

Article

Integrating Network Centrality and Node-Place Model to Evaluate and Classify Station Areas in Shanghai

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Abstract: Transit-oriented development (TOD) is generally understood as an effective urban design model for encouraging the use of public transportation. Inspired by TOD, the node-place (NP) model was developed to investigate the relationship between transport stations and land use. However, existing studies construct the NP model based on the statistical attributes, while the importance of travel characteristics is ignored, which arguably cannot capture the complete picture of the stations. In this study, we aim to integrate the NP model and travel characteristics with systematic insights derived from network theory to classify stations. A node-place-network (NPN) model is developed by considering three aspects: land use, transportation, and travel network. Moreover, the carrying pressure is proposed to quantify the transport service pressure of the station. Taking Shanghai as a case study, our results show that the travel network affects the station classification and highlights the imbalance between the built environment and travel characteristics.

Keywords: node-place model; transport network; TOD; transit station



Citation: Dou, M.; Wang, Y.; Dong, S. Integrating Network Centrality and Node-Place Model to Evaluate and Classify Station Areas in Shanghai. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 414. <https://doi.org/10.3390/ijgi10060414>

Academic Editors: Maria Antonia Brovelli, Xiao-Guang Zhou, Hussein Abdulmuttalib and Wolfgang Kainz

Received: 11 April 2021
Accepted: 10 June 2021
Published: 16 June 2021

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1. Introduction

Rapid urbanization and population growth worldwide have caused many urban problems, such as air pollution, traffic congestion, and excessive reliance on fossil fuels. An essential reason for this phenomenon is the absence of clear and effective integrated development plans for land use and transportation. Transit-oriented development (TOD) has been adopted as a commonly followed urban planning strategy for achieving such integration, promoting efficient and mixed land use near public transportation hubs and stations [1,2]. At the metropolitan scale, metro stations provide greater accessibility to their catchment area and play a crucial role in the public transport network. Meanwhile, stations offer sufficient opportunities to develop diversity and intensity land use, aiming at creating walkable, activity-friendly communities. The implementation of TOD at station level has been a major focus of attention in scholarly work.

Various researchers have attempted to establish comparable TOD typologies for better strategic planning, investment guidance, and station quantification [3,4]. The best-known approach for evaluating TOD typology is the node-place (NP) model developed by [5], which is essentially a conceptual framework for assessing the transport supply and land use characteristics of a station simultaneously. Based on the NP model, various modifications to the original model have been introduced. The most notable modification is the extension of design dimension, which represents a considerable improvement regarding walkability and pedestrian comfort [6]. Specifically, three aspects need to be investigated to achieve effective integration of transportation and land use: (1) multimodal accessibility of the station, (2) land use diversity and intensity, and (3) pedestrian-oriented design [7]. In a similar vein, Ref. [8] extended the model by adding the experience dimension with indicators, which reflect the transit quality from a traveler's perspective.

Recently, traveler-related attributes, such as ridership, as critical indicators have been studied. For example, Ref. [9] elaborated on the correlation between the travel volume and NP index. Ref. [10] investigated the interaction between node value, place value, and ridership. However, ridership has limitations to reflect the travel network characteristics (e.g., transfer behavior). There is scant research on the synergies between the actual rail transit travel characteristic and the functional configuration of its physical context. To the best of our knowledge, Ref. [11] made the first exploratory study on the relationships between travel network features and the classification results of the node-place-design model.

Inspired by these efforts, we attempt to extend the node-place model by adding a new dimension of network for metro station classification, which contributes to illuminating the complex links between the built environment, land use, and travel network characteristics of stations. The main contributions of this study are as follows:

1. Combined official data and open geographic big data, an extended node-place-network (NPN) model was proposed to measure the synergy between the built environment and travel characteristics around stations. Moreover, the carrying pressure indicator was utilized for the quantitative evaluation;
2. Employed the proposed analytical methodology to complement empirical knowledge concerning TOD of the station's area in Shanghai, which verified the effectiveness of the proposed NPN model.

The paper is organized as follows. The next section is a literature review of the NP model and relevant theory. Then, we elaborate on the methodology used and a case study of Shanghai. Afterwards, the results are discussed in Section 5, followed by conclusions in Section 6.

2. Literature Review

2.1. The Node-Place Model

In the past, many researchers examined the gaps between public transport supply and demand. Various approaches were employed to access the public transport performance, for example, network supply model [12], Gini coefficients [13,14], and node-place model [4], etc.

Among these models, the node-place (NP) model, as the best-known approach leading to a TOD typology, was developed by [4]. It defined the double nature of the station: nodes of networks and place in the city. The funding principle of the NP model is balancing transportation with land use to achieve a state of cooperative development between them. An analysis framework, based on a dual axis of node and place indexes, is used to represent the conceptual model (Figure 1). The node dimension measures the offer of transport services (e.g., number of directions served, daily frequency), reflecting the accessibility of the station area by several transportation modes. The place dimension measures the land use features (e.g., density and diversity of activities) found around a station area, reflecting the potential demand for transport services. By identifying five types of station areas (Figure 1), the conceptual framework provides an integrated quantitative indicator for measuring the integration level of transportation and land use as well as assessing the evolution of a system over time [15,16].

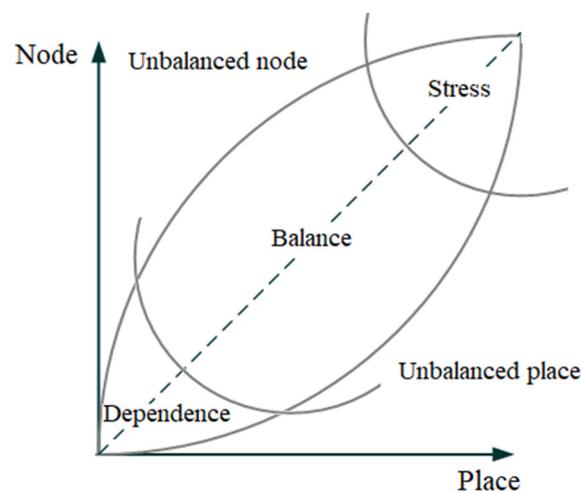


Figure 1. The NP model [17].

During the last two decades, the dimension of NP has been extended in many diverse aspects [18,19]. One major modification is its expansion to the urban design dimension. [6] first investigated the usefulness of adding the walking environment evaluation to the NP model as an urban planning tool. Based on that evaluation, Ref. [20] emphasized the functional and morphological interrelation between transportation and urban conditions, and extended a third, ‘oriented’ dimension to quantify the accessibility of station areas. Likewise, [7] considered different access modes to stations and introduced the design index to measure the influence of the pedestrian accessibility of the station areas. Other feeder modes, such as bicycles, cars were considered in the work of [21], which focused on geographical contexts characterized by medium or low population densities. In a similar vein, several extra dimensions, such as ‘proximity’ [22], ‘user-friendliness’ [23,24], and the spatial configuration of the street network design [25,26] were also investigated in previous studies.

In addition to the extension of the design dimension, some scholars conducted research from a user-based perspective. For instance, the experience value [8] is added to reflect the traveler’s experience at the station in terms of comfort (sheltered waiting, toilets), ambient elements (architecture and recent renovation), and social elements (presence of personnel). The people dimension proposed by [27] includes motivation (education, work, and other), ridership (using the station as an origin station, destination), and effort (walking, biking, and travelling a farther distance).

Furthermore, the high salience of transit-related attributes, especially human mobility in the studies, are identified. Two approaches have been suggested to include travel features in the NP model. The first approach highlighted the importance of the passenger frequencies [20] and adds passenger volume to calculate the node index [26,28]. Given unique characteristics and importance of travel flow data, the second approach made a comparative analysis between the travel characteristics and the results of station classification. According to this point, Ref. [29] explored the intersection of two created classifications for New York City and unveiled the consistency between context and use of the station. Similarly, Ref. [11] added the centrality analysis of the movement network to investigate the performance of the Greater London metro station areas at both local and system levels. They found that there were substantial discrepancies in the criticality of station areas within the same cluster with similar node-place-design, suggesting the various roles they played at multiple levels.

2.2. TOD and the Travel Network

Although improvements of the NP model varied to some extent, they have the common objective to increase transit ridership and create a more sustainable transit system. Compared with other NP indicators, travel flow has its own unique characteristics. First, it

is the objective data generated by individual travel, reflecting the actual demand of people. Second, travel distribution reflects the characteristics of the entire travel system rather than those of a local station. Based on that, it is reasonable to think that taking travel flow as an indicator of the node index within the classification of TOD has limitations.

As for the specific index calculation method of the passenger travel dimension, most previous studies have used passenger frequency as an indicator [3,30,31]. One exception is [11], who introduced a strategic network (criticality) component to enhance the value of the NP model from a perspective of network analysis. As pointed by [32], ‘characterizing the network anatomy is important because structure always affects function and vice versa’. The study of networks pervades all of science. In particular, this new wave of spatial networks and flows in cities using moving data provides new insights into understanding traffic network systems and urban spatial structure. For example, Refs. [33,34] used three-year smart card data to reveal a polycentric urban development phenomenon in Singapore. Similarly, Ref. [35] constructed a multi-layer network from three sources (i.e., bus GPS observations, smart card data, and roadside Blue tooth detector records) to identify the network structure at each layer and reveal comparable features of the network organization for different spatial layers. In addition, some scholars also used other moving flows, such as the bicycle sharing flow and social media check-in stream to reveal the hierarchical structure of urban space [36,37].

