with areas having a high degree of land use function mixing [57]. Administrative districts such as Qingpu, Songjiang, Jinshan, and Fengxian exhibit lower population density and less vibrant economic activity compared to the central urban areas. Consequently, there is a reduction in the frequency of behavioral activities related to work, consumption, and leisure purposes. Additionally, longer commuting distances serve as a significant impediment to population mobility. Thus, these conditions foster the distribution and changing patterns of dynamic traffic dominance in the region, similar to observations from previous studies [48,58]. For this area, we recommend adopting a compact development approach dominated by public transport, focusing on regional transport network nodes to form "small yet complete" communities, thereby achieving harmony between resident travel and urban traffic.

Meanwhile, different modes of transport have peak periods of highest network node importance. While previous studies have focused on some aspects of dynamic evaluation in cities [59–61], research on traffic dominance is still scarce. Bike-sharing shows the highest network node importance from 12:00–18:00, subways exhibit strong traffic dominance from 6:00–18:00, and taxis have the highest number of higher-level traffic nodes from 18:00–24:00. Local governments and transportation departments should devise and implement strategies based on the usage of different modes of transport at different times to ensure the city's transportation capacity can help maintain relative stability. For example, from 12:00–18:00, shared bikes could be strategically placed, performing macro-control on bicycles that are less used but widely distributed, concentrating them around nodes of high traffic importance to achieve efficient resource utilization. Overall, the study's observation of distinct centrality patterns for shared bicycles, subways, and taxis at different times of the day suggests the potential for optimizing public transit schedules and infrastructure to meet fluctuating demand, thereby reducing congestion and emissions. Understanding these variations can lead to more efficient allocation of resources and improved service quality, contributing to a more sustainable urban transport system.

4.3. Limitations and Prospects

Although this paper uses multisource spatiotemporal data to construct indicators for assessing traffic dominance in Shanghai, it is still limited by incomplete data collection. We only used dynamic OD data for shared bicycles, subways, and taxis, while actual travel involves many more types of transport, such as buses and private cars. Many residents commute using these modes, but due to socioeconomic conditions and privacy concerns, it is difficult to obtain relevant data. This may lead to uncertainties in the general patterns of the study results.

Furthermore, when assessing comprehensive traffic dominance, we adopted a method of weighting static and dynamic traffic dominance equally at 1:1. However, this weighting method is somewhat scientifically insufficient because the importance of static and dynamic traffic dominance is hard to match exactly. Therefore, how to effectively assess comprehensive traffic dominance remains a subject for further in-depth study and discussion.

This paper primarily underscores the profound influence of the network shaped by human activity trajectories on evaluating the extent of local traffic dominance. However, the study predominantly concentrates on mobility behaviors alone, neglecting the functional aspect of origin points. Individuals often move with specific purposes tied to the functionality of a location, such as employment, recreation, or consumption. This appears to be inadequately considered.

To improve model accuracy, it is recommended that future research refine the weight distribution of static and dynamic indicators to achieve more realistic assessment results. Further incorporating functional classification factors can comprehensively consider the characteristics and patterns of comprehensive traffic dominance with greater practical significance, thus optimizing the use of traffic resources and promoting harmony between humans and the environment. The research methodology presented in this paper can be extended to studies in other cities, not only helping to explore the spatial structure of human mobility and urban transportation but also holding significant policy guidance significance.

5. Conclusions

In this study, we focused on Shanghai as our research area, using the analytic hierarchy process (AHP) to conduct a weighted evaluation of static traffic dominance based on the impact of main traffic arteries, spatial accessibility, and traffic network density. We then utilized road networks, three types of spatiotemporal traffic trajectories, points of interest (POI) data, and multisource geographic data. Based on complex network theory and employing community detection modular algorithms, we established a framework for assessing dynamic traffic dominance. Finally, by weighting and overlaying static traffic dominance and dynamic traffic dominance on a 1:1 basis, we developed a comprehensive traffic dominance model for the region. Our findings are summarized as follows:

1. In the static traffic dominance indicator system, the accessibility of new urban areas in Shanghai is low relative to the accessibility of the main urban areas. For transportation hubs, infrastructure accessibility such as terminals in ports and bus stations in airports is spatially dispersed. Both static and dynamic traffic dominance in Shanghai exhibit a core-periphery structure centered around the Huangpu District, with high-value areas of traffic dominance clustering in the city center. The results align closely with the actual situation, reflecting that the transportation network is more developed in areas with concentrated populations, capital, and information.

2. We specifically analyzed the dynamic traffic dominance segmented by time periods. From 0:00–6:00, the spatial distribution of the relative weighted centrality (RWC) for bike-sharing differed significantly from other periods, subway networks saw a notable reduction in RWC but maintained a consistent spatial form, and taxis were intermediate between the two. During the 6:00–12:00 and 18:00–24:00 periods, the RWC generally increased for all three modes of transport, with a significant reduction in subway RWC in the evening period from 18:00–24:00.

3. With the inclusion of dynamic traffic dominance, traditional static assessment results underwent significant changes. The traffic dominance in Jiading, Baoshan, Pudong New Area, Minhang, Qingpu, Songjiang, Fengxian, and Jinshan districts showed a noticeable weakening, demonstrating the significant impact of population movement on regional traffic dominance.

Our study employed innovative methods, integrating multiple data sources and basing the dynamic evaluation model on the characteristics of traffic networks at different times to establish a comprehensive assessment system for traffic network characteristics. By addressing key issues surrounding the application of complex network theory and the integration of multisource spatiotemporal data, this research greatly enhanced our understanding of urban transportation systems. Furthermore, the study explored how the assessment results could provide valuable decision support for urban planners and traffic managers, offering more comprehensive and systematic scientific support for the city's transportation infrastructure development.

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