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DOI

[10.3390/SU11247241](https://doi.org/10.3390/SU11247241)

Publication date

2019

Document Version

Final published version

Published in

Sustainability

Citation (APA)

Zhang, Y., Song, R., van Nes, R., He, S., & Yin, W. (2019). Identifying Urban structure based on transit-oriented development. *Sustainability*, 11(24), Article 7241. <https://doi.org/10.3390/SU11247241>

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Article

Identifying Urban Structure Based on Transit-Oriented Development

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Received: 30 October 2019; Accepted: 13 December 2019; Published: 17 December 2019



Abstract: The fast development of urbanization has led to imbalances in cities, causing congestion, pollution, and urban sprawl. In response to the growing concern over the distribution of demand and supply, a more coordinated urban structure is addressed in comprehensive planning processes. In this study, we attempt to identify urban structure using a Network–Activity–Human model under the Transit-Oriented Development (TOD) concept, since TOD is usually regarded as an urban spatial planning tool. In order to explore the strengths and weaknesses of the urban structure, we define the TOD index and unbalance degree and then classify the urban areas accordingly. We take the city of Beijing as a case study and identify nine urban types. The results show a hierarchical urban structure: the city center covers most of the hotspots which display higher imbalances, the surroundings of the city center are less developed, and the city edges show higher potentials in both exploitation and transportation development. Moreover, we discuss the extent to which the spatial scale influences the unbalance degree and apply a sensitivity analysis based on the goals of different stakeholders. This methodology could be utilized at any study scale and in any situation, and the results could offer suggestions for more accurate urban planning, strengthening the relationship between TOD and spatial organization.

Keywords: TOD; imbalance; urban structure; transportation network; activity; human

1. Introduction

There are three core concepts of urban systems: urban form, urban interaction, and urban spatial structure [1]. The urban spatial structure is defined as the geo-location and integrated relationship of different urban elements [2,3], and it is also the internal mechanism between urban form and urban interaction.

In urban planning, policy makers and the government always attach great importance to urban structure since it reflects both physical and dynamic contexts [4]. Identifying urban structure can give planners a deeper insight into the evolution of the city. The rapid development of urbanization has resulted in a prominent aggregation of people and buildings among metropolises, creating new urban growth poles or subcenters. Urban structure evolution, from a monocentric to a polycentric model, always emerges along with the economic development and the growth of urban scale.

Uncontrolled development gives rise to urban issues, most of which derive from the imbalances between supply and demand [5]. Urban elements such as land and transportation belong to the static

supply side, and human behavior always belongs to the demand side (see Figure 1). The limitation of urban boundaries restricts urban land supply, thus enhancing urban densities. The lack of an efficient public transportation system results in congestion and pollution, especially in some rapidly developing countries. Meanwhile, unaffordable housing prices and rents in downtown areas force people to relocate to the undeveloped suburbs, generating crowded and lengthy commutes. Owing to the economic bubble and financial crisis, the unemployment rate is high, resulting in a vacancy problem in both residential houses and commercial houses [6]. All of these phenomena reflect the urban disequilibrium.

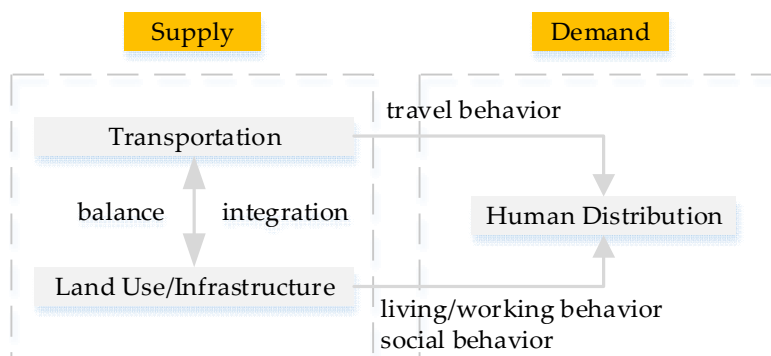


Figure 1. The relationship of supply and demand in urban dynamics.

In order to catch up to the high speed of urban development, it is necessary to build a compact, balanced, and sustainable city. In this context, it is of great significance to analyze the relation and interaction of different urban elements and their comprehensive impact on urban structure.

A variety of studies have been done on urban structure, and significant urban elements are recognized as forming and influencing the urban structure, such as transportation [7,8], road networks [9], distribution of buildings [10], land-use patterns [11], economic performance [12], and human behaviors [13].

By analyzing the distribution of different urban elements, urban structure can be understood in multiple perspectives. According to the land-use data, urban functional areas such as industrial areas and residential areas are distinguished [14]. Building densities or employment densities can help identify the polycentric structure, and high-density places are always regarded as the city centers and subcenters [15]. In the field of urban structure identification, most existing studies emphasize how a given urban element influences the urban form and, thus, only focus on the geo-distribution of this single urban element. Their comprehensive influences on urban structure and relations are rarely studied.

On the other hand, there are many literatures discussing the interactions of different urban elements and the most frequently used method is the Geographically Weighted Regression [16–19]. However, these works mainly focus on the relations between urban elements and ignored the geo-distribution and the urban structure identification process.

In order to fill this research gap, we focus not only on urban structure recognition but also on the relations of urban elements. This paper examines the urban elements through three aspects: adapted space with potential activity, dynamic space with the aggregation of humans, and channel space with multiple transportation services. Places that are well covered by public transportation services, aggregating commercial and social institutions and attracting human activities, are defined as urban vibrancy. Places aggregating one or two types of elements are defined as potential urban growth poles. Our aim is to identify urban vibrancy and potential urban growth poles and to judge urban imbalances according to the distribution of different urban elements. By analyzing the correlation between the areas' development potential and their imbalances, we can offer suggestions for urban planning.

2. TOD Concept and Urban Structure

In this paper, we try to identify the urban spatial structure under the concept of Transit-Oriented Development (TOD). TOD emphasizes the development and opportunities provided by high-quality public transportation [20]. It underlines the integration and cooperation of transportation and land use, aiming to attract activities to areas around the main transit stations and contributing to a habitable and walkable community.

TOD is one of the key tools in urban spatial planning. Different TOD projects may occur at different scales such as at the station level [21–23], local level, corridor level, city level [14,24], regional level, and national level [25,26]. In this paper, we limit our discussion to TOD potential in areas smaller than the city scale. There are three aspects showing how TOD is related to urban spatial structure:

Firstly, TOD performance is the comprehensive measurement of diverse urban elements. Areas with TOD potential are usually sufficient in transportation service, commercial activities, ecological environment, well-designed built environment, social diversity, good social quality, and so forth [27,28]. Using the TOD concept could help us explore urban structures from different perspectives, thus developing a new approach and a deeper understanding of the relationships among different urban elements.

Secondly, TOD evaluation can be used as a technique to recognize the urban vibrancy or urban growth poles. The typical characteristic for TOD used to be regarded as the 3 Ds, which are high *density*, the *diversity* of land-use patterns, and the habitable *design* [29]. Then, the 3 Ds were extended to the 4 Ds, the 5 Ds, and the 6 Ds, where the importance of *destination* value, the *distance* to transit, and the *demand* management were successively proposed [30–32]. Generally, density is regarded as the key concept in the description of urban spatial structure [33], and it is also the key factor in forming city centers and subcenters [4]. Diversity represents mixed land use. By analyzing different land-use patterns, the activity centers, residential centers, urban areas, suburban areas, and neighborhoods are distinguished [14]. Furthermore, commercial activities are always considered in measuring the TOD potential. One study [11] used commercial land-use data to discover the economic structure and recognized the city center based on urban centrality and spatial proximity.