Numerous empirical studies have shown that the importance of nodes and the type of metro stations can be further identified using the metrics of complex network theory [38]. For example, Ref. [39] developed a new weighted composite index to position hub stations in a subway network. Ref. [40] used several improved network indexes to distinguish the key stations and sections of the metro network in Beijing, China. Ref. [41] used human mobility patterns and improved the PageRank algorithm to evaluate station importance.

Consequently, we develop a new model, which is called the node-place-network (NPN) model with an extended network dimension, as a complement to the NP model. Below we discuss how we developed and applied this extended model in a case study of Shanghai.

3. Methodology

In this section, we first introduce the node-place-network model including the index selection and station classification with the K-means++ method. Second, we calculate the carrying pressure to verify the meaning of travel network dimension. Taken Shanghai as case study, our methodology has been depicted in Figure 2.

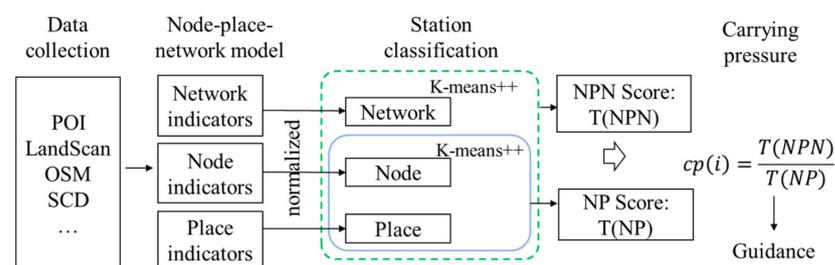


Figure 2. Research methodology (Taken Shanghai as case study).

3.1. Node-Place-Network Model

As discussed in Section 2, the actual travel characteristics of passengers and the importance of the station in the network system were ignored in previous node-place model. Hence, an extended node-place-network model, as shown in Figure 3, is proposed. The node and place dimension represent the traffic services and land use around the stations, respectively. The network dimension indicates the importance of the station in the whole subway network system.

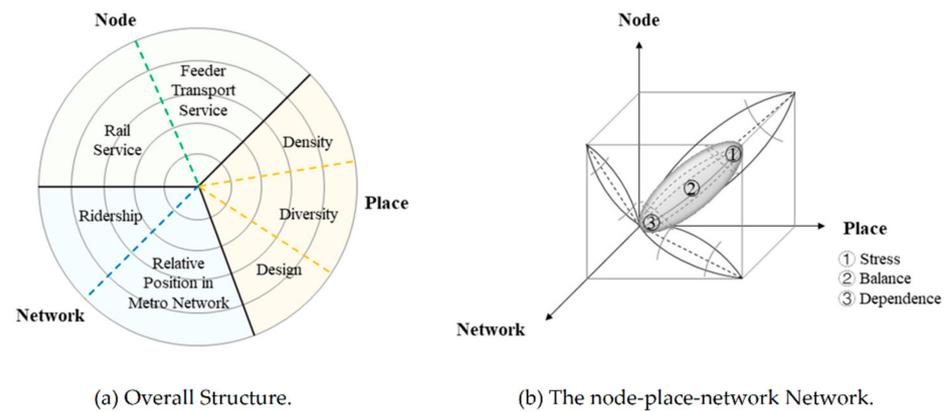


Figure 3. Illustrations of the node-place-network model. (a) Overall structure, (b) the node-place-network network (NPN).

3.1.1. Index Selection

(1) Network indicators

Based on the smart card data (SCD), we first construct an OD (origin-destination) matrix of travel between all metro stations, and then convert it to an undirected weighted network form, viewed as a passenger movement network:

$$G = (V, E, W), E = W * W \quad (1)$$

where V is a list of vertices (i.e., stations) of network G . E is a set of edges of network G , and W , which includes the weights w_{ij} denoting the volume of travel between stations i and j .

Degree centrality and centrality betweenness are the two most representative indicators in complex network studies [42,43].

- Degree centrality

The degree centrality refers to the number of links connected to a node in the network, which is the number of travel records of a metro station in our study.

$$S_i = \sum_{j \in N_i} w_{ij} N_i \quad (2)$$

where N_i is the set of adjacent stations of node i , and w_{ij} is the weight between nodes i and j . In our study, it indicates the number of travel flow between stations i and j .

- Betweenness centrality

Betweenness centrality is an index that measures the level of node connectivity, which is a key indicator for identifying metro network hubs. A node has a higher centrality $C_{betweenness}(k)$, the greater the number of shortest paths that traverse it and is defined as follows:

$$C_{betweenness}(k) = \sum_{ij} \delta_{ij}(k) / \delta_{ij} \quad (3)$$

where $\delta_{ij}(k)$ is the number of shortest paths between any two stations i and j that pass through the station k and δ_{ij} is the total number of such paths between i and j .

One point to note here is that both centrality indicators are calculated based on the passengers' movement network instead of the features of transit infrastructure network.

(2) Node indicators

Node indicators can be divided into two groups depending on the transit mode: the transit quality of rail and feeder transport (Table 1).

Table 1. Indicators of the node dimension.

Node Index	Description
Rail	
Number of directions served by metro	n1 = number of metro services offered at station
Daily frequency of metro services	n2 = number of metro departing from station on working day
Number of stations within 20 min of travel	n3 = number of stations reachable within 20 min by metro
Feeder transport	
Number of directions served by other public transport	n4 = number of public transport services offered at station
Number of car parking places	n5 = number of car parking within 600 m.
Distance from the closest motorway access	n6 = distance to closest motorway access

(3) Place indicators

In terms of place indicators, three aspects of the station's area are measured following the 'three-Ds' principle, namely density, diversity, and design [2]. Based on previous studies [20,27,44], the indicators of place are summarized in Table 2.

Table 2. Indicators of the node dimension.

Place Index	Description
Density	
Population density	p1 = density of population within 600 m
Number of residences	p2 = number of establishments in residence within 600 m
Number of workers in business	p3 = number of establishments in business within 600 m
Number of workers in green space	p4 = number of establishments in green space within 600 m
Number of workers in transportation	p5 = number of establishments in transportation within 600 m
Number of workers in public service	p6 = number of establishments in public service within 600 m
Number of workers in industry	p7 = number of establishments in industry within 600 m
Number of POIs	p8 = number of points of interest (POIs) within 600 m
Diversity	
Land use mix	$p9 = -\frac{\sum_{i=2}^7 (p_{1i} \cdot \ln p_{1i})}{6}$, where p_{1i} is the normalization of p_i
Design	
Intersection density	p10 = density of intersections per hectare
Accessible network length	p11 = length of the accessible network (meters)

(4) Data normalization

The first step in descriptive statistical analysis is data transformation. With formula (4) and (5), all indicators were box-cox transformed [45] and rescaled to reduce the skewness of their univariate distribution and improve their comparability.

$$x'_i = \begin{cases} \frac{x_i^\lambda - 1}{\lambda}, & \text{if } \lambda \neq 0; \\ \log x_i, & \text{if } \lambda = 0. \end{cases} \quad (4)$$

where x'_i is the transformed variable; λ is the transformation parameter, ranging from -5 to 5 . The optimum value of λ is obtained using the maximum likelihood estimate.

$$x^* = \frac{\max(x'_i) - x'_i}{\max(x'_i) - \min(x'_i)} \quad (5)$$

Then, the two-sided Spearman correlation analysis was also conducted to understand the direction and strength of the relations between the indicators. Furthermore, the relative importance of independent variables will be explored with the entropy method [46].

3.1.2. Station Classification

After data preprocessing, the similarity of metro stations was explored by applying the K-means++ method [47]. K-means++ can choose the initial cluster centers as far apart from

each other as possible. The silhouette coefficient, ranging of $[-1, 1]$, is used to evaluate the clustering performance [48].

3.2. Carrying Pressure

To verify to what extent the travel network dimension adds meaning to the findings of a traditional NP type of classification, we conduct a comparative analysis based on two classification strategies. The first strategy primarily focuses on the original NP model, which describes the built environment properties around the station. The second strategy focus on the NPN model, including extended passenger travel characteristics, which describes the real travel flow distribution of rail transit externally.

Furthermore, a new index called the carrying pressure of the node was proposed to quantitatively describe the development synergy between the travel flow and the supporting physical environment of the station. The carrying pressure value of the node can be determined using the following formula:

$$cp(i) = \frac{T(NPN)}{T(NP)} = \frac{[Index(Node) + Index(Place) + Index(Network)]/3}{[Index(Node) + Index(Place)]/2} \quad (6)$$

where T , the score of model, is the average of integrated indices, representing the comprehensive measure of TOD development status of the station. $Index(.)$ represents the score of one dimension. For example, $Index(Node)$ represents the composite score after weighting node indicators.

4. Study Area and Data

4.1. Study Area

China has been experiencing rapid urbanization and a massive expansion of infrastructure construction during the past decades. Shanghai, as China's largest economic center, has a 548 km network, which is officially the largest network by route length in the world [49]. In 2018, the daily ridership of Shanghai Metro exceeded 10 million on weekdays and 7 million on weekends. The total number of subway passengers reached approximately 3.7 billion, which increased 1.62 billion over that of 2017.

