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# Spatial-interaction network analysis of built environmental influence on daily public transport demand

## Abstract

Many studies have evaluated the influence of the built environment on public transport. Some studies assign subjective weights to environmental factors, which could oversimplify spatial heterogeneity and overlook the temporal dimension. On the other hand, the spatial-interaction network of public transport system is seldom considered. In this paper, we propose an improved framework to explore how individual factors unevenly affect public transport demand over space and time using a geographically and temporally weighted regression (GTWR) model. The proposed framework extends the local built environmental factors by including two network factors extracted from the spatial-interaction network of the public transport system. We conduct a case study in Beijing, China using 686 traffic analysis zones (TAZs). The actual usage of public transport, namely the public transport index (PTI), is estimated by passenger flow divided by the total amount of human flow in a given TAZ. The daily patterns of the spatial heterogeneity in some selected places in the study area is identified and analyzed. It is also found that the estimated coefficient of the variables of the spatial-interaction network is significantly larger than other static environmental factors, indicating that spatial-interaction network can more effectively reflect spatiotemporal heterogeneity in public transport demand. This study provides a better decision-making support for more accurately identifying which factors are most worthy of development, and when and where they can be implemented to improve public transit services.

**Keywords**: Smart Card Data; Spatiotemporal Heterogeneity; Geographically and Temporally Weighted Regression; Public Transport

## 1. Introduction

Many studies have examined the association between public transport and the built environment, as well as socioeconomic characteristics (e.g., Crane & Scweitzer, 2003; Titze et al., 2008; van Acker et al., 2013; Marti & Weidmann, 2016; Zhang et al., 2017; Yu et al., 2019). These studies quantitatively measured the impact of local built environmental factors (the 5Ds: density, diversity, design, distance to transit, and destination accessibility) (e.g., Renne & Wells, 2005; Evans & Pratt, 2007; Renne, 2009a; Kamruzzaman et al., 2014; Wey et al., 2016) on public transport. Most early studies assumed that public transport travel choice is only affected by local factors within the same spatial unit (e.g., traffic analysis zones (TAZs)) and most relied on empirical observations and surveys of the local spatial unit. However, city consists of a set of actions, interactions, and transactions (Batty, 2013; Liu, 2015), and studies must consider dynamic spatial interactions over space and time (Nasri & Zhang, 2014; Singh et al., 2017). This suggests that spatial interactions within a built environment should be considered from a network science perspective.

Rapid urbanization creates challenges for urban development (e.g., traffic congestion, carbon emissions, energy consumption), which inevitably affect the quality of city life (Waddell, 2002; Sudhira et al., 2004; Waddell et al., 2007; Meerow & Newell, 2017). Public transport is regarded as one of the most important sustainable approaches to solving transport-related challenges, such as traffic congestion and air pollution, and has received considerable attention from governments, researchers, and city planners (Calthorpe, 1993; Jabareen, 2006; Liu et al., 2010; Higgins & Kanaroglou, 2016). The major goal of research in this field is to encourage the use of public transport services and reduce the use of private automobiles by improving a transit-oriented built environment (Lund, 2006; Cervero & Day, 2008; Renne, 20009a; Sung & Oh, 2011). However, most studies have assumed that each influential factor operates evenly over space and time, to some extent ignoring spatial heterogeneity. In reality, a factor may affect certain locations more strongly than others. To more accurately identify the association between the built environment and public transport demand, a spatially heterogeneous model must be applied to identify the uneven impact of both environmental and network factors from a global network perspective.

Motivated by these shortcomings, this work proposes an improved framework to evaluate the uneven influence of various built environmental and spatial interaction factors on public transport demand across space and time. A large dataset of urban sensing big data (i.e., smart card data (SCD) and mobile phone data) is used. Because the goal of public transport is to encourage use, we apply tap-in-tap-out SCD to estimate the passenger flow on public transit, which is expected to reflect the actual use of public transport services in a spatial unit (i.e., a TAZ in this paper). We also use mobile phone data to estimate the total people flow in a TAZ. The passenger flow divided by the total amount of people flow constitutes what we term the public transport index (PTI), which we believe more accurately reflects the relative ratio of public transport use in an area. A spatial interaction network of 686 TAZs in Beijing is generated using this dynamic passenger flow, where the TAZs represent the network nodes. Two network factors of the passenger flow network are combined with eleven commonly used local built environmental factors, and the geographically and temporally weighted regression (GTWR) model is applied to quantify how these factors unevenly shape public transport travel. The findings reveal the spatiotemporal patterns of the influential factors and provide quantitative measures to improve the planning and design of public transport policy.

The remainder of this paper is structured as follows. Section 2 reviews the previous and related work and introduces the factors used to evaluate the built environment and its association with public transit. Section 3 illustrates the proposed framework and research methodology of this paper in detail. In Section 4, we present the study area, data processing, and main results, including the uneven spatiotemporal distribution of the factors and the relationships between public transit service and the built environment. The conclusions and potential directions for future work are presented in Section 5.