Thirdly, TOD emphasizes a sustainable and balanced city and neighborhood structure. At the station scale or local scale, the balance between transit and land use is frequently studied. For instance, the resolution of the tension between node and place is one of the five main goals for TOD [26]. It derives from the Node–Place model, where nodes are the stations of transportation networks, and places are the areas, in the city, surrounding the nodes [34,35]. This model defines “balanced areas” as areas where the scales of node and place are roughly equal. The Node–Place model has been extended to create new models, such as the Node–Density–Accessibility model [36] and the Butterfly model [37]. At the urban scale, a job–housing balanced structure is required in order to reduce the commuting time [38,39], and the balance degree is measured by the ratio of job and housing.

However, there are still some topics which require further examination. Though urban imbalance is a long-standing topic, there are few studies on the quantification of imbalance. Generally, previous studies have been concerned with what a balanced situation looks like and how to address imbalance. Researchers use the ratio to this end. For example, in a Node–Place model, a balanced ratio of node and place should be 1 [21]. Case studies in the USA indicate that, when the employment–resident ratio reaches 2, the community is more balanced [40]. In one study [41], the authors define that, if a one-way commute is less than half an hour, the area is balanced. Then, they select some typical urban nodes and illustrate that the large-scale work centers and residence centers are more unbalanced. However, most studies mentioned above only focus on selected or typical areas and not on the behavior of the whole urban areas.

Urban structure could be regarded as a comprehensive interaction of activities, humans, and urban resources. However, early studies for TOD evaluation show less concentration on human behavior. The frequently used indicator to describe human distribution is the population census or the ridership, and the data source is always statistical data for a district [13,27]. The population census presents

the distribution of residents, and the ridership reflects the traffic demand around the transit nodes. We mapped those location-fixed data as the static distribution. The human dynamic distribution can reflect population movements over time. Due to the high population mobility and the social diversity, it is necessary to measure different types of human behaviors around the whole urban area instead of in fixed areas only. With the development of data-acquisition techniques, dynamic data sources such as smart card data [42], Point of Interest (POI) data [43], social media data [4], and remote sensing data [44] are organized to study the urban agglomeration. Those datasets show different types of human activities at different places, such as entertainment, dining, and shopping. However, to the authors' knowledge, such data have not been used in TOD evaluation and most researchers only analyze how one kind of data source influences the human distribution. The relations between data sources and the combined influences have not been studied yet.

Urban structure is generally treated by geography techniques and includes a multi-scaled spatial phenomenon. The distribution of TOD potential may vary according to different study scales. However, there are no uniform standards for the scale of a TOD area and no uniform approach to measure TOD potential for different scales. As for the definition of TOD, the reasonable distance is within an 8–10-min walk, which is considered to be 500–800 m in distance [14,25,45,46]. Another commonly used size is a 700-m buffer around the station [21,22,35,47–49]. Smaller sizes such as a 400-m or a 600-m radius circle are also considered based on the physical situation [25,50]. Due to the high density and large construction land area, the study scale in some Asian cities is larger than that in European or American cities. In China, the areas within a 1000-m radius [51] and a 1500-m radius [52] have been studied based on average length of road links between intersections and average stop spacing, respectively. Furthermore, the extent to which study scale influences TOD and urban imbalance is still a research gap.

In order to identify the urban structure under TOD concept, we address the following topics in this paper:

- How can TOD potential and urban imbalance around the entire urban areas be measured?
- How are urban vitality and new growing poles distributed throughout the city, and how do they behave?
- How are urban imbalances distributed throughout the city, and what causes such imbalances?
- What is the relationship between development and imbalance in any given area?

This paper is organized as follows: In Section 3, we create a Network–Activity–Human model and describe the main method to measure urban structure. In Section 4, we take Beijing city as a case study, analyzing its characteristics and distinguishing different kinds of urban types according to the distribution of imbalances. In Section 5, we make deeper discussions on the Network–Activity–Human model in order to see its internal relationships and how it is sensitive to different factors. Section 6 reports the conclusions.

3. Methodology

In this section, we first identify indicators for TOD performance and group them according to the Network–Activity–Human model. Then, we define and calculate a TOD index using Spatial Multi-Criteria Analysis to measure TOD potential, which is the comprehensive impact of the Network structure, Activity structure, and Human structure. Areas with good transportation systems, enormous land-use potential, and close human interactions are definitively recognized as city vibrancy. Finally, we define unbalance degree in order to see the distribution of urban imbalances and to classify urban areas into different categories using the spectrum clustering method.

3.1. A Network–Activity–Human Model

By summarizing a variety of indicators in TOD evaluation [14,22,45,47,53–59] as well as by considering the availability of the data, we separated the indicators into the network group, the activity group, and the human group.

The purpose of the Network structure is to measure transit service. Furthermore, it not only decides the connectivity of the city but also influences economic vitality. Areas around transit hubs and transit corridors promote economic opportunities and boost investment, thus attracting people and activities.

The Activity structure is closely related to land-use patterns. It represents a precondition for the spatial distribution of individuals such as residents, employees, entrepreneurs, and so on, which means that areas with higher activity level show more opportunities and developing potential. Due to overexploitation and unemployment, many places with high building densities have high vacancy rates, which is a waste of resources.

The Human structure reflects the demand side. It shows both the static and the dynamic distribution of people, mapping human interests and preferences. Actual human movements are influenced by the supply side, such as the availability of transportation and the attractiveness of a place.

The three structures all have positive impacts on TOD implementation. Six basic urban issues including lack of transportation service, traffic congestion, excessive concentration, high vacancy rate, lack of exploitation, and overexploitation are raised according to the imbalances between the structures, with each of the three imbalances corresponding to one pair of issues (see Figure 2). Areas with similar network, activity, and human levels are defined as balanced areas. The network–activity–human model presents an overview of the urban structure. It could help identify urban strengths and weaknesses, thus providing references for government, transit agencies, developers, and investors, since different stakeholders could find their own interest in this model.

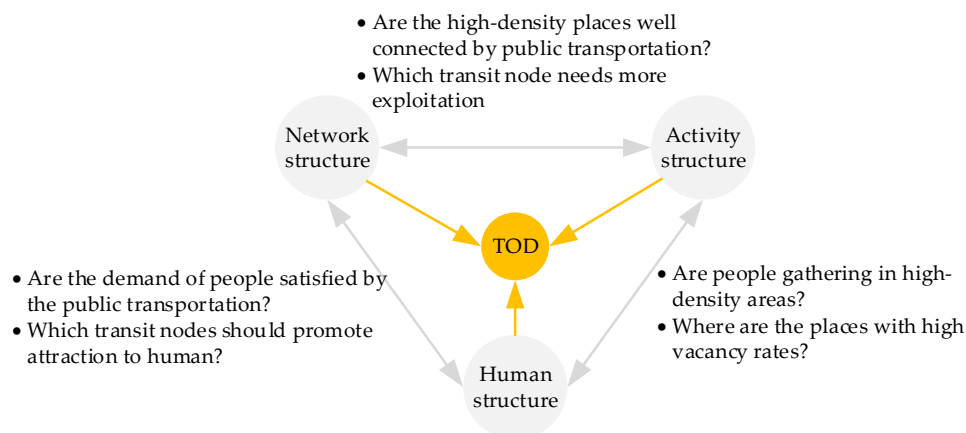


Figure 2. Network–Activity–Human model.