According to the Master Plan, officials intend to have over 1000 km of network by track length, and over 600 metro stations, forming an extensive network covering the entire city. In particular, the conception of TOD has been introduced and considered a promising solution by local governors in land use planning. In this regard, it is necessary to have a universal approach to identifying the TOD variations and typology among the metro station areas and providing general knowledge on understanding the complex relationship between metro trip demands, transportation, and land use. Based on our data source, all 286 metro stations, covering over 600 km that are part of the analysis, are shown on the map (Figure 4).

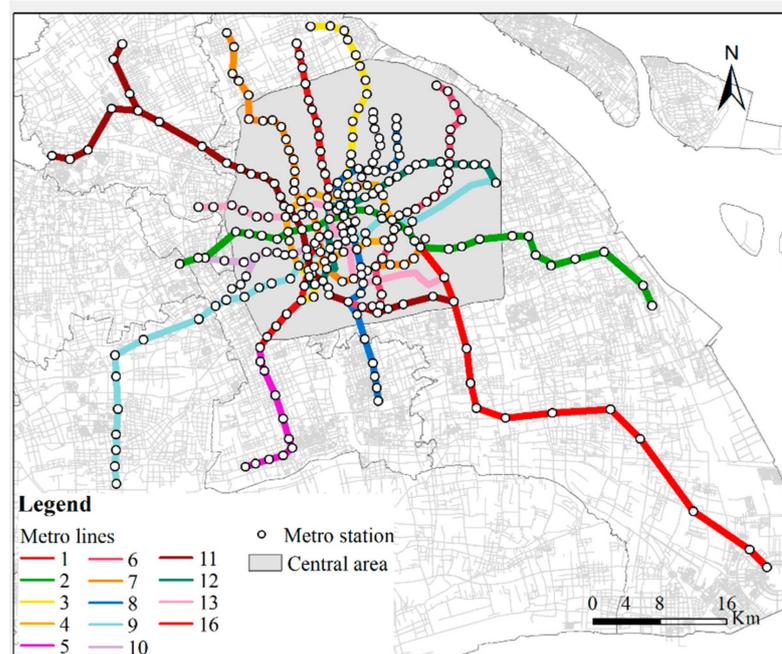


Figure 4. Study areas and the metro system in Shanghai (2018).

4.2. Data

This study used three sources of open data, including 642,724 POIs extracted from Gaode Map, LandScan, OpenStreetMap (OSM), government website data, and a month of smart card data (SCD) from Shanghai Metro during March 2018.

The recorded SCD contains detailed information on each trip, including the card ID, time, fare, and the station name. From the fare field, the state of travel can be detected (i.e., whether boarding or alighting). The government website data offers the basic information of the metro network, such as the metro daily frequency, number of directions served by metro, etc. In addition, road-related information, like intersection density and accessible network length, can be obtained from OSM data. The population distribution data was from the LandScan (<http://web.ornl.gov/sci/landscan>, accessed on 1 September 2020). The description of data can be seen in Appendix A.

5. Results and Discussion

In this section, we first carried on the variable selection and the comprehensive score calculation of node, place, and network dimensions. Then, the indexes of NP and NPN were clustered respectively to obtain different station categories. Finally, the difference of station categories under NP and NPN were investigated and the guidance for individual stations are discussed.

5.1. Node-Place-Network Model

5.1.1. Variables

The direction and strength of correlations between the indicators were examined (Pearson's), and the results show a high and significant correlation between the variables (see Appendix B). Nevertheless, the high correlation between some variables was not considered problematic, as the indexes of each dimension are then given different weights and finally integrated into one index.

Table 3 shows the relative importance of independent variables with the entropy method. For the node index, the number of directions served by the metro is the most important variable, which emphasizes the importance of a transfer station. For the place index, the density and diversity of land use have greater weight, followed by the mixing degree of land use, and finally, the density of intersections. This result is consistent with

the previous study [50] that the population density and employment density are strongly positively associated with ridership. For the network index, the degree and betweenness indicator have identical weights, which indicates that these two variables are equally important in reflecting the importance of stations.

Table 3. Indicators of the node dimension.

Dimensions	Independent Variables	Rank	Relative Importance (%)
Node	n1: Number of directions served by metro	1	23
	n2: Daily frequency of metro services	3	16
	n3: Number of stations within 20 min of travel	2	27
	n4: Number of directions served by other public transport	5	14
	n5: Number of car parking places	4	15
Place	p1: Population density	3	10
	p2: Number of residences	1	15
	p3: Number of workers in business	3	10
	p4: Number of workers in green space	6	9
	p5: Number of workers in transportation	2	11
	p6: Number of workers in public service	3	10
	p7: Number of workers in industry	6	9
	p8: Number of POIs	8	8
	p9: Land use mix	9	7
	p10: Intersection density	11	4
	p11: Accessible network length	9	7
Network	c1: Degree	1	50
	c2: Betweenness	1	50

5.1.2. Indexes

A descriptive statistical analysis of the three dimensions is shown in Table 4. The ranges of data indicate that the distribution of real passenger flow distribution between subway stations has a greater variation (which is 0.046) than the node dimension (0.020). The result indicates that the average network accessibility is not being fully incorporated into transportation development.

Table 4. Descriptive statistics of the node, place, and network indexes.

Index	Minimum	Maximum	Mean	Std. Deviation
Node	0.1480	0.8674	0.4908	0.0204
Place	0.1135	0.8167	0.5351	0.0231
Network	0.1556	1	0.5235	0.0457

The geographic distribution of the node and place indexes follows a broadly concentric circle-shape, generally radiating away from the central area of Shanghai (Figure 5). The node and place with better development status are basically located in the central region, while the relatively underdeveloped regions occur on the outskirts of the city, which also reflects the strong monocentric urban structure of Shanghai. Notably, the spatial distribution pattern of the network dimension shows a substantial difference between node and place indexes. A higher value of network index is no longer located in the central area and appears in the periphery of city. It is evident that the periphery/suburbs of the city have a high travel demand, whereas the supply of these places is in relatively short supply with an undeveloped physical environment (including traffic facilities and land use allocation).

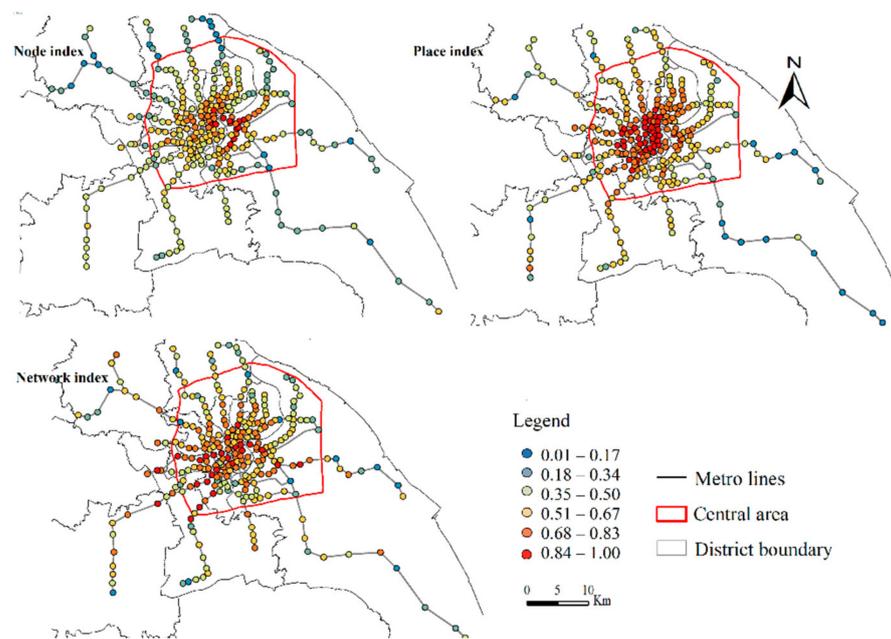


Figure 5. Node, place, and network indexes of the metro stations.

In addition to the spatial analysis of all station areas, the relationships among these indexes were also analyzed to reveal the complex links between stations. As shown in Figure 6, Shanghai metro station areas exhibit substantial differences among these indexes: the results of a positive relationship between node and place ($r^2 = 0.69$) indicate that the public transport accessibility has a good synergy associated with land use patterns. The relationship between network index and the other two dimensions is relatively low (0.36 and 0.48), which is consistent with [11] and that there is a significant difference between network centrality and the attribute of local station areas.

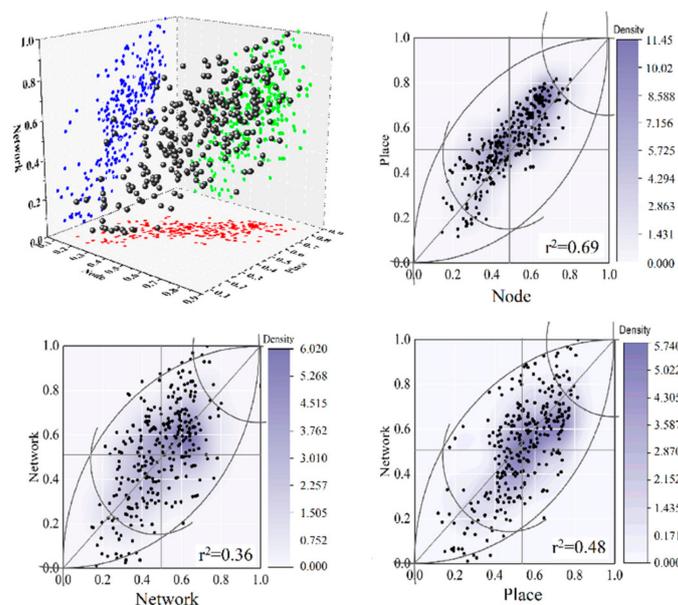


Figure 6. Node, place, and network indexes of the metro stations.