## 2. Related work

Human activities occur in geographic space, and human-environment interactions have recently received considerable attention in a variety of fields. It is agreed that the built environment is related to human activities and even shapes them to some extent. For example, some studies have claimed that space is a part of human activity, instead of the background (e.g., Hiller et al., 1976; Hiller & Hanson, 1984), and the structure of space determines human mobility patterns. Hillier and his colleagues (1976) proposed the concept of space syntax to model space as a unique line-based spatial network, and several studies have demonstrated a strong correlation between human movement flow and network structural parameters, such as degree and betweenness (e.g., Jiang et al., 2009; Penn & Turner, 2002; Jiang & Liu, 2012). The association between the built environment and human activities therefore fundamentally affects various aspects of society, including public transport system.

Public transport is an important sub-system within an urban system, and is associated with and affected by the built environment. Some studies have explored how public transport systems interact with the built environment from different perspectives. For example, Crane and Scweitzer (2003) investigated the role of the built environment in the sustainable development of transport, and Yu et al. (2019) explored how the built environment influences public transit choices in urban villages. Marti and Weidmann (2016) addressed the integration of public transport and the built environment at the neighborhood scale, and Zhang et al. (2017) examined the impact of built environment factors on the use of public bikes at bike stations. A general consensus of previous research is that a successful public transport area demands high diversity, high density, and an excellent urban structure design to ensure that pedestrians can easily fulfill their social activities by foot or public transit rather than private car, which achieves the goal of public transit-oriented development (Gu et al., 2019; Kumar and Parida, 2020).

The built environment can be characterized according to several factors. Cervero and Kockelman (1997) suggested the 3Ds concept (i.e., density, diversity, and design) for evaluating the built environment of public transport systems. Density reflects the transit usage, diversity represents the richness of social activities, and design indicates pedestrian convenience. Ewing and Cervero (2010) integrated an additional 2Ds (i.e., destination accessibility and distance to transit) to the 3Ds concept. Destination accessibility and distance to transit reflect pedestrian convenience and the innate qualities of a transit system from another perspective. Schlossberg and Brown (2004) evaluated the walkability and pedestrian environment of public transport sites in Portland, USA, using GIS-based measures such as pedestrian catchment areas, network classification, and impedance-based intersection intensities. Renne (2009b) evaluated public transport in Perth, Australia, based on six outcome aspects: travel behavior, local economy, natural environment, built environment, social environment, and policy context. These public transport evaluation studies demonstrated that ideal public transport is multi-functional with manifold intended outcomes, and the evaluation results can be reflected by the environmental factors.

Batty and Cheshire (2011) suggested that an urban system should consider the spatial interaction and connection between space and place, rather than simply locations. Human sensing big data (e.g., personal trajectory, call-detail records, and social media check-in data) have been widely applied in empirical studies to assess public transport from the perspective of spatial interaction. For instance, Pan et al. (2017) used integrated circuit card data and cellular signaling data to empirically examine the effects of rail transit station-based public transport on daily station passenger volume. Using a large dataset crowdsourced from smart cards, Zhou et al. (2019) explored how to quantify, monitor, and visualize the transit-served areas (TSAs) of southeast Queensland, Australia. A TSA is a type of transit-oriented development. The study analyzed six months of SCD from TransLink related to the total trips generated by or attracted to a TSA and temporal and spatial variations over days using four metrics corresponding to transit agency scenarios. Some traditional statistical models (e.g., ordinary least squares (OLS), geographical weighted regression model (GWR) and temporal weighted regression model (TWR), etc.), are inadequate to model spatial-temporal non-stationarity data (e.g., public transit demand) simultaneously (Huang et al, 2010). On the other hand, some studies may only focus on the heterogeneity of the impacts of built environment on human activities and transport system, whereas the time dimension and spatial interaction are ignored (Du et al, 2018; Fotheringham et al, 2015).

In summary, previous studies have considered the influence of the built environment and human mobility on public transport separately and statically, but network analysis and temporal dimension are seldom considered together to evaluate the heterogeneity. The dynamic nature of transit services and their spatial heterogeneity result in the uneven influence of a given factor on public transport over space and time (Huang et al., 2010). To better understand the factors and their relationships with public transport, we select a set of local environmental factors such as the 3Ds (density, diversity, and design) and measures of economic development (Singh et al., 2014; Singh et al., 2017; Guo et al., 2018). A passenger flow network is generated based on the passenger flow between TAZs. Two network factors are selected to assess spatial interactions. A geographically and temporally weighted regression (GTWR) model is adopted to explore how each factor influences public transport in different TAZs.

## 3. Methodology

Fig. 1 illustrates the proposed four-step framework for evaluating the impact of the built environmental and its spatial interaction on public transport demand. We first preprocess the SCD and then generate the passenger flow network. A set of local factors in the built environment and the flow network are then selected and used to examine the public transport. The public transit index (PTI) is then calculated as a proxy for the level of public transport demand and then both the ordinary least squares (OLS) and GTWR models are used to conduct regression analyses. The spatiotemporal patterns of the factors' influence on public transport demand are then presented and analyzed.