3.1.1. Network Structure

The transportation network is the skeleton of the city. A public transportation system usually consists of railway, bus/rapid bus, tram, and so on, and each type of transportation network consists of transit lines and transit nodes. Areas with proper and efficient transit network and facilities always lead to convenient traveling. In a typical Node–Place model, the service frequency and the number of directions for each type of transportation are the main factors to measure a transit node value [34]. Such indicators are appropriate for smart cities with accurate transportation schedules, such as cities in Germany, the Netherlands, and Japan. In cities with large populations and motor vehicles, the road condition is complicated, so a steady timetable and service frequency might not be guaranteed. Under such conditions, the density of bus lines/rail lines, the density of bus nodes/rail nodes, and the density of bus lanes within a given area are chosen to measure the service quality.

As the basic principle of TOD, people are encouraged to walk or ride a bike within a certain distance. Especially in recent years, the increasing bike-sharing market increases opportunities for bike riding. Sharing bikes from companies such as *Ofo* and *Mobike* have spread to many cities, and more facilities and infrastructures are constructed. This being the case, our work also considers the pavement and bike-lane density and the bike-parking density.

3.1.2. Activity Structure

Different Activity structures result in multiple land-use patterns. Building/organization densities [45,60] and job/employment densities [22,35,36,47] are the common factors that determine activity types, such as routine activities, institutional activities, and production activities [61]. The data source of job/employment opportunity is always the regional statistical data from the government, which, however, does not make sense at the community or station level. Therefore, we selected building densities and organization densities to measure the Activity structure, since such data are more accurate in smaller study scales and are easier to obtain.

A livable and sustainable community should have sufficient manufacturing, service, recreation, education, and health [62]; accordingly, in this paper, resident density, enterprise density, commerce density, restaurant density, education density, and health density are considered. The land-use mix index is selected to measure the land-use diversity [63].

Additionally, the area's attraction can be reflected by the market potential [64], and we selected land value [62] and Return On Investment (ROI) [65] to measure the economic characteristic. Land value varies with different land-use patterns. Generally, the land value declines as the distance to the city center increases. Areas with high location attraction, vigorous commerce, and preferential policies have high land value [66]. In this paper, we used the average housing price to judge land value, since housing price is usually driven by land value [67]. ROI reflects the potential for investment, which is calculated by the ratio of rent and housing price.

3.1.3. Human Structure

Human structure reflects living space and the agglomeration of people. Population density is commonly used to describe the static distribution of inhabitants. We created a Thiessen polygon for the regional census data so that we could estimate population density at any study scale.

In order to measure diverse human behaviors, we have taken a synthetical perspective, which includes travel behavior, recreation behavior, social behavior, parking behavior, and consuming behavior. TOD has a strong effect on travel behavior and mode choice, which can be reflected by the transit ridership [68,69]. It has been proven that TOD areas usually have a higher ridership [70]. With the development of web crawler technology, social density and recreational density can be collected through location-based mobile apps (e.g., Facebook, Weibo, and WeChat) and map service apps (e.g., Google maps and Amap). People check in while shopping, dining, or interacting with others, and their locations are marked at the same time. The parking density is selected to judge car ownership within the area, since TOD encourages public transportation and discourages cars. We used the Air Quality Index (AQI) to measure the quality of the living environment. AQI is the comprehensive measurement of air emissions, including CO, SO₂, NO₂, and PM_{2.5} (particles smaller than 2.5 microns). Different countries may have different standards and calculation methods for measuring AQI [71]. To standardize AQI and to make it convenient for TOD measurement, we considered places with higher AQI more livable (For cases where the AQI is lower when the air quality is better, we normalize the initial AQI data by the reciprocal transformation). The average consumption is selected too, since it is associated with purchasing power, income, and quality of life. As people pay bills through mobile apps, amounts can be collected. By compiling total amount in a given area, we were able to judge the consumption level.

3.2. Spatial Multi-Criteria Analysis

In this paper, we use Spatial Multi-Criteria Analysis (SMCA) to measure TOD index (see Figure 3). SMCA is commonly used in geography planning [72–74], which is efficient in evaluating objects with multiple properties. We create a group of grids G ($g_i \in G, i = 1, 2, \dots, m$) covering the whole study area. Each grid G_i has n indicators (attributes). The set of the indicators is A ($a_j \in A, j = 1, 2, \dots, n$). For each grid g_i , the indicators are divided into object set $O_{i,k}$ ($k = 1, 2, 3$), including the network set $O_{i,1}$, the activity set $O_{i,2}$, and the human set $O_{i,3}$. Each object $O_{i,k}$ is related to J_k indicators; for each grid g_i , there is always a value x_{ij} for indicator a_j and a value $O_{i,k}^{index}$ for objective $O_{i,k}$ (we define $O_{i,1}^{index}$ as the Network index, $O_{i,2}^{index}$ as the Activity index, and $O_{i,3}^{index}$ as the Human index).

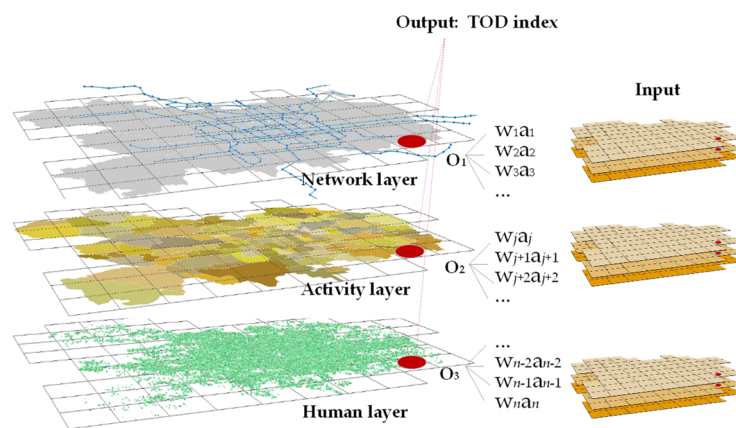


Figure 3. Layout of the Spatial Multi-Criteria Analysis.

We calculated the indicators in each grid in ESRI ArcGIS 10.3.1 for desktop [75]. To unify the dimensions, linear scale transformation is used to standardize the indicators (see Equation (1)).

$$x_{i,j}^{index} = \frac{x_{i,j} - x_{min,j}}{x_{max,j} - x_{min,j}} \quad (1)$$

Analytic Hierarchy Process is used to measure the Network index, the Activity index, the Human index, and the TOD index. This method is to derive a ratio matrix from paired comparisons of the indicators [62]. Since TOD involves different stakeholders, we made the survey among experts from different organizations. Actors such as members of the local government, members of the transit agency, developers, investors, and the travelers all participated in the survey [76]. The input is obtained from subjective opinions and preferences of those experts, and the output is the relative weights. For each indicator a_j , the weight is w_j , and for each object $O_{i,k}$, the weight is v_k . Both w_j and v_k are from the comprehensive measurement of the stakeholders' score. All the scores are shown in Table 1. The Network index, the Activity index, and the Human index in each grid is calculated by Equation (2), and the TOD index TOD_i^{index} is a comprehensive measurement of the Network index, the Activity index, and the Human index and is shown in Equation (3).

$$O_{i,k}^{index} = \sum_{j=1}^{J_k} w_j x_{i,j}^{index} \quad (2)$$

$$TOD_i^{index} = \sum_{k=1}^3 v_k O_{i,k}^{index} \quad (3)$$

Table 1. Hierarchy and description of the Network–Activity–Human model.