5.2. Cluster Analysis

5.2.1. Typologies of the NP Model

Through K-means++ cluster, five clusters are chosen with the best silhouette value 0.38. The F-statistics of clusters of the place index are 541, higher than node index, which

are 428. The lower descriptive power of the node index indicates that the transportation service level does not differ greatly. The reason for this situation may be that we mainly analyzed the urban area of Shanghai, which has developed public transportation.

Using the geographic map and NP scores, the node index and place index in Shanghai are generally in a state of equilibrium (Figure 7 and Table 5). The geographic distribution follows a broadly concentric circle-shape radiating from the central area of Shanghai. For instance, cluster 1 and cluster 2, two better performing clusters, are primarily located in central urban areas with good traffic accessibility and diverse land use. Followed by cluster 3, which is mostly located from the edge of the central city area and has a moderate level of development in terms of urban traffic and land use. The last two clusters, cluster 4 and cluster 5, are located at the edge of the city or at the end of the rail transit station.

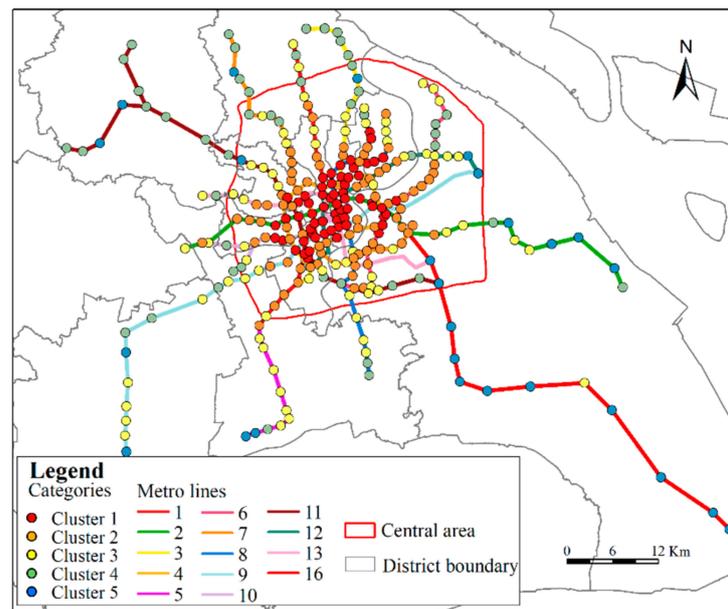


Figure 7. Results of the NP model.

Table 5. Summary of the five clusters.

ID	Num	Example of Stations	Node (Avg.)	Place (Avg.)	All (Avg.)
1	62	People's Square, Jing'an Temple	0.67	0.72	0.69
2	80	Hongqiao railway station, Xinzhuang	0.57	0.59	0.58
3	70	Jiuting, Huinan	0.44	0.49	0.47
4	48	An'ting, Nanxiang	0.32	0.41	0.36
5	26	Xinchang, Zhoupu east	0.27	0.22	0.25

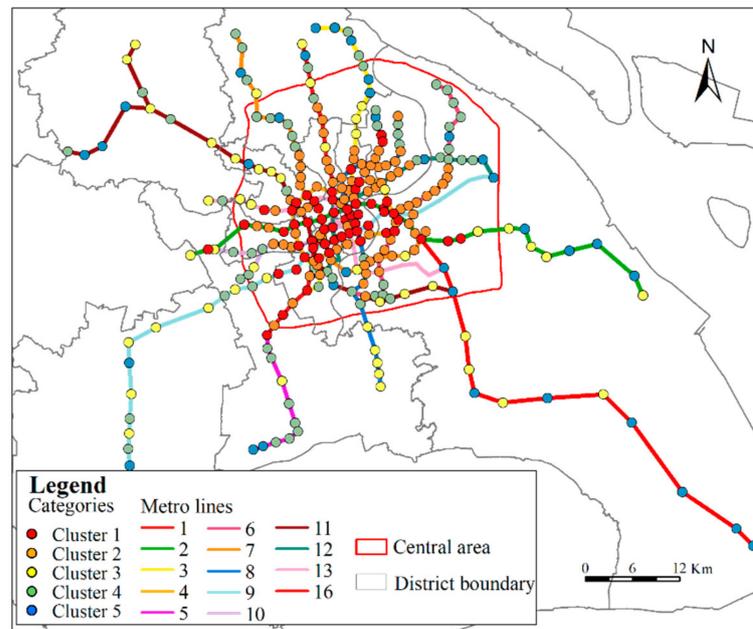
5.2.2. Typologies of the Node-Place-Network Model

The same cluster analysis was again applied to the NPN model and five clusters are identified (the best silhouette value is 0.32). The F-statistics (network index = 345, place index = 204, and node index = 205) shows that higher descriptive power of the network. Further, in the case of similar built environment, the actual travel flow distribution among different stations is quite different. This result once again proves the necessity of travel flow for site classification.

Each of the five categories has its own distinctive characteristics (Table 6 and Figure 8). Cluster 1 (the number of stations is 57) is characterized by the three highest indexes, predominantly located in the central area of the city. Two exceptions are Hongqiao Railway Station (0.69, 0.66, 0.87) and Xinzhuang (0.59, 0.65, 0.89), which are clearly positioned as sub-centers of urban development according to the Master Plan of Shanghai (2017–2035).

Table 6. Description summary of the five clusters.

ID	No.	Stations	Node (Avg.)	Place (Avg.)	Network (Avg.)	All (Avg.)
1	57	People's Square, Jing'an Temple	0.65	0.70	0.79	0.71
2	84	Baoshan Road, Longqiao Road	0.60	0.62	0.56	0.59
3	49	Jiuting, Zhuanqiao	0.39	0.46	0.61	0.48
4	61	An'ting, Longhua	0.41	0.47	0.36	0.41
5	35	Longyao Road, Luoshan Road	0.28	0.28	0.16	0.23

**Figure 8.** Results of the NPN model.

Cluster 2 (the number of stations is 84) has most stations, which has a balanced development status. Cluster 3 has a similar score for network with cluster 2, with relatively high scores for the network but a low score for node and place. This is possibly because around these stations, the land use is usually dominated by residential types, and more commuters need to travel between workspace in the city center and residential areas in the suburbs. One typical case is Sijing station (0.32, 0.42, 0.78), a typical living place, located in an area with a dense residential population, large travel flow during the peaks and insufficient facilities.

Cluster 4 (the number of stations is 61) and cluster 5 (the number of stations is 35), are generally located at the end of a metro line. Both of them have a relatively low score of network, corresponding to lower demand for transportation. Furthermore, the cluster 5 needs to be improved comprehensively in terms of travel demand, transport services, and land supply.

5.3. Comparative Analysis

Figure 9 provides an alluvial diagram that depicts how the clusters in different strategies interact with one another. Between the two categories, there are thick edges that connect the clusters. This situation indicates that the set of nodes that form a particular cluster within the NP model constitutes a substantial portion of another cluster within the NPN model, reflecting the similar development consistencies under different dimensions. Cluster 1 to 5 is arranged in order of the average score from large to small. A large number of thin edges change to the neighbor cluster IDs, which indicates that some stations perform slight differences between the two categories. However, several thin edges change to the non-neighbor cluster IDs, reflecting the significant mismatches between environmental

attributes and travel demand. For example, Jinke station (network = 0.82, node = 0.55, place = 0.49), which belonging to cluster 3 under NP classification, is transferred to cluster 1 under NPN classification.

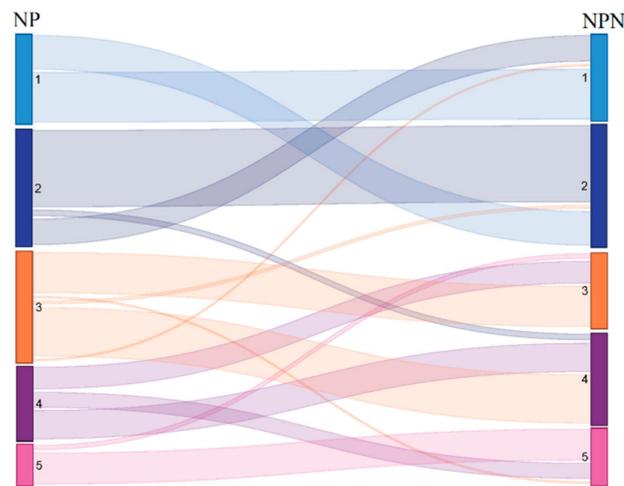


Figure 9. Clusters for different classification strategies and the relationships between them (clusters 1 to 5 are arranged in order of TOD values from largest to smallest).

To quantitatively describe the development synergy between the travel flow and the physical environment of the station, we compare the carrying pressure within different categories across these two classifications. As shown in Figure 10, the score of NPN shows more variability and comparability, while there is no clear distinction in the NP model. The results from the NPN model also clearly show that the nodes in cluster 3 have a higher T(NPN) score, while cluster 5 shows a lower performance in the public transport system. The results of the comparison study show the validity of the extended NPN method.