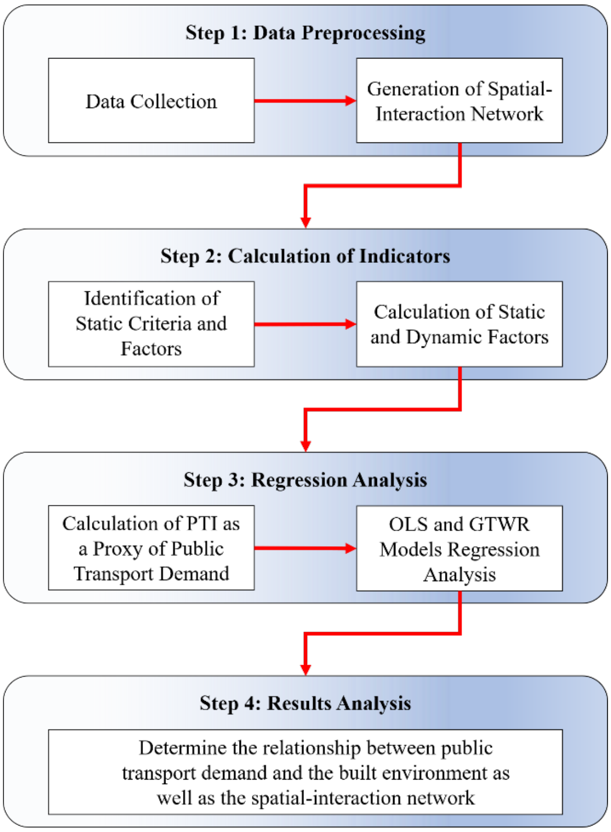



**Figure 1.** Four-step framework for evaluating the impact of the built environmental on public transport demand.

### 3.1. Generation of a spatial-interaction network of passenger flow

Spatial-interaction networks are networks in which the nodes are located in a space equipped with a metric (Barthelemy, 2011). In this study, we generate the public transit spatial-interaction network by regarding the TAZs as nodes, and the public transit passenger flow among them as links (Fig. 2). The weight of the links is assigned based on the volume of the passenger flow, which is derived from the SCD. The spatial network is processed using NetworkX software (Hagberg et al., 2019).

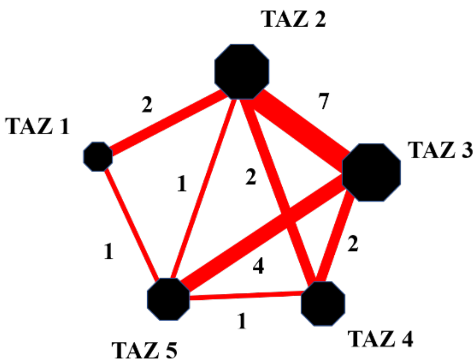



**Figure 2.** Illustration of a spatial interaction network of passenger flow using TAZs (black octagons) as nodes and weighted edges (red lines). The node size reflects its strength and the edge width corresponds to its weight.

### 3.2. Computation of PTI as a proxy for public transport demand

As mentioned, the goal of public transport is to encourage public transit use, which can be estimated using tap-in-tap-out SCD between TAZs. In the study area, there is a large proportion of people who use smart phones. When people move around the city, their locations can be inferred by the towers to which their phones re connect. Thus, the total traveling population between TAZs can be counted regardless of travel mode. To better reflect the relative ratio of public transit users to non-users among TAZs, we propose the following formula:

$$PTI_i = \frac{V_i}{R_i}, \tag{1}$$

where $i$ is a TAZ, $V_i$ represents the ridership on public transit, and $R_i$ is the total people flow for all travel modes in TAZ $i$.

In general, higher PTI values indicate a higher proportion of people using public transit. Higher PTI values are therefore associated with higher public transit demand or attractiveness.

### 3.3. Computation of influential factors

To evaluate public transport demand, eleven local factors of the built environment are selected and divided into four groups (density, diversity, design, and economic development), and two network factors are proposed based on the passenger flow network generated in Section 3.1. Table 1 provides a summary of the factors used to evaluate the public transport demand.

**Table 1.** Factors for evaluating public transport demand.

| **Public transport demand** | | | |
|---|---|---|---|
| **Type** | **Criteria** | **Factors** | **Source** |
| Environment | Density | Residential Density (RD)<br>Commercial Density (CD) | Singh et al., 2014 |
| | | Administrative Density (AD) | Motieyan & Mesgari, 2019 |
| | | Public Service Density (PSD) | Cervero & Kockelman, 1997 |
| | Diversity (Land use) | Entropy (Ent) | Singh et al., 2014 |
| | Design | Total Length of Walkable and Cyclable Paths (TWP) | Singh et al., 2017 |
| | | Intersection Density (ID) | Ewing & Cervero, 2010 |
| | | Street Connectivity (SC) | Motieyan & Mesgari, 2019 |
| | Economic Development | Density of Business Establishments (DBE) | Singh et al., 2017 |
| | | Population Density (PD) | Ewing & Cervero, 2010 |
| | | Employee Density (ED) | Singh et al., 2014 |
| Network | Spatial interaction network of passenger flow | Degree (Deg)<br>Betweenness (Bet) | |

#### 3.3.1 Built environmental factors

***Density.*** There are four types of density factors calculated based on the points of interest (POIs): residential density, commercial density, administrative density, and public service density. It should be noted that commercial density differs from business density. Commercial establishments include service and retailing (e.g., hotels, restaurants, shopping malls), whereas business establishments mainly include companies and enterprises. In this paper, density is based on the POI density in a spatial unit (i.e., TAZ). The density factors can be calculated as follows:

$$\text{Density}_i = \frac{\text{Number of POI}_i}{\text{Total number of POIs}}, \tag{2}$$

***Diversity***. Land use diversity is a critical factor in transport demand. There are several different methods to derive land use diversity, including dissimilarity index, entropy, and vertical mixture (Cervero & Kockelman, 1997). In this paper, we choose the widely used method of entropy. As defined by Ritsema Van Eck and Koomen (2008), entropy is adopted to calculate land use diversity as follows:

$$Entropy(i) = \frac{-\sum_{lu_i=1}^{n} \frac{S_{lu_i}}{S_i} \times \ln p_{lu_i}}{\ln n}, \tag{3}$$

where $lu_i$ is the land use class (1, 2, …, n) within a TAZ $i$, $\frac{S_{lu_i}}{S_i}$ is the share of a specific land use class within TAZ $i$, $S_{lu_i}$ is the number of POIs of the specific land use category within TAZ $i$, $S_i$ is total number of POIs within TAZ $i$, and $n$ is the number of land use categories.