Object	Object Weight (v_k) ¹	Index	Indicator	Indicator Weight (w_j) ¹	Calculation
Network (O₁)	0.27/0.25/0.39/0.24/0.34/0.30	a_1	bus line density	0.11/0.14/0.10/0.12/0.13/0.12	length of bus lines/surface area
		a_2	rail line density	0.17/0.18/0.19/0.20/0.17/0.18	length of rail lines/surface area
		a_3	bus node density	0.14/0.16/0.15/0.15/0.18/0.16	number of bus nodes/surface area
		a_4	rail node density	0.21/0.18/0.21/0.24/0.20/0.21	number of rail nodes/surface area
		a_5	bus lane density	0.10/0.11/0.16/0.10/0.10/0.11	length of bus lanes/surface area
		a_6	pavement and bike lane density	0.14/0.13/0.07/0.08/0.08/0.10	length of pavement and bike lanes/surface area
		a_7	bike parking density	0.13/0.09/0.12/0.11/0.14/0.12	number of bike parking areas/surface area
Activity (O₂)	0.41/0.35/0.28/0.40/0.28/0.34	a_8	enterprise density	0.11/0.12/0.09/0.09/0.13/0.11	number of enterprises/surface area
		a_9	commerce density	0.12/0.10/0.07/0.08/0.09/0.09	number of commercial organizations/surface area
		a_{10}	restaurant density	0.11/0.11/0.13/0.13/0.15/0.13	number of restaurants/surface area
		a_{11}	resident density	0.12/0.13/0.15/0.13/0.13/0.13	number of residences/surface area
		a_{12}	educatiodensity	0.08/0.06/0.08/0.07/0.09/0.07	number of educational organizations/surface area
		a_{13}	health denty	0.07/0.04/0.07/0.05/0.11/0.07	number of health organizations/surface area
		a_{14}	land-use mix index	0.15/0.17/0.11/0.13/0.19/0.15	$-\sum_{j=1}^t P_t \ln(P_t) / \ln(t)$, P_t is ratio of land-use pattern t
		a_{15}	land value	0.12/0.13/0.13/0.15/0.07/0.12	housing prices
		a_{16}	ROI (Rern on Investment)	0.13/0.15/0.16/0.16/0.04/0.13	rent per year/housing price
Human (O₃)	0.32/0.40/0.33/0.35/0.38/0.36	a_{17}	population density	0.14/0.17/0.16/0.14/0.08/0.14	number of people living in the area/surface area
		a_{18}	AQI	0.10/0.07/0.08/0.07/0.18/0.10	Air Quality Index
		a_{19}	car parking density	0.12/0.10/0.11/0.10/0.19/0.12	car parking area/surface area
		a_{20}	ridership	0.16/0.14/0.23/0.15/0.10/0.16	travel demand within the area
		a_{21}	recreational density	0.17/0.12/0.14/0.17/0.18/0.15	check-in times of recreational apps during one month
		a_{22}	social density	0.16/0.21/0.19/0.18/0.21/0.19	check-in times of social apps during one month
		a_{23}	consumption	0.15/0.19/0.09/0.19/0.05/0.14	average consumption within the area

¹ Object weight/indicator weight is the weight organized by different measurement groups: developer score/local government score/transit agency score/investors score/traveler score/average score; the general results in Section 4 are calculated by the average score.

Furthermore, we divided the urban area using different grid sizes in order to discuss how the modifiable areal unit influences identification of the urban structure.

3.3. Urban Imbalance Identification

Our goal is to discover the relations among the Network structure, the Activity structure, and the Human structure. Since there is no criterion for what is “imbalanced”, we normalized the Network index, the Activity index, and the Human index in each grid, represented as $O'_{i,k}^{index}$. Then, we calculated the variance among $O'_{i,1}^{index}$, $O'_{i,2}^{index}$, and $O'_{i,3}^{index}$ (See Equation (4)). The unbalance degree measures variation from the average. It is a relative number, not an absolute number. In other words, a grid with a higher unbalance degree means that, compared to the other grids, it is more unbalanced.

$$unbalance\ degree_i = \frac{1}{2} \sum_{k=1}^3 (O'_{i,k}^{index} - \overline{O'_{i,k}^{index}})^2 \quad (4)$$

The unbalance degree is the overall reflection of urban performance. In order to know what causes such imbalance, we used cluster analysis to classify the urban land. Under cluster analysis, we can discover the relationship among the Network index, the Activity index, and the Human index in a given area. Previous studies often use the density-based cluster method or the hierarchical clustering method for TOD cluster, which are fit for clustering a small quantity of transit stations. Our work concentrates on the entire urban area, and when the study area (grid size) is smaller, there are a large number of grids, leading to higher computation time. In this paper, we used the spectrum clustering method [77] to identify how the transportation network, activity patterns, and human aggregation were matched; the spectrum clustering method is more efficient and faster in large-scale calculation and can be widely used in any scale of study area.

The selected indicators in the Network–Activity–Human model and how they are calculated are shown in Table 1. The object weights and the indicator weights which are calculated by the Analytic Hierarchy Process are shown in Table 1, too.

4. Case Study

4.1. Study Area and Data Preparation

Beijing is a typical developing city in China with a high population density and large surface area. In 2017, the external population from outside Beijing reached 36.6%. Beijing has a large scale of both public transportation and private transportation, leading to serious traffic congestions and long commutes. It consists of seven ring roads and radial roads in total. The average bus station spacing is 300–1000 m, and the average subway spacing is 450–3000 m. According to previous studies and in the case of Beijing, we worked with different study scales (grid size) from 500 m × 500 m to 3000 m × 3000 m to see the scale effect.

In this paper, the discussion is focused on Beijing’s central districts. Figure 4 presents the study field and basic information on Beijing. In the Beijing center master plan for 2016–2035, the whole area is divided into four zones and the main functional nodes are marked red in the map. The Finance Street Center and the three high-speed rail stations are at the core area, the Center Business District (CBD) is located at the northeast, and the other industrial parks are distributed around the whole area. Rail nodes are distributed mainly among the core area, and some extend to the city edges.