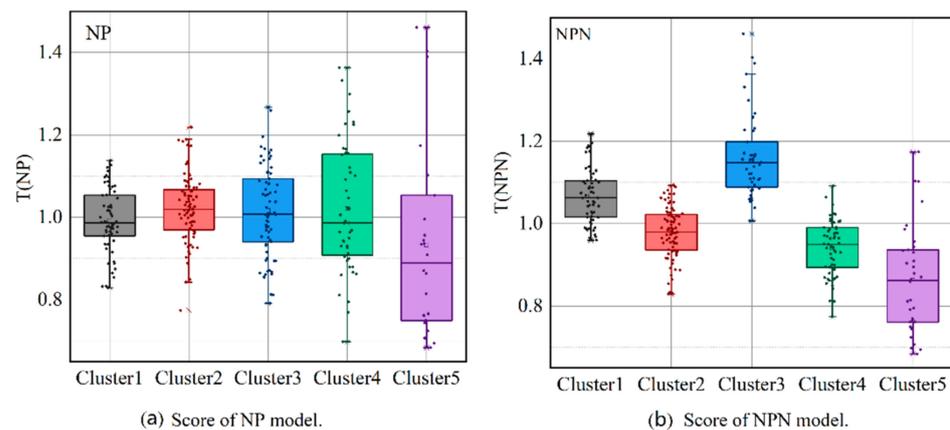


Figure 10. Score of the NP and NPN models.

5.4. Guidance for Individual Stations

The carrying pressure analysis on different clusters provides us not only a general impression of station groups, but also specific details for 286 stations in Shanghai (see Table 7). The stations with a high carrying pressure can be characterized as follows: (1) transportation hubs, such as Hongqiao Railway Station and Pudong International Airport, which are reasonable for having large travel demand because of the dominant position of transportation; (2) large residential districts, such as Jiuting and Guanglan Road stations, which are generally located on the edge of a main urban area or outside the city. These areas serve as sub-centers for future urban development. (3) The terminal stations, such as Shenshe Road station, which have a low degree of the physical environment but

a large travel demand. Moreover, our findings are consistent with the Shanghai Master Plan 2017–2035. For instance, four integrated and promoted town clusters are found in Figure 11 (Areas 1 to 4), in planning that includes Nanxiang-Jiangqiao, Jiuting-Sijing-Dongjing-Xinqiao, Pujiang-Zhoupu-Kangqiao-Hangtou, Tangzhen-Caolu-Heqing. There are also two prominent clusters, which correspond to the planned central towns, Jiading and Nanhui.

Table 7. Top 10 stations of carrying pressure.

Station	Clusters (NPN)	Clusters (NP)	Score (NPN)	Score (NP)	CP
Hesha Hangcheng	3	5	0.37	0.26	1.46
Xinchang	3	5	0.33	0.23	1.40
Zhoupu East	3	5	0.36	0.26	1.39
Sijing	3	4	0.51	0.38	1.36
Shenshe Road	3	4	0.51	0.38	1.33
Nanxiang	3	4	0.53	0.41	1.30
Jiuting	3	3	0.59	0.47	1.27
Guanglan	3	3	0.53	0.42	1.26
Jiading North	3	4	0.45	0.36	1.26
Jiading Xincheng	3	4	0.40	0.32	1.23

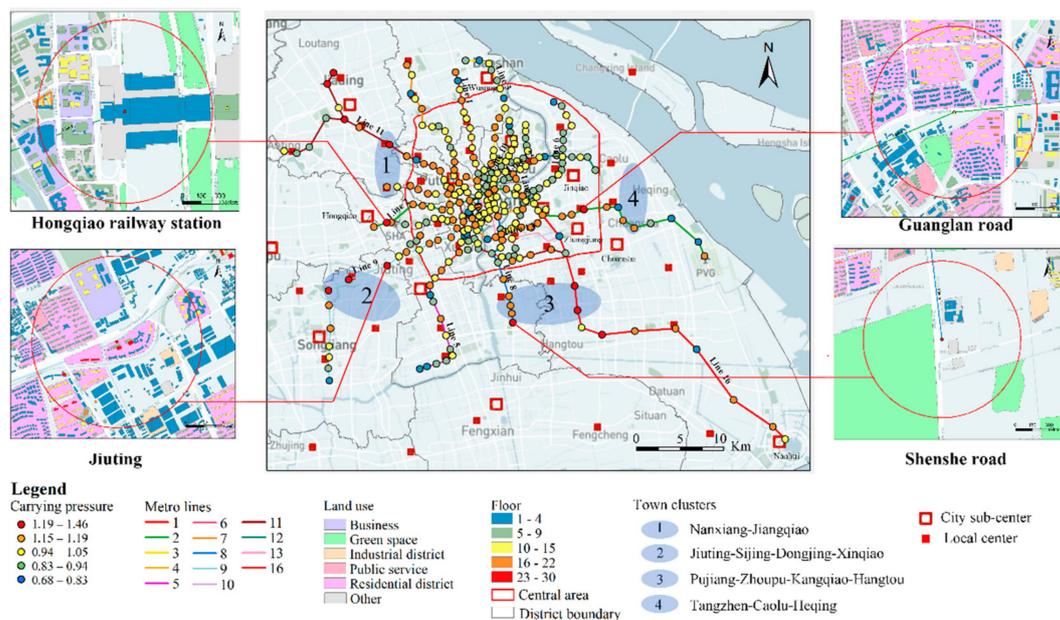


Figure 11. Carrying pressure of stations.

6. Conclusions

In this paper, we extended the existing node-place (NP) model by adding a third dimension—the network dimension, which results in a new model, the node-place-network (NPN) model. The NPN model can be used to assess the extent to which the cooperation between the land use and public transport as well as travel demand. An empirical case study of Shanghai demonstrated the effectiveness of our method. Three key findings are obtained: First, the results show that the TOD guidelines have already been implemented in Shanghai, although there is also a large mismatch between the travel demands and the surrounding environment of stations. This result is largely due to the complex relationship between transport systems and travel patterns. Second, a comparative analysis of the discrepancies between two classifications, the stations that need possible improvements are identified. Third, through the index of the carrying pressure, the matching degree of travel

characteristics and environmental development can be quantitatively evaluated, which provides a guideline for the development of multi-center cities.

Our results also provide recommendations for policy making. The stations with a relatively high carrying pressure have the potential for encouraging densification and diversification to increase the land use efficiency. We recommend planners to apply our methodology to a selection of potential places as sub-centers. Moreover, the reason for the occurrence of stations with a high carrying pressure is worth monitoring. Heavy commuting burdens pose a major challenge to improving the quality of public transportation. In particular, the rapid growth of urban populations has placed enormous pressure on transportation services and land use allocation [51].

This study can be extended in several directions for future investigations. First, we only used the entire travel records during a day, while more fine-grained event resolution, such as 1-h temporal interval can be considered. In other contexts, Ref. [29] used smart card data to conduct station classification, which brings finer resolution for boarding and alighting information. Second, we chose a buffer zone of 600 m in this study, which is the service scope planned by the Shanghai Municipal Government. Due to the presence of the modifiable areal unit problem (MAUP) [52,53], the influence of different research scopes and research scales can be considered in the future. Third, the different methods of index weighting can be adopted, e.g., the fuzzy approach and ANN [54,55]. Furthermore, as Shanghai is a monocentric city, further research will be carried out in cities with polycentric development to verify the performance of the proposed method.

Author Contributions: Conceptualization, Mingxuan Dou and Shihai Dong; methodology, Mingxuan Dou and Yandong Wang; validation, Mingxuan Dou; data curation, Shihai Dong; writing—original draft preparation, Mingxuan Dou; writing—review and editing, Yandong Wang; visualization, Mingxuan Dou and Shihai Dong; supervision, Yandong Wang; project administration, Yandong Wang; funding acquisition, Yandong Wang. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Key Research Program of China (2016YFB0501403) the National Natural Science Foundation of China (Grant No. 41271399), China Special Fund for Surveying, Mapping and Geoinformation Research in the Public Interest (Grant No. 201512015).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Restrictions apply to the availability of these data. POI data was obtained from Gaode Map (<https://lbs.amap.com/>, accessed on 1 September 2020). OpenStreetMap (OSM) data was obtained from <https://www.openstreetmap.org/> (accessed on 1 September 2020). Subway operation data is from the government's official website (<http://service.shmetro.com/>, accessed on 1 September 2020).

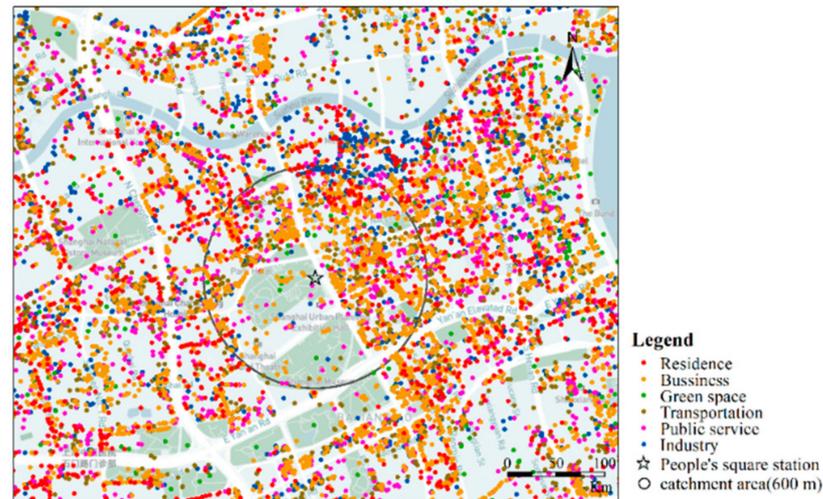
Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Data Description

Approximately one million POI data were acquired from Gaode Map (<https://www.amap.com>, accessed on 1 September 2020) in 2018, which has detailed information of addresses, titles, and the coordination of spatial location. They were coded into several levels of catalogs, depending on their attributes. Referring to urban land classification and planning construction land standard, we reclassified the POIs, and some POIs with a low public awareness were removed, such as public toilets, kiosks, and house numbers. After deletion and integration, the raw data were reclassified into commercial service, industry, residence, green space, public services, and transportation, as shown in Figure A1. And 642,724 POI data points were obtained (Table A1).