In this paper, six land use categories are chosen based on the keywords of available POI data, including residential, commercial, administrative, public service, business, and other. The entropy range is from 0 to 1, where 0 indicates no land use diversity and 1 indicates high land use diversity (i.e., the area is evenly distributed among all land use categories).

***Total length of walkable and cyclable paths.*** This factor is chosen based on the study of Schlossberg and Brown (2004), who classify the street network into two categories: potential walking routes and automobile-dominant roads. In this paper, roadways are classified into 32 types (mainly bridleways, cycleways, footways, motorways, and primary roads) according to their functional class. This factor is derived by calculating the length of minor roads for which pedestrians or cyclists are easily accessible. The road types include cycleways, footways, paths, pedestrians, residential, steps, trails, and living streets. Automobile-dominant roads are not selected.

***Intersection density.*** The construction of intersections is an effective method to optimize the pedestrian environment. Ewing and Cervero (2010) explored the correlation between intersection density and walk trips and found that high intersection density can shorten access distances and provide more routing options for transit users and transit service providers. This also indicates that high intersection density is associated with high walkability and cyclability. Eq. (4) is used to calculate intersection density. In this paper, the number of intersections is calculated based on the number of road crossings using ArcGIS, and intersection density is represented by the number of intersections per square kilometer in a TAZ:

$$ID(i) = \frac{S_{t_i}}{A_i}, \tag{4}$$

where $S_{t_i}$ is the number of intersections within TAZ $i$ and $A_i$ is the total area of TAZ $i$.

***Street connectivity***. Similar to intersection density, street connectivity is also a common factor to represent the walkability of an area. High street connectivity around a workplace or destination is significantly and positively related to walk and transit choice. In this paper, we use the alpha index to calculate street connectivity. The alpha index is derived using the concept of a circuit, which is a finite, closed path starting and ending at a single node, and is calculated as the number of actual circuits divided by the maximum number of circuits in a network (Dill, 2004):

$$\alpha(i) = \frac{(e-v+1)}{2v-5}, \tag{5}$$

where $e$ is the number of links within TAZ $i$ and $v$ is the number of nodes within TAZ $i$. The alpha index ranges from 0 to 1, and higher values indicate greater street connectivity.

***Population and employee density.*** The economic development criteria are selected based on some factors proposed by Renne and Wells (2005). These factors include the density of business establishments, population density, and employee density. Population density is calculated as:

$$PD(i) = \frac{S_{p_i}}{A_i}, \tag{6}$$

where $PD(i)$ is the population density index of TAZ $i$ and $S_{p_i}$ is the population within TAZ $i$. Employee density can be derived in a similar manner.

### 3.3.2 Public passenger flow network factors

The following network is generated based on the network described in Section 3.1, where the TAZs are the nodes and the passenger flow amount along the flow edges is the weight.

***Degree.*** The degree of a focal node represents the number of its neighbors in a network (Freeman, 1978) and is the most common and easiest way to calculate the centrality of a node. In an undirected graph, degree centrality is used to measure the degree to which one node is connected to all of the other nodes in the network. In this paper, a TAZ is the network node and the measure can be formalized as:

$$A_{ij} = \begin{cases} = 1 & \text{if } i \text{ and } j \text{ are connected} \\ = 0 & \text{otherwise.} \end{cases} \tag{7}$$

$$k_i = \sum_j^N A_{ij}, \tag{8}$$

where $i$ is the focal TAZ node, $j$ represents all other nodes, $N$ is the total number of nodes, and $A_{ij}$ is the adjacency matrix, which is a graph with $N$ nodes and $E$ edges, that can be described by its $N \times N$ adjacency matrix $A$.

***Betweenness.*** The betweenness centrality relies on the shortest paths, similar to the closeness centrality, but is defined in terms of the flow of passengers in the network and relies on the identification of the shortest paths and the allocation of the number of passengers passing through a node. Mathematically, the betweenness centrality of node $i$ is defined as:

$$B_i = \sum_{(a,b)} \frac{\sigma(a,i,b)}{\sigma(a,b)}, \tag{9}$$

where $\sigma(a,i,b)$ is the number of shortest paths from TAZ nodes $a$ to $b$ through node $i$ and $\sigma(a,b)$ is total number of shortest paths between nodes $a$ and $b$. The sum is over all pairs $(a,b)$ of distinct vertices.