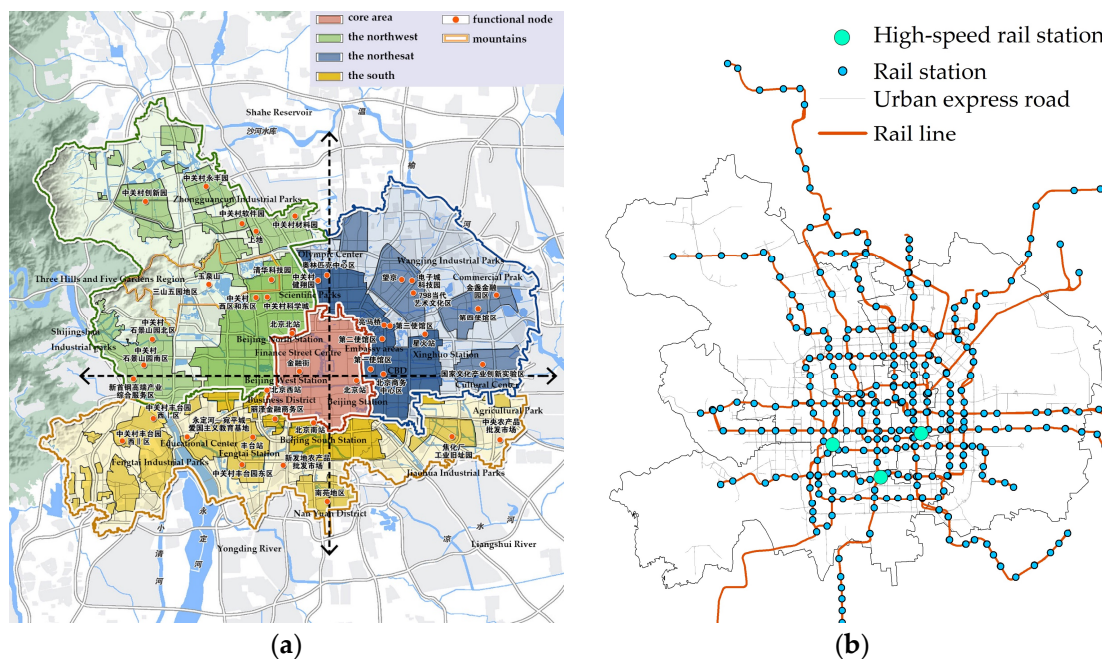


Figure 4. Basic information on Beijing: (a) The master plan and functional zone for Beijing central districts (2016–2035); (b) the Beijing rail network (2019).

The transportation network, including bus lines/nodes, rail lines/nodes, and urban roads, is collected from Amap, as are the POIs of car/bike parking areas, buildings, and facilities. The source of population density is Beijing's 2010 census data. Housing prices and rent prices were acquired using a web crawler through a house-selling website. The AQI was obtained from the air quality website of Beijing for the entirety of 30 November 2017, and the travel demand was calculated using smart card data from Beijing Public Transport Corporation, displaying all Origin-Destination (OD) pairs for the same day. The recreational data, the social behavior data, and the average consumption data were collected from location-based social network websites and social media apps. When customers check in or pay their bills, their locations, consumptions, and time are recognized.

4.2. Overview of Urban Vibrancy

The Network index, the Activity index, the Human index, and the TOD index for the whole urban area are shown in Figure 5. It can be concluded that buildings, human behaviors, and the main modes of public transportation are all centralized in the core areas. Several subcenters are gradually formed around the main center. The locations of those new growth poles are similar to the distribution of functional zones in Figure 4. Furthermore, there is a comparatively lower value in the very center of the city due to the famous Tiananmen Square, of which the area is near 0.44 km².

In order to see how certain areas behave as well as to verify the accuracy of the model, we selected 220 grids (14.45%) containing rail nodes, 721 grids (47.37%) containing large residential blocks, 1291 grids (84.82%) containing working buildings, and 171 grids (11.24%) containing business centers. The results are shown in Figure 6.

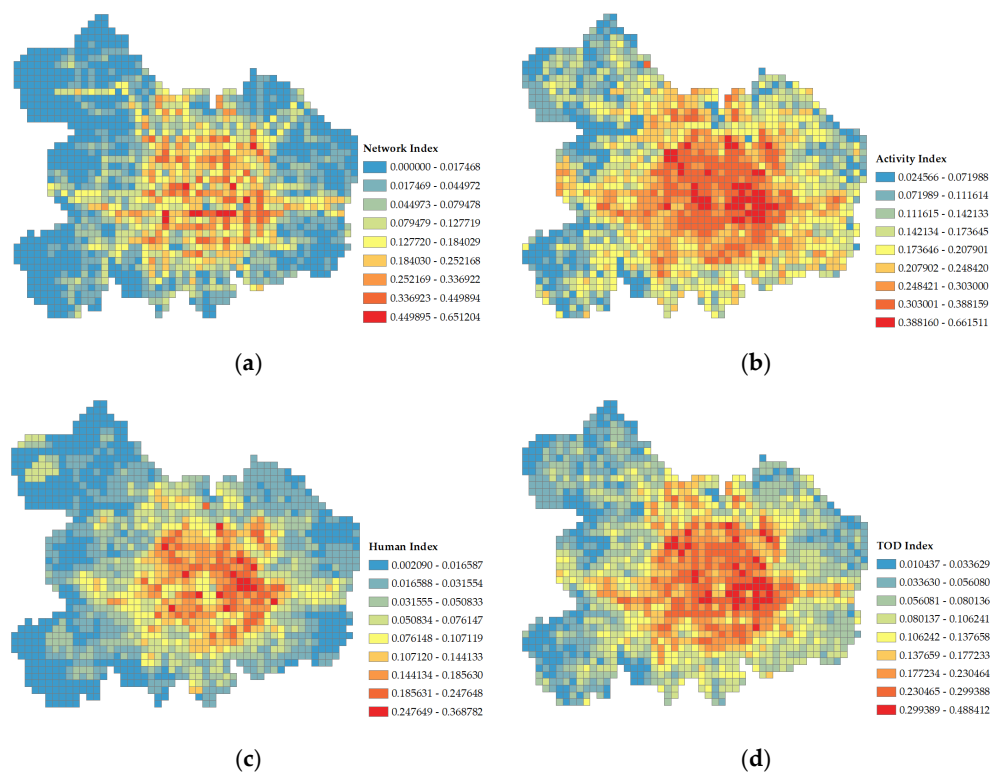


Figure 5. Overview of the urban structure for a 1000-m grid size: (a) Network structure, (b) Activity structure, (c) Human structure, and (d) TOD index.

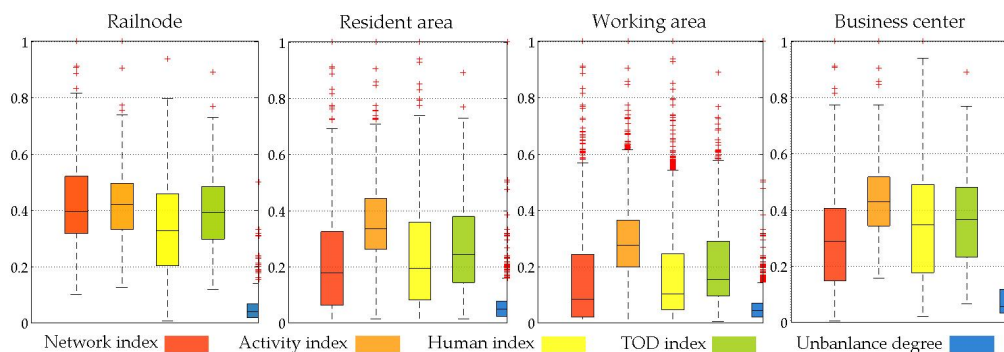


Figure 6. Box plots of the Network index, the Activity index, the Human index, the TOD index, and the unbalance degree for different areas (1000-m grid size).

The best performance for the TOD index occurs around rail nodes and business centers. It is easy to understand why the surroundings of rail nodes have a higher value in the Network index, for there are abundant transfer choices. Business centers are usually hotspots in the city center with high population density, diversified land use, and good transportation services, aggregating commercial and social activities. These centers show the highest Activity index and Human index. However, compared to other situations, the unbalance degree is the highest. The average Network index scores around residential areas are lower, explaining the reason for the congestion during peak hours. Due to the high population density in Beijing, job opportunities are widely distributed and such discreteness results in a low score in TOD index. The lack of transportation facilities around residential and working areas stresses the deficiency in the public transportation network, since it cannot satisfy the demand of a large number of commuters.