Table A1. The results of reclassification POI.

Code	Category	Number	Percentage
1	Business	158,938	24.7%
2	Transportation	41,283	6.4%
3	Residence	119,818	18.6%
4	Industry	206,724	32.2%
5	Green space	3749	0.6%
6	Public service	112,212	17.5%

**Figure A1.** POI distribution around People's Square.

The recorded SCD contains detailed information on each trip, including the card ID, time, fare, and the station name (Table A2). From the fare field, the state of travel can be detected (i.e., whether boarding or alighting). And based on the travel time, we can construct a travel chain for every user, which contains the concrete origin and destination of the station. As shown in Figure A2, more than one million trips were carried by Shanghai's metro system during the morning peak hour.

The government website data offers the basic information of the metro network, such as the metro daily frequency, number of directions served by metro, etc. And road-related information, like intersection density and accessible network length can be obtained from OSM data. The population distribution data was from the LandScan (<http://web.ornl.gov/sci/landscan/>, accessed on 1 September 2020).

Table A2. Examples of the SCD.

Card ID	Date	Time	Line	Station Name	Fare
2900***4556	1 March 2018	19:04:05	Line1	Jinhong Road	0
2900***5306	1 March 2018	16:02:03	Line3	Minhang	4
2900***5324	1 March 2018	08:05:02	Line7	Xinzhuang	5
2900***5339	1 March 2018	22:45:50	Line1	People's Square	0

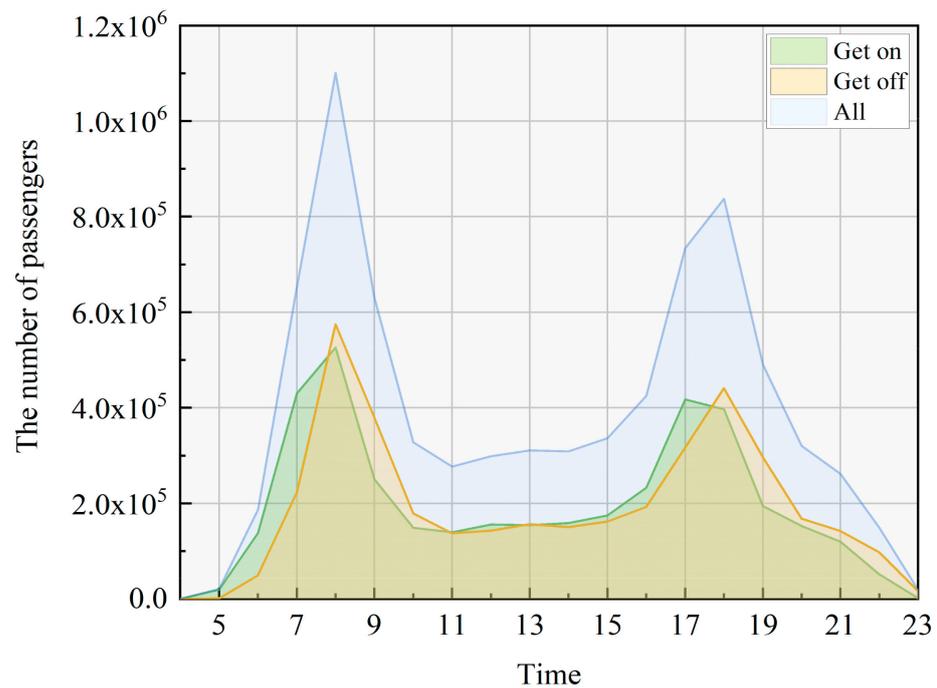


Figure A2. Average daily distribution of the passengers' travel flow.

Directed Weighted Network Analysis

To estimate the actual distribution of travel flow of the Shanghai subway system, we used SCD data to construct the directed weighted travel network. This network consists of 286 nodes (stations) and 78,375 edges. The average clustering coefficient is 0.946, which is much larger than the value of the random network (which is 0.5), which shows that the small world characteristics and degree distribution obeys a power-law distribution. As shown by Figure A3, the first weighted node is People's Square station, which has the largest travel flow all day. This is because People's Square station is the transfer station of Shanghai Metro Line 1, Shanghai Metro Line 2, and Shanghai Metro Line 8, which are also the central point of the Shanghai metro network structure. Moreover, Shanghai People's Square is also the political, economic, cultural, tourism, and transportation hub of Shanghai. The next highest value of weighted degree is Shanghai Railway station, which is the largest transit hub in Shanghai. And Jing'an temple, Xujiahui, East Nanjing Road, and Zhongshan Park are no longer transfer stations, but also have plenty of commercial, residential and recreational facilities. Lujiazui is well known as one of the top business circles, with excellent business facilities, and Xinzhuang is a mature leisure area.

The direct weighted network of travel flow, it shows that the subway around Shanghai is closely connected with the subway station in the central area, while some regional central stations are distributed along the inner ring road to share part of passenger volume. The direct evidence is in Table A3, which shows that the top station interaction pairs are located between Sijing and Caohejing Development Zone metro stations. Sijing is located outside the inner ring line, while Caohejing Development Zone metro station is inside the inner ring line. This situation also indicates that there remains a high demand for travel in the surrounding areas of Shanghai, with substantial interaction intensity between stations.

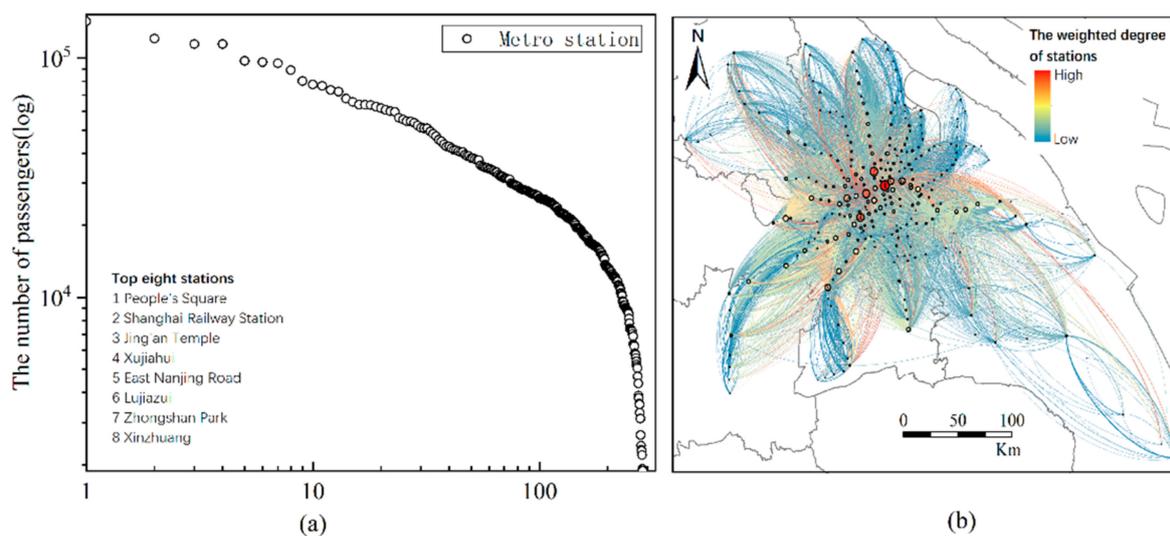


Figure A3. (a) Rank of the weight degree (log). (b) Direct weighted network of travel flow.

Table A3. Top 5 station interaction pairs.

Rank	Station Name	Station Name	Volume
1	Sijing	Caohejing Development Zone	7145
2	Jiuting	Caohejing Development Zone	5551
3	Qibao	Sijing	4839
4	West Nanjing Road	Lujiazui	4791
5	Xujiahui	Xinzhuang	4790

Appendix B. Correlation between the Indicators

	c1	c2	n1	n2	n3	n4	n5	n6	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11
c1	1.000	0.851 **	0.412 **	0.283 **	0.017	0.610 **	0.561 **	−0.353 **	0.486 **	0.500 **	0.686 **	0.478 **	0.609 **	0.610 **	0.591 **	0.676 **	0.298 **	0.422 **	0.393 **
c2	0.851 **	1.000	0.458 **	0.287 **	0.053	0.655 **	0.582 **	0.394 **	0.458 **	0.519 **	0.671 **	0.480 **	0.655 **	0.616 **	0.600 **	0.681 **	0.275 **	0.466 **	0.446 **
n1	0.412 **	0.458 **	1.000	0.496 **	0.099	0.644 **	0.583 **	0.560 **	0.583 **	0.610 **	0.628 **	0.555 **	0.643 **	0.702 **	0.560 **	0.666 **	0.293 **	0.541 **	0.587 **
n2	0.283 **	0.287 **	0.496 **	1.000	0.412	0.418 **	0.417 **	0.158 **	0.348 **	0.388 **	0.416 **	0.356 **	0.418 **	0.451 **	0.360 **	0.439 **	0.183 **	0.264 **	0.250 **
n3	0.017	0.053	0.099	0.412	1.000	0.369	0.118 *	0.006	0.120 *	0.103	0.064	0.020	0.070	0.066	0.108	0.072	0.151 *	0.093	0.048
n4	0.610 **	0.655 **	0.644 **	0.418 **	0.418 **	1.000	0.729 **	0.412 **	0.691 **	0.746 **	0.856 **	0.620 **	1.00 **	0.844 **	0.806 **	0.907 **	0.388 **	0.646 **	0.621 **
n5	0.561 **	0.582 **	0.583 **	0.417 **	0.118 *	0.729 **	1.000	0.372 **	0.664 **	0.710 **	0.753 **	0.574 **	0.729 **	0.755 **	0.665 **	0.765 **	0.330 **	0.585 **	0.488 **
n6	0.353 **	0.394 **	0.560 **	0.158 **	0.006	0.412 **	0.372 **	1.000	0.364 **	−0.386 **	0.394 **	0.329 **	0.412 **	0.391 **	0.384 **	0.406 **	0.163 **	0.333 **	0.359 **
p1	0.486 **	0.458 **	0.583 **	0.348 **	0.120 *	0.691 **	0.664 **	0.364 **	1.000	0.764 **	0.733 **	0.514 **	0.690 **	0.761 **	0.648 **	0.738 **	0.191 **	0.458 **	0.407 **
p2	0.500 **	0.519 **	0.610 **	0.388 **	0.103	0.746 **	0.710 **	0.386 **	0.764 **	1.000	0.842 **	0.670 **	0.746 **	0.869 **	0.715 **	0.844 **	0.299 **	0.567 **	0.476 **
p3	0.686 **	0.671 **	0.628 **	0.416 **	0.064	0.856 **	0.753 **	0.394 **	0.733 **	0.842 **	1.000	0.695 **	0.856 **	0.893 **	0.801 **	0.943 **	0.369 **	0.615 **	0.548 **
p4	0.478 **	0.480 **	0.555 **	0.356 **	0.020	0.620 **	0.574 **	0.329 **	0.514 **	0.670 **	−0.695 **	1.000	0.620 **	0.709 **	0.590 **	0.708 **	0.375 **	0.508 **	0.513 **
p5	0.609 **	0.655 **	0.643 **	0.418 **	0.070	1.00 **	0.729 **	0.412 **	0.690 **	0.746 **	0.856 **	0.620 **	1.000	0.844 **	0.806 **	0.907 **	0.388 **	0.645 **	0.620 **
p6	0.610 **	0.616 **	0.702 **	0.451 **	0.066	0.844 **	0.755 **	0.391 **	0.761 **	0.869 **	0.893 **	0.709 **	0.844 **	1.000	0.775 **	0.943 **	0.362 **	0.592 **	0.572 **
p7	0.591 **	0.600 **	0.560 **	0.360 **	0.108	0.806 **	0.665 **	0.384 **	0.648 **	0.715 **	0.801 **	0.590 **	0.806 **	0.775 **	1.000	0.900 **	0.516 **	0.589 **	0.501 **
p8	0.676 **	0.681 **	0.666 **	0.439 **	0.072	0.907 **	0.765 **	0.406 **	0.738 **	0.844 **	0.943 **	0.708 **	0.907 **	0.943 **	0.900 **	1.000	0.441 **	0.643 **	0.584 **
p9	0.298 **	0.275 **	0.293 **	0.183 **	0.151 *	0.388 **	0.330 **	0.163 **	0.191 **	0.299 **	0.369 **	−0.375 **	0.388 **	0.362 **	0.516 **	0.441 **	1.000	0.430 **	0.379 **
p10	0.422 **	0.466 **	0.541 **	0.264 **	0.093	0.646 **	0.585 **	0.333 **	0.458 **	0.567 **	0.615 **	0.508 **	0.645 **	0.592 **	0.589 **	0.643 **	0.430 **	1.000	0.727 **
p11	0.393 **	0.446 **	0.587 **	0.250 **	0.048	0.621 **	0.488 **	0.359 **	0.407 **	0.476 **	0.548 **	0.513 **	0.620 **	0.572 **	0.501 **	0.584 **	0.379 **	0.727 **	1.000

Note: ** $p < 0.05$; * $p < 0.1$.

References

1. Ibraeva, A.; Correia, G.H.D.A.; Silva, C.; Antunes, A.P. Transit-Oriented Development: A Review of Research Achievements and Challenges. *Transp. Res. Part A Policy Pract.* **2020**, *132*, 110–130. [[CrossRef](#)]
2. Cervero, R.; Kockelman, K. Travel Demand and the 3Ds: Density, Diversity, and Design. *Transp. Res. Part D Transp. Environ.* **1997**, *2*, 199–219. [[CrossRef](#)]
3. Zemp, S.; Stauffacher, M.; Lang, D.J.; Scholz, R.W. Classifying Railway Stations for Strategic Transport and Land Use Planning: Context Matters! *J. Transp. Geogr.* **2011**, *19*, 670–679. [[CrossRef](#)]
4. Papagiannakis, A.; Vitopoulou, A.; Yiannakou, A. Transit-Oriented Development in the Southern European City of Thessaloniki Introducing Urban Railway: Typology and Implementation Issues. *Eur. Plan. Stud.* **2021**, *29*, 117–141. [[CrossRef](#)]
5. Bertolini, L. Nodes and Places: Complexities of Railway Station Redevelopment. *Eur. Plan. Stud.* **1996**, *4*, 331–345. [[CrossRef](#)]
6. Vale, D.S. Transit-Oriented Development, Integration of Land Use and Transport, and Pedestrian Accessibility: Combining Node-Place Model with Pedestrian Shed Ratio to Evaluate and Classify Station Areas in Lisbon. *J. Transp. Geogr.* **2015**, *45*, 70–80. [[CrossRef](#)]
7. Vale, D.S.; Viana, C.M.; Pereira, M. The Extended Node-Place Model at the Local Scale: Evaluating the Integration of Land Use and Transport for Lisbon's Subway Network. *J. Transp. Geogr.* **2018**, *69*, 282–293. [[CrossRef](#)]
8. Groenendijk, L.; Rezaei, J.; Correia, G. Incorporating the Travellers' Experience Value in Assessing the Quality of Transit Nodes: A Rotterdam Case Study. *Case Study Transp. Policy* **2018**, *6*, 564–576. [[CrossRef](#)]
9. Caset, F.; Blainey, S.; Derudder, B.; Boussauw, K.; Witlox, F. Integrating Node-Place and Trip End Models to Explore Drivers of Rail Ridership in Flanders, Belgium. *J. Transp. Geogr.* **2020**, *87*, 102796. [[CrossRef](#)]
10. Cao, Z.; Asakura, Y.; Tan, Z. Coordination between node, place, and ridership: Comparing three transit operators in Tokyo. *Transp. Res. Part D Transp. Environ.* **2020**, *87*, 102518. [[CrossRef](#)]
11. Zhang, Y.; Marshall, S.; Manley, E. Network Criticality and the Node-Place-Design Model: Classifying Metro Station Areas in Greater London. *J. Transp. Geogr.* **2019**, *79*, 102485. [[CrossRef](#)]
12. Peungnumchai, A.; Miyazaki, H.; Witayangkurn, A.; Kim, S.M. A Grid-Based Spatial Analysis for Detecting Supply–Demand Gaps of Public Transports: A Case Study of the Bangkok Metropolitan Region. *Sustainability* **2020**, *12*, 10382. [[CrossRef](#)]
13. Currie, G. Gap analysis of public transport needs: Measuring spatial distribution of public transport needs and identifying gaps in the quality of public transport provision. *Transp. Res. Rec.* **2004**, *1895*, 137–146. [[CrossRef](#)]
14. Delbosc, A.; Currie, G. Using Lorenz curves to assess public transport equity. *J. Transp. Geogr.* **2011**, *19*, 1252–1259. [[CrossRef](#)]
15. Chorus, P.; Bertolini, L. An Application of the Node Place Model to Explore the Spatial Development Dynamics. *J. Transp. Land Use* **2011**, *4*, 45–58. [[CrossRef](#)]
16. Bruinsma, F.; Pels, E.; Priemus, H.; Rietveld, P.; Van Wee, B. *Railway Development: Impacts on Urban Dynamics*; Wiley: Hoboken, NJ, USA, 2008; ISBN 9783790819717.
17. Bertolini, L. Spatial development patterns and public transport: The application of an analytical model in the Netherlands. *Plan. Pract. Res.* **1999**, *14*, 199–210. [[CrossRef](#)]
18. Lee, J.; Choi, K.; Leem, Y. Bicycle-Based Transit-Oriented Development as an Alternative to Overcome the Criticisms of the Conventional Transit-Oriented Development. *Int. J. Sustain. Transp.* **2016**, *10*, 975–984. [[CrossRef](#)]
19. El-Geneidy, A.; Grimsrud, M.; Wasfi, R.; Tétreault, P.; Surprenant-Légault, J. New Evidence on Walking Distances to Transit Stops: Identifying Redundancies and Gaps Using Variable Service Areas. *Transportation* **2014**, *41*, 193–210. [[CrossRef](#)]
20. Lyu, G.; Bertolini, L.; Pfeffer, K. Developing a TOD Typology for Beijing Metro Station Areas. *J. Transp. Geogr.* **2016**, *55*, 40–50. [[CrossRef](#)]
21. Nigro, A.; Bertolini, L.; Moccia, F.D. Land Use and Public Transport Integration in Small Cities and Towns: Assessment Methodology and Application. *J. Transp. Geogr.* **2019**, *74*, 110–124. [[CrossRef](#)]
22. Singh, Y.J.; Fard, P.; Zuidgeest, M.; Brussel, M.; van Maarseveen, M. Measuring Transit Oriented Development: A Spatial Multi Criteria Assessment Approach for the City Region Arnhem and Nijmegen. *J. Transp. Geogr.* **2014**, *35*, 130–143. [[CrossRef](#)]
23. Park, S.; Choi, K.; Lee, J.S. To Walk or Not to Walk: Testing the Effect of Path Walkability on Transit Users' Access Mode Choices to the Station. *Int. J. Sustain. Transp.* **2015**, *9*, 529–541. [[CrossRef](#)]
24. Noord-Holland, P.; Deltametropool, V. *Maak Plaats! Werken aan knooppuntontwikkeling in Noord-Holland*; Provincie Noord-Holland & Vereniging Deltametropool: Haarlem, The Netherlands, 2013.
25. Van Nes, A.; Stolk, E. Degrees of Sustainable Location of Railway Stations: Integrating Space Syntax and Node Place Value Model on Railway Stations in the Province of North Holland's Strategic Plan for 2010–2040. In Proceedings of the 8th International Space Syntax Symposium, Santiago, Chile, 3–6 January 2012.
26. Monajem, S.; Ekram Nosrati, F. The Evaluation of the Spatial Integration of Station Areas via the Node Place Model; an Application to Subway Station Areas in Tehran. *Transp. Res. Part D Transp. Environ.* **2015**, *40*, 14–27. [[CrossRef](#)]
27. Caset, F.; Teixeira, F.M.; Derudder, B.; Boussauw, K.; Witlox, F. Planning for Nodes, Places, and People in Flanders and Brussels: An Empirical Railway Station Assessment Tool for Strategic Decision-Making. *J. Transp. Land Use* **2019**, *12*, 811–837. [[CrossRef](#)]
28. Reusser, D.E.; Loukopoulos, P.; Stauffacher, M.; Scholz, R.W. Classifying Railway Stations for Sustainable Transitions—Balancing Node and Place Functions. *J. Transp. Geogr.* **2008**, *16*, 191–202. [[CrossRef](#)]