## 3.4. Spatiotemporal heterogeneity analysis

To determine the relationships between public transport demand and the built environment and the spatial interaction network, we use the OLS regression model and GTWR model (Gollini et al., 2013; Lu et al., 2014) to relate the PTI to the built environment criteria and network parameters at the level of the TAZs. As mentioned in Section 3.1., thirteen independent variables are selected to evaluate the public transport demand (ref. Table 1) and the PTI is used as the dependent variable for the regression analysis.

We use the corrected Akaike information criterion (AIC) and adjusted $R^2$ combined with the analysis of variance (ANOVA) test to compare the results of these two models. The multi-collinearity of the independent variables is assessed by the variance inflation factor (VIF) index: a VIF greater than 10 indicates that multi-collinearity exists (Wheeler, 2007). An OLS model is used to explain the global relations between the dependent and independent variables. Note that the average value of PTI over all 7 days in each TAZ as dependent variable in the OLS model. The GTWR model is then applied to simultaneously deal with spatial and temporal non-stationarity and detect the spatiotemporal variations in the relationships between two geographic phenomena. The PTI is calculated for each TAZ over 7 days (from Monday to Sunday), and the regression of the GTWR parameters is estimated using the Euclidean distance and Gaussian distance-decay-based functions with a fixed bandwidth for cross-validation purposes.

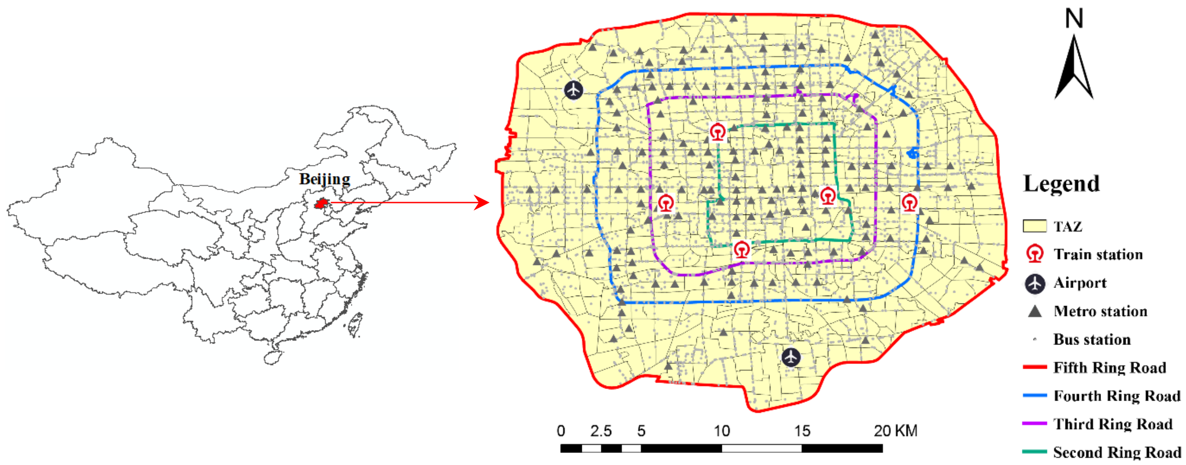
It should be noted that the PTI is used as a proxy for the level of public transport demand for two reasons. First, there is no ground truth measurement of public transport demand level currently available, and the passenger flow estimated by the tap-in-tap-out SCD is one of the best proxies. Second, the PTI reflects the spatial interaction between TAZs, and can be used to generate a network that can be used to rank and describe the TAZs in the context of public transport policy (e.g., demographics).

## 4. Study area and data processing

Beijing, China (Fig. 3a) is selected as the study area for two main reasons. The first is the availability of a large volume of public transport data (i.e., tap-in-tap-out SCD), and the second is that Beijing is rapidly urbanizing and urgently requires the sustainable development of public transport. By January 2017, there were 19 subway lines in operation in Beijing, covering 11 municipal districts with 345 stations and a total length of 574 km. Beijing has 1,020 bus routes with 29,515 buses covering a total of 19,158 km. Most subway and bus stations are located within Fifth Ring Road. This region has a high population density and high trip generation, attraction rates, and is perhaps the most prosperous core area with the largest population flow in Beijing. The administrative region of Beijing covers a land area of 667 km$^2$, but only the area within Fifth Ring Road is selected as the study area because there are very few or no public transport services in other areas. As transport demand modelling and application require spatial data aggregation in traffic analysis zone (TAZ), we thus select TAZ as the spatial units in this study (Martínez et al., 2009).

The average area of the 686 TAZs within the Fifth Ring Road region (left in Fig. 3b) is about 0.9 km$^2$. Another reason for using TAZs as the spatial units in this study is that they are defined according to the census block information, administrative boundaries, and the main roads in the city. Therefore, for each TAZ, it is possible to collect the information about public transport, land use, and socio-economic characteristics needed to calculate the criteria and factors of public transport demand.

The SCD data were generated when users tapped in/out of a subway or bus station between April 11, 2016 and April 17, 2016. They were collected by the College of Metropolitan Transportation, Beijing University of Technology. Other datasets include the POI data from the Baidu map API (https://api.map.baidu.com/lbsapi/) and road network from OpenStreetMap (www.osm.org). In particular, the SCD provide a chance to analyze spatiotemporal variations of passenger flows at a highly detailed scale because of their fine granularity. The SCD consist of a large collection of non-aggregated records that represent single events (i.e., a bus or metro journey), and each record contains a specific spatial location and time stamp.