4.3. Identifying Urban Imbalances

The unbalance degrees for grid sizes from 500 m–3000 m in Figure 7 demonstrate the scale effect. It is important to note that, as the grid size grows, there is a more obvious aggregation effect of the disequilibrium and the unbalanced areas tend to move to the city's edges.

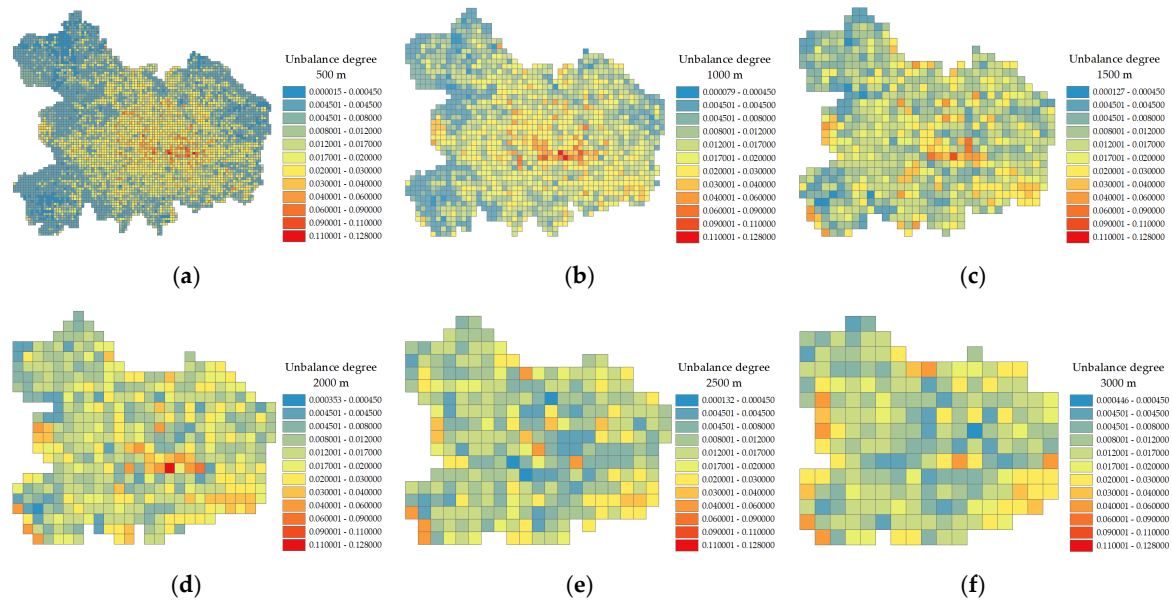


Figure 7. Unbalance degree of the urban area (grid size from 500 m–3000 m): (a) 500-m grid size, (b) 1000-m grid size, (c) 1500-m grid size, (d) 2000-m grid size, (e) 2500-m grid size, and (f) 3000-m grid size.

As the grid size grows, people and facilities are more decentralized and dispersed across a larger area in the city center, leading to a lower density, and public transportation is more easily found, so that the unbalance degree decreases from Figure 7a–f. At the city's edges, when the grid size becomes larger, the transportation system's weakness is highlighted, where it is unable to catch up with exploitation, thus generating imbalances.

We classify the whole urban area according to the characteristics of the Network index, Activity index, and Human index. Our aim for the urban category can be separated into two parts. First, we aim to locate the hotspots and potential TOD areas; second, we aim to identify where the imbalances derive from. The basic principles for urban classification are to find the minimal urban typology, to find where the differences within each typology are minimal, and to maximize the differences between each typology. We tested the cluster number from 5–50 to find the proper classification for three indexes, and the cluster effectiveness (calculated using Equation (5)) is shown in Figure 8.

$$\text{cluster effectiveness} = \frac{\text{between cluster sum of squares}}{\text{the total within cluster sum of squares} + \text{between cluster sum of squares}} \quad (5)$$

When the cluster number is small (less than 7), it is difficult to distinguish the core area, since all three indexes are relatively high, which leads to an aggregation effect. As the cluster number grows within the limits, the output of the clustering effectiveness is higher. We find that, when the cluster number is larger than 9, the cluster output of urban edges does not change too much. Considering both accuracy and complexity, we made 9 clusters according to Network index, Activity index, and Human index. The cluster centers are shown in Figure 9, and the geographical distribution is shown in Figure 10. Some typical areas are then recognized.

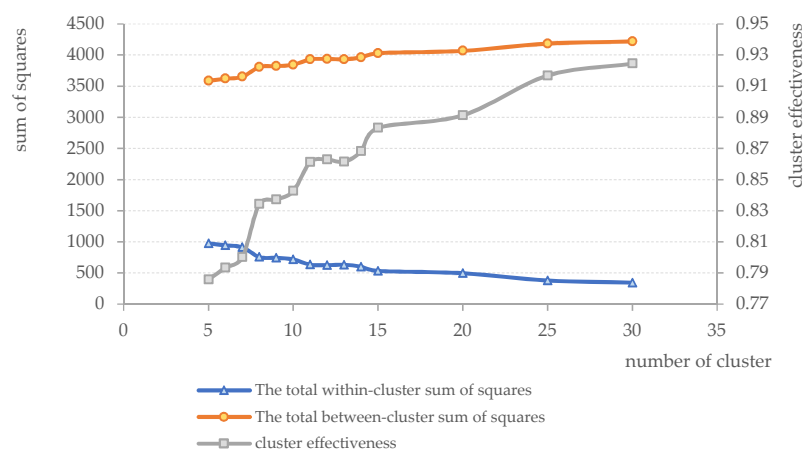


Figure 8. The cluster effectiveness for different cluster numbers.

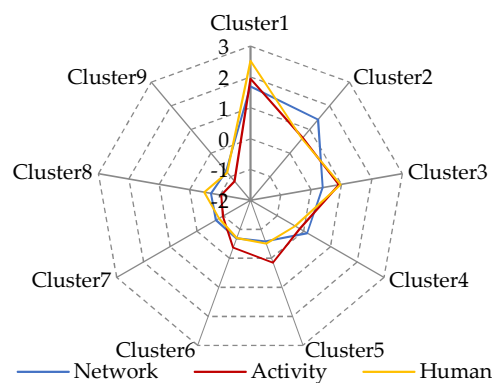


Figure 9. Cluster centers for a 1000-m grid size.

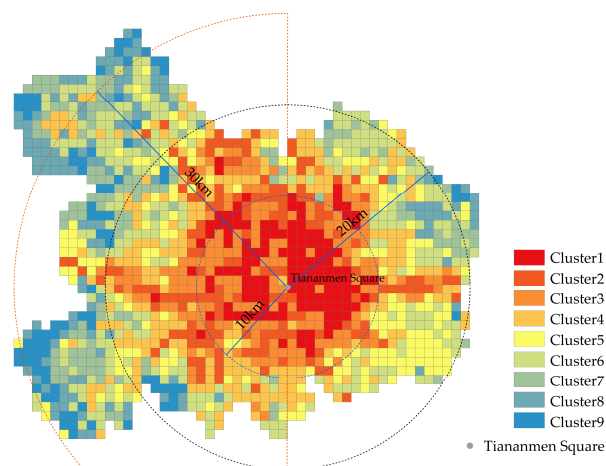


Figure 10. Cluster output for a 1000-m grid size.

Cluster 1 is made up of the highly developed areas which contain many business zones, the majority of the commercial facilities, and places of employment, so that the Network index, the Activity index, and the Human index are the highest among all clusters. However, these areas also have high unbalance degrees (see Figure 4b). Cluster 2 is made up of the areas with higher public transportation level but the land is less developed and lacks in attraction to humans, which indicates that there is a high potential for exploitation around transit nodes. In Cluster 3, the case is the reverse of Cluster 2 and public transportation cannot match the demand.

Clusters 1–3 always surround the main transit nodes in the city center, having an aggregation phenomenon for fundamental facilities and human events. Most Cluster 1 and Cluster 3 areas are within the 10-km circle around the Tiananmen Square, and they show the transportation level's inability to match the activity density and demand, which also explains the reason for high congestion.

Clusters 4 and 5 are mainly areas that encircle the center city. These are mostly newly exploited areas, which in recent years are welcomed by property developers at the periphery of the city (e.g., Cluster 4 in the northwest of Figure 10 is a new Science and Technology Park). Cluster 4 is better connected by public transportation, which brings more convenience to humans, while Cluster 5 has almost no rail line connected, so that the Human index as well as the unbalance degree in Cluster 5 are generally lower than in Cluster 4.

Clusters 6–9 are the main marginal areas, where all three indexes are lower. The clusters show slight differences according to the distance to the city center and the land-use types. Cluster 6 gather many cultural parks and some luxurious recreational centers, such as the northeast and the south parts in Figure 10. Each of these two places are both near the airport, showing a higher Activity index than the other two indexes. Cluster 7 is composed mostly by industry zones with a single function such as steel industry area, software industry area, and so on. Cluster 8 is mainly made up of recreation clubs and scenic areas, which lead to a higher Human index. However, the lack of service facilities also results in a disequilibrium. Most of Cluster 9 is made up of natural parks and mountains, and all three indexes are the lowest here.

5. Discussion

5.1. Correlation Analysis for the Network–Activity–Human Model

After normalization of the Network index, the Activity index, and the Human index, we made scatter plots to see the relations among them (see Figure 11).

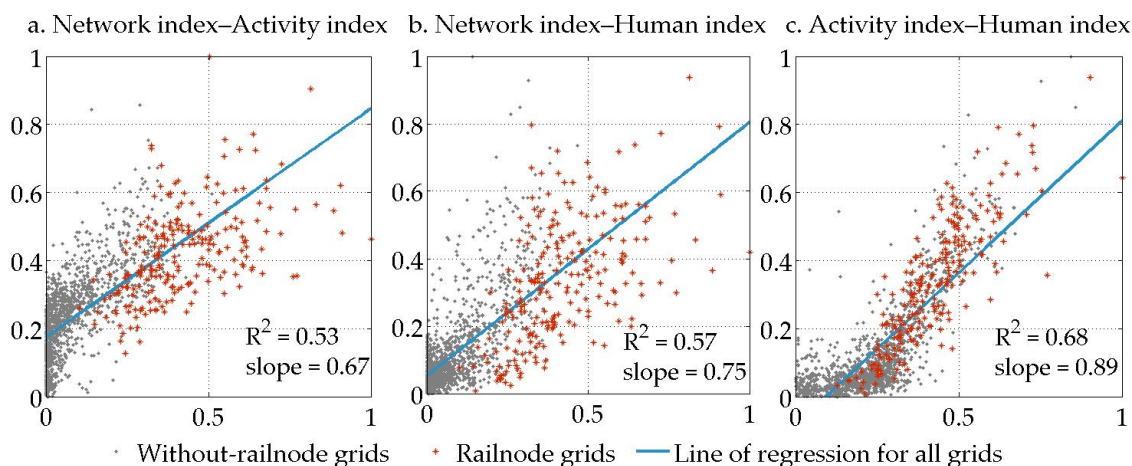


Figure 11. Correlation analysis for a 1000-m grid size.

It is clear that there is a close relationship between each pair of indexes, which means that the design of public transportation, the desired activities, and actual human behavior have the tendency to match each other. In Figure 11, the areas containing rail nodes were selected and marked red in order to see how those surroundings behave. For most of the areas containing rail nodes, there is a global trend for higher scores in all three indexes, reflecting the balance between demand and supply.

By varying the grid size from 500 m to 3000 m, each index shows a similar trend for the whole urban area and each coefficient of determination between the Network index, the Activity index, and the Human index has the tendency to be closer to 1 (see Figure 12), which means that the relationship among the network, the facility, and human behavior appears more prominently in a larger regional scale. When the grid size is less than 1000 m, the coefficient of determination is always less than 0.5,

illustrating a relatively low correlation. This is also the reason why our analysis mainly focuses on the case of a 1000 m \times 1000 m study unit.

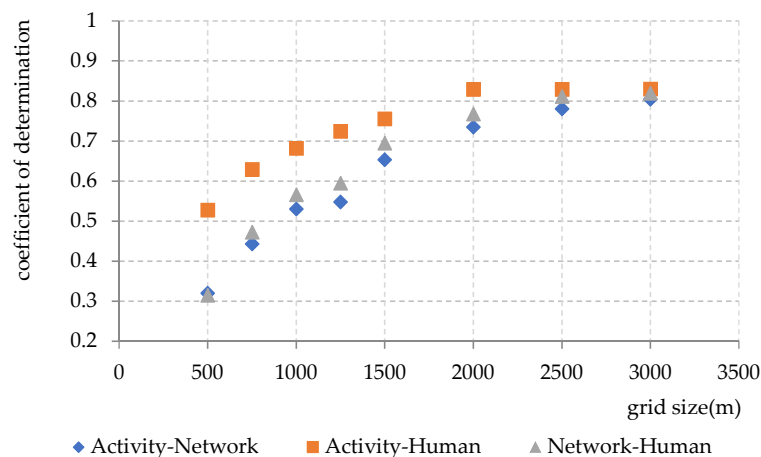


Figure 12. Coefficient of determination for different grid sizes.

5.2. Relation Between the Unbalance Degree and the TOD Index

In order to find out the relation between vibrancy and imbalance, we made a series of scatter plots in Figure 13, with each node representing a grid. There is no obvious dependence relationship between TOD index and unbalance degree. When the grid size is small (e.g., in the case of the 500-m scale), there are many grids with both a high TOD index and a high unbalance degree, meaning that the developed areas are more unbalanced. As the study scale grows, there are fewer areas with both a high TOD index and a high unbalance degree and more areas with a low TOD index and a higher unbalance degree (e.g., in the cases of the 2000-m scale and the 2500-m scale). When the study scale reaches 3000 m, unbalance degrees tend to be stable.

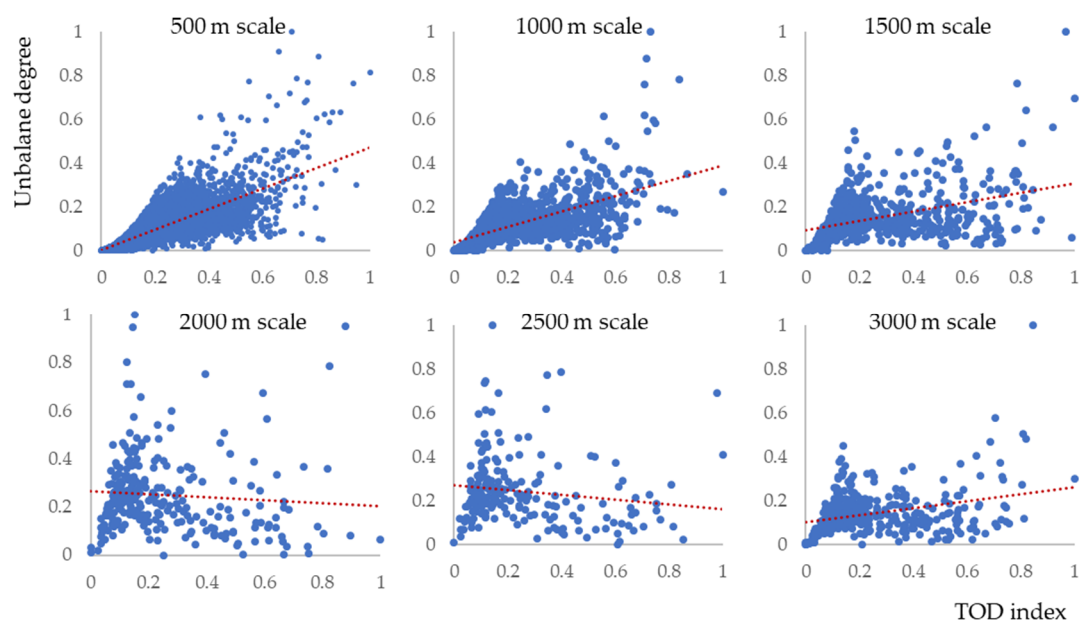


Figure 13. The relation between the TOD index and the unbalance degree.

This result is similar to what we learned from Figure 7. It indicates that, when we study the community-level or station-level cases, higher unbalance degrees tend to appear around highly

developed areas. When we focus on the urban-level or regional-level cases, the rural–urban imbalance is more obvious, since rural areas with lower development potential present higher unbalance degrees.

5.3. Sensitivity Analysis for Different Stakeholders

The standards of TOD outcome may vary with different benefit groups since different organizations may have different concerns [76,78]. For policy makers, their aim is usually at the macroscopic level. Their concerns might be in improving the economy's prosperity, in releasing traffic congestion, in improving living quality, or in redeveloping blighted spaces. They are responsible for planning, facilitating, and shaping development [26]. For developers and investors, the concerns are value capture and the risk of investment; once they decide to invest on a project, they keep a watchful eye on the revenue. From the perspective of transit agencies, increasing the ridership and monetary return as well as reducing the operational cost are the main concerns since they are eager to increase their revenues and to minimize their subsidies [79]. On the other hand, for travelers or riders, convenient traveling, high station access and mobility choices, favorable inhabiting environments, and multifunctional areas for living are major concerns [26].

In order to find out to what extent the objects of different authorities influence the urban structure, we make the sensitivity analysis for stakeholders by varying the indicator's weight in 5 basic scenarios, which derive from 5 measurement groups (see Table 1). The weights of indicators varied according to different scenarios.

How stakeholders can be involved during the implementation of TOD is usually influenced by the context and their different targets [80]. Each actor has the tendency to think of their own benefit but ignore other actors in TOD. For example, travelers only care about whether it is convenient to travel, shop, and work. They pay no attention to transit revenue and urban development. Developers show higher interest when transit construction is certain [81]. They concentrate on ROI but ignore the importance of AQI.

We calculated the variance of 5 TOD indexes for each grid and rank the results. As we can see in Figure 14, the more sensitive areas are at the margins of the city. Meanwhile, most of the more sensitive areas in Figure 14 are residential land (except for the very center of the city, which is Tiananmen Square). We speculate that the unaffordable housing prices and rent force people to move to urban fringes and that the saturated city center creates fewer opportunities for investors and developers, thus creating development potential at the urban fringe.

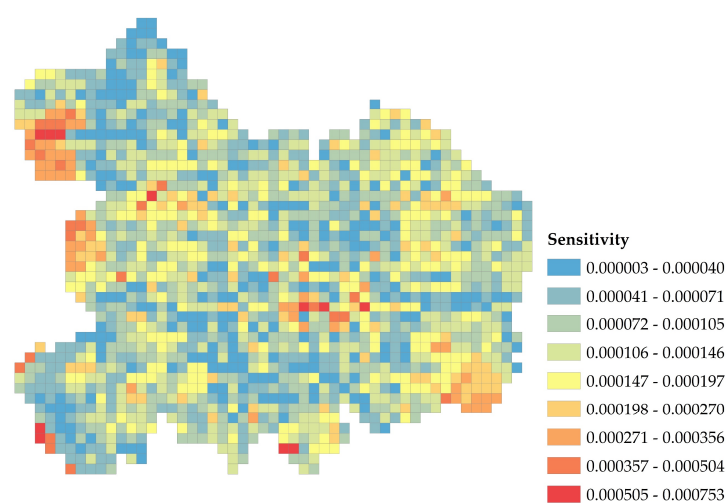


Figure 14. Sensitivity analysis for stakeholders.

6. Conclusions

The target of the paper was to identify urban structure based on a Network–Activity–Human model. We progressively analyzed the urban structure in its different aspects. By ranking the TOD index, we first had an overview of the hierarchical structure of the city, distinguishing the urban vitality and the urban growth poles. Apparently, there is a large and excessively active area in central Beijing, which aggregates around the main rail nodes. We found that, though the current transportation network, the activity opportunities, and human behaviors have positive correlations with each other, there is still disequilibrium around the city. By defining the unbalance degree, we obtained the unbalanced structure of the city, and the urban area was divided into 9 types using the spectrum clustering method according to the Network index, the Activity index, and the Human index. We could know not only where and to what extent the disequilibrium was but also what causes the disequilibrium. We found that most of the highly unbalanced areas were in the central city, for the transportation network could not match the demand of humans, thus causing social problems, leading to more cars, and generating congestion. Some surroundings of the city center were well connected by public transportation but attracted fewer people and activities. There was also a trend for migration to the urban edges with simpler land-use patterns. Newly exploited residential areas and industrial parks brought new growth poles to the suburban areas, which may lead to more opportunities and investment.

We also compared the TOD index for typical areas. The results indicated that commercial centers and transit nodes were higher in TOD index, while residential areas and working areas were lacking transportation service.

With such results in hand, we have a deep understanding of the relationship among transportation, activity, and human distribution. However, limitations are still addressed in this paper. We separated the whole area into different numbers of grids and the boundaries could not be guaranteed to be the same, so that the results for each study scale could only show an overall trend for development. Even so, the results could also offer some recommendations for better urban planning:

Firstly, in terms of the overactive areas in the city center, it is necessary to control the scale of the hot rail stations and business centers, adjusting to a rational exploitation strength to release the aggregation effect. Secondly, a more complete public transportation network and sufficient transit facilities should be constructed in areas where the transportation services could not match the demand, such as the urban edges. Thirdly, the lack of interdepartmental coordination leads to difficulty in integrated utilization of a transit node and its surroundings. Therefore, a collaborative design system is required for a win-win situation, integrating government, developers, and transit agencies. Lastly, high concentration should be distributed throughout suburban areas. Increasing the land development intensity around large residential blocks and developing a diversified TOD community in the suburban areas could also reduce the tension of the city center.

Author Contributions: Conceptualization, Y.Z. and R.v.N.; formal analysis, Y.Z.; funding acquisition, S.H.; methodology, Y.Z. and S.H.; resources, R.S.; software, W.Y.; validation, R.S.; writing—original draft, Y.Z.; writing—review and editing, R.v.N.

Funding: This research was funded by National Key R&D Program of China, grant number 2018YFB1201402, and by Fundamental Research Funds for the Central Universities, grant number 2017JBZ106.

Acknowledgments: The authors would like to thank the editors and the anonymous referees for their valuable comments and suggestions that improve the quality of this paper.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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