29. Liu, Y.; Singleton, A.; Arribas-Bel, D. Considering Context and Dynamics: A Classification of Transit-Orientated Development for New York City. *J. Transp. Geogr.* **2020**, *85*, 102711. [[CrossRef](#)]
30. Singh, Y.J.; Lukman, A.; Flacke, J.; Zuidgeest, M.; Van Maarseveen, M.F.A.M. Measuring TOD around Transit Nodes—Towards TOD Policy. *Transp. Policy* **2017**, *56*, 96–111. [[CrossRef](#)]
31. Kim, H.; Sultana, S.; Weber, J. A Geographic Assessment of the Economic Development Impact of Korean High-Speed Rail Stations. *Transp. Policy* **2018**, *66*, 127–137. [[CrossRef](#)]
32. Strogatz, S.H. Exploring Complex Networks. *Nature* **2001**, *410*, 268–276. [[CrossRef](#)]
33. Zhong, C.; Arisona, S.M.; Huang, X.; Batty, M.; Schmitt, G. Detecting the Dynamics of Urban Structure through Spatial Network Analysis. *Int. J. Geogr. Inf. Sci.* **2014**, *28*, 2178–2199. [[CrossRef](#)]
34. Zhong, C.; Manley, E.; Müller Arisona, S.; Batty, M.; Schmitt, G. Measuring Variability of Mobility Patterns from Multiday Smart-Card Data. *J. Comput. Sci.* **2015**, *9*, 125–130. [[CrossRef](#)]
35. Yildirimoglu, M.; Kim, J. Identification of Communities in Urban Mobility Networks Using Multi-Layer Graphs of Network Traffic. *Transp. Res. Part C Emerg. Technol.* **2018**, *89*, 254–267. [[CrossRef](#)]
36. Munoz-Mendez, F.; Han, K.; Klemmer, K.; Jarvis, S. Community Structures, Interactions and Dynamics in London’s Bicycle Sharing Network. In Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers, New York, NY, USA, 8–12 October 2018; pp. 1015–1023. [[CrossRef](#)]
37. Liu, Y.; Sui, Z.; Kang, C.; Gao, Y. Uncovering Patterns of Inter-Urban Trip and Spatial Interaction from Social Media Check-in Data. *PLoS ONE* **2014**, *9*. [[CrossRef](#)] [[PubMed](#)]
38. Borgatti, S.P. Centrality and Network Flow. *Soc. Netw.* **2005**, *27*, 55–71. [[CrossRef](#)]
39. Yang, Y.; Liu, Y.; Zhou, M.; Li, F.; Sun, C. Robustness Assessment of Urban Rail Transit Based on Complex Network Theory: A Case Study of the Beijing Subway. *Saf. Sci.* **2015**, *79*, 149–162. [[CrossRef](#)]
40. Lin, P.; Weng, J.; Fu, Y.; Alivanistos, D.; Yin, B. Study on the Topology and Dynamics of the Rail Transit Network Based on Automatic Fare Collection Data. *Phys. A Stat. Mech. Appl.* **2020**, *545*. [[CrossRef](#)]
41. Xia, F.; Wang, J.; Kong, X.; Zhang, D.; Wang, Z. Ranking Station Importance with Human Mobility Patterns Using Subway Network Datasets. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 2840–2852. [[CrossRef](#)]
42. Senousi, A.M.; Liu, X.; Zhang, J.; Huang, J.; Shi, W. An Empirical Analysis of Public Transit Networks Using Smart Card Data in Beijing, China. *Geocarto Int.* **2020**, 1–24. [[CrossRef](#)]
43. Tang, J.; Zhang, S.; Zhang, W.; Liu, F.; Zhang, W.; Wang, Y. Statistical Properties of Urban Mobility from Location-Based Travel Networks. *Phys. A Stat. Mech. Appl.* **2016**, *461*, 694–707. [[CrossRef](#)]
44. Ritsema van Eck, J.; Koomen, E. Characterising Urban Concentration and Land-Use Diversity in Simulations of Future Land Use. *Ann. Reg. Sci.* **2008**, *42*, 123–140. [[CrossRef](#)]
45. Box, G.E.P.; Cox, D.R. An Analysis of Transformations. *J. R. Stat. Soc. Ser. B* **1964**, *26*, 211–243. [[CrossRef](#)]
46. Qiyue, C. Structure Entropy Weight Method to Confirm the Weight of Evaluating Index. *Syst. Eng. Theory Pract.* **2010**, *30*, 1225–1228.
47. Arthur, D.; Vassilvitskii, S. *K-Means++: The Advantages of Careful Seeding*; Stanford University: Stanford, CA, USA, 2006.
48. Rousseeuw, P.J. Silhouettes: A Graphical Aid to the Interpretation and Validation of Cluster Analysis. *J. Comput. Appl. Math.* **1987**, *20*, 53–65. [[CrossRef](#)]
49. An, D.; Tong, X.; Liu, K.; Chan, E.H.W. Understanding the Impact of Built Environment on Metro Ridership Using Open Source in Shanghai. *Cities* **2019**, *93*, 177–187. [[CrossRef](#)]
50. Ding, C.; Cao, X.; Liu, C. How Does the Station-Area Built Environment Influence Metrorail Ridership? Using Gradient Boosting Decision Trees to Identify Non-Linear Thresholds. *J. Transp. Geogr.* **2019**, *77*, 70–78. [[CrossRef](#)]
51. Zhao, P.; Cao, Y. Commuting Inequity and Its Determinants in Shanghai: New Findings from Big-Data Analytics. *Transp. Policy* **2020**, *92*, 20–37. [[CrossRef](#)]
52. Dark, S.J.; Bram, D. The Modifiable Areal Unit Problem (MAUP) in Physical Geography. *Prog. Phys. Geogr. Earth Environ.* **2007**, *31*, 471–479. [[CrossRef](#)]
53. Zhou, X.; Yeh, A.G.O. Understanding the Modifiable Areal Unit Problem and Identifying Appropriate Spatial Unit in Jobs–Housing Balance and Employment Self-Containment Using Big Data. *Transportation* **2021**, *48*, 1267–1283. [[CrossRef](#)]
54. D’Urso, M.G.; Masi, D.; Zuccaro, G.; De Gregorio, D. Multicriteria Fuzzy Analysis for a GIS-Based Management of Earthquake Scenarios. *Comput. Aided Civ. Inf.* **2018**, *33*, 165–179. [[CrossRef](#)]
55. Gu, Y.; Wang, Y.; Dong, S. Public Traffic Congestion Estimation Using an Artificial Neural Network. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 152. [[CrossRef](#)]