(a) Map of China and Beijing (b) Public transport within the Fifth Ring Road in Beijing

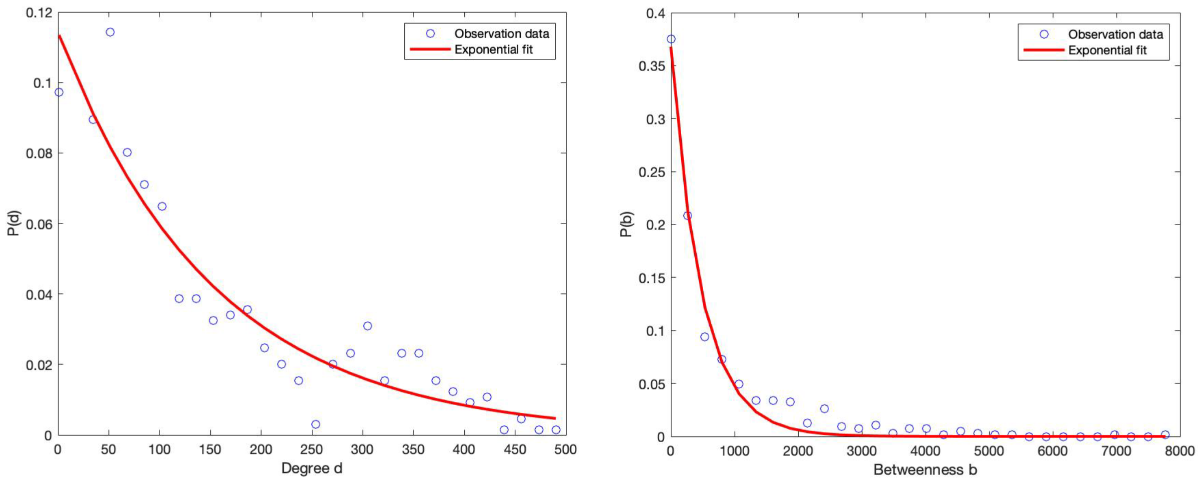
**Figure 3.** Study area in Beijing within Fifth Ring Road with the 686 TAZs.

# 5. Results and discussion

## 5.1. Spatial interaction network analysis

According the description in Section 3.1, Fig. 4 provides the spatial interaction network of passenger flow between the TAZs in Beijing, China; the points in red are the central points of each TAZ and the 3D lines in yellow are the edges. It should be noted that the passenger flows and connections between TAZs change with time; thus, the network structure also changes with time. The network therefore dynamically reflects how people, public transport, and the built environment interact with each other across space and time. The network structure can be measured by the probability distribution of its centralities. In this paper, two centralities are selected (i.e., degree and betweenness) and the calculation is conducted using Eqs. (7)-(9).

As shown in Fig. 4, both the degree and betweenness follow an exponential distribution, which indicates the scaling property of a complex network. Compared with a normal distribution, this scaling property reflects an imbalanced phenomenon: a high percentage (~80%) of the spatial interactions have passenger flows less than the average value, whereas ~20% of the spatial interactions have passenger flows greater than the average value. As stated above, this is a clear indicator that the structure of the spatial interaction network changes when the passenger flow changes over time (e.g., the centrality measures of the nodes). However, the overall probability distribution of the network structure remains the same over time, i.e., a heavy-tailed distribution that indicates the emergence of a complex network.




(a) Degree (b) Betweenness

**Figure 4.** Exponential distribution of the spatial-interaction network structure reflecting the scaling property of the complex network.

In summary, the dynamic spatial interaction network reveals the complex relationship between the public transport system and the built environment. Thus, the assessment of the influence of the built environment on public transport can be biased if only the local built environmental factors are considered. The spatial interaction network structure (e.g., degree and betweenness) allows a more comprehensive evaluation of this influence from the network science perspective.

## 5.2. Spatiotemporal characteristics of public transport demand in Beijing

PTI is calculated as a proxy for public transport demand. Fig. 5 shows the spatial distribution of the PTI of the TAZs, in which red represents higher PTI values and yellow represents lower

PTI values. We divide the TAZs into five groups for better visualization using the natural break classification method, which reduces the variance within groups and maximizes the variance between groups. The visualized spatial patterns in Fig. 5 show that more TAZs have high PTI values on weekdays than on weekends. One possible reasons is that the commuters who live and work in compact neighborhoods with well-built public transit facilities tend to use public transport for commuting on weekdays. For instance, certain office areas (e.g., Zhongguancun, Electronic City, Embassy Area) and residential areas (e.g., Nanmencang Community and Wangjing Station) located in the northeastern or northwestern corners of the study area, have higher PTI values on weekdays.

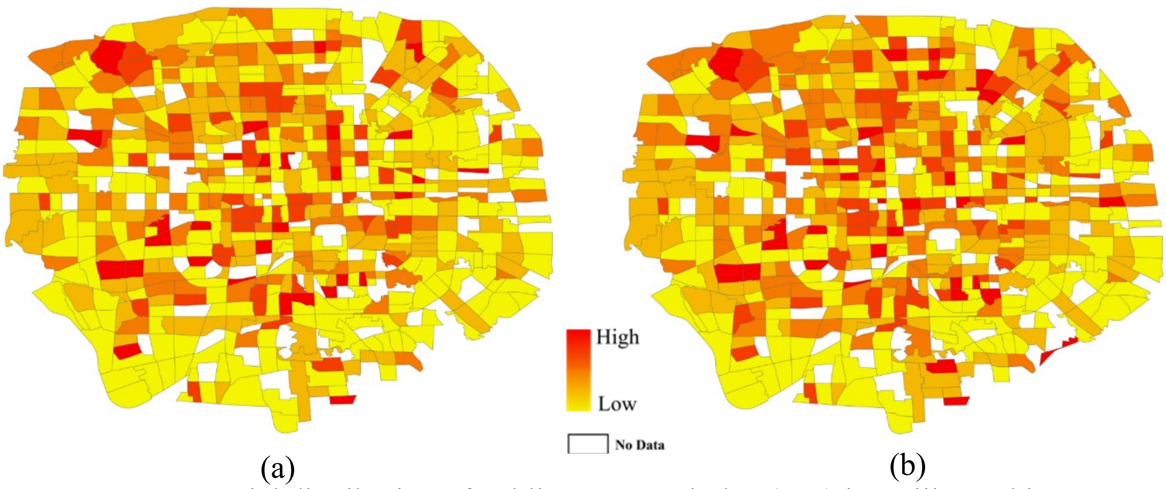



**Figure 5.** Spatial distribution of public transport index (PTI) in Beijing, China on an average (a) weekday and (b) weekend.

The finer temporal granularity of the SCD used in the analysis makes it possible to observe meaningful variations in the PTI over time, which significantly helps to understand how the TAZs are unevenly affected by the features of the built environment and the spatial interaction networks . In this paper, nine typical TAZs are selected from nine typical regions, which include four types: tourist attractions (Summer Palace and Olympic Village); office areas (Embassy Area and Electronic City); commercial areas (West of Tiananmen Square and Wangfujing Street); and residential areas (Nanmencang Community, Imperial College, and Wangjing Station) as shown in Fig. 6.

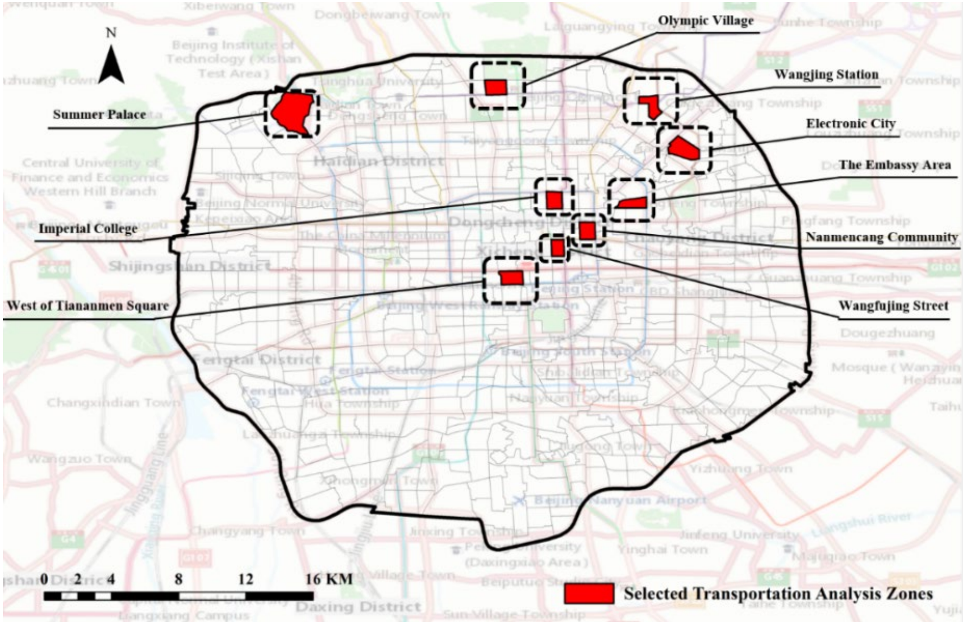



**Figure 6.** Nine TAZs selected for temporal analysis.

Fig. 7 shows the temporal variation of the PTIs for the nine selected TAZs (Fig. 6) on a daily basis, which highlights the different patterns. All regions show a medium or high PTI value during the week except for the Olympic Village, possibly because it is mainly a tourist attraction. The Summer Palace is also a tourist attraction but its PTI value is substantially higher than that of the Olympic Village, which may be related to their different locations, the development of public transport services, and/or the level/type of tourist attraction. The results also indicate that residential and office regions (Nanmencang Community, Imperial College, Wangjing Station, Electronic City, and Embassy Area) have higher PTI values from Monday to Friday than from Saturday to Sunday. This means that the spatial characteristics of the PTI must be examined using finer granularity. Interestingly, the PTI values of most regions reach a peak on Friday, which indicates that most regions have high public transit use on this day. This demonstrates the importance of evaluating public transport demand on both spatial and temporal scales.

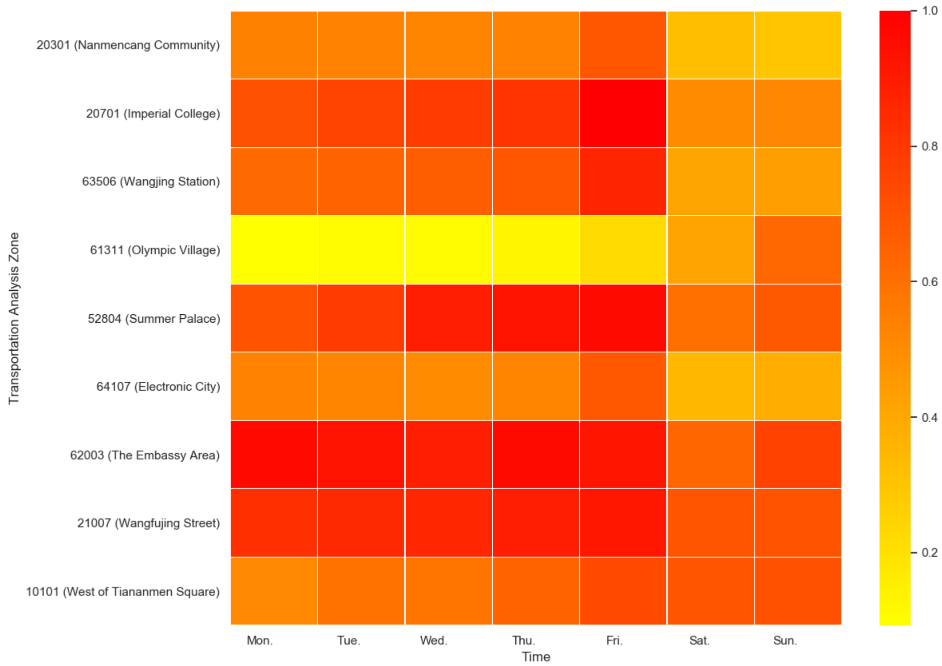



**Figure 7.** Daily variation in PTI for nine TAZs over 7 days.

### 5.3. Heterogeneous patterns of influential factors

In this section, we explore the relationships between public transport demand and the selected factors (Table 1) of the built environment and the spatial interaction network of passenger flow. The built environment and network factors are used as independent variables, and the public transport demand, represented by the PTI, is used as the dependent variable for the subsequent regression analysis. Both the OLS regression and GTWR are used to examine the relationships between the PTI and the built environment and network factors. Further, to examine the effect of network factors on the passenger flow over space and time, we create six groups of variables, each of the groups includes one or more independent factors from the three environmental criteria (i.e., density, diversity and design).

Then we apply OLS regression to the six group of variables, which are model 1, 2, 3, 4, 5, 6. Similarly, we apply GTWR model to the six group of variable, which are model 7, 8, 9, 10, 11 and 12. Note that the models 1, 3, 5, 7, 9, and 11 are models without network factors, while models 2, 4, 6, 8, 10, and 12 are models with network factors. The ANOVA results (see Table 2) report the residual sum of squares (RSS), the degrees of freedom (DF), and the residual mean squares (MS) for the 12 OLS and GTWR models.

The ANOVA results indicate that there is significant spatial and temporal non-stationarity over the study area, and the GTWR models is more suitable than the OLS models.

**Table 2.** ANOVA comparison between OLS and GTWR models.

| *Groups* | Independent variables | Source of Variation | OLS residuals | GTWR residuals | GTWR/OLS improvement |
|---|---|---|---|---|---|
| | | | **Model 1** | **Model 7** | |
| *1* | RD, CD, Ent, SC, PD | RSS | 167.00 | 1.48 | 165.52 |
| | | DF | 4016 | 162 | 3854 |
| | | MS | 0.04 | 0.01 | 0.03 |
| | | | **Model 2** | **Model 8** | |
| *2* | RD, CD, Ent, SC, PD, Deg, Bet | RSS | 66.01 | 2.84 | 63.17 |
| | | DF | 4014 | 922 | 3092 |
| | | MS | 0.02 | 0.00 | 0.02 |
| | | | **Model 3** | **Model 9** | |
| *3* | RD, CD, Ent, SC, PD, DBE, TWP | RSS | 163.40 | 0.19 | 163.21 |
| | | DF | 4014 | 65 | 3950 |
| | | MS | 0.04 | 0.00 | 0.04 |
| | | | **Model 4** | **Model 10** | |
| *4* | RD, CD, Ent, SC, PD, DBE, TWP, Deg, Bet | RSS | 85.73 | 2.67 | 83.06 |
| | | DF | 4016 | 1026 | 2990 |
| | | MS | 0.02 | 0.00 | 0.02 |
| | | | **Model 5** | **Model 11** | |
| *5* | RD, CD, Ent, SC, PD, DBE, TWP, AD,PSD,ID,ED | RSS | 154.42 | 0.73 | 153.69 |
| | | DF | 4010 | 380 | 3630 |
| | | MS | 0.04 | 0.00 | 0.04 |
| | | | **Model 6** | **Model 12** | |
| *6* | RD, CD, Ent, SC, PD, DBE, TWP, AD, PSD, ID, ED, Deg, Bet | RSS | 83.10 | 3.66 | 79.44 |
| | | DF | 4008 | 1662 | 2346 |
| | | MS | 0.02 | 0.00 | 0.02 |

The results of the OLS and GTWR regressions are listed in Table 3 and Table 4. The VIF results (all <10) indicate that the OLS estimations are not biased by multi-collinearity. The OLS regression models without network factors can explain 3%, 5% and 10% of the variation (i.e., $R^2 = 0.03$, 0.05 and 0.10) for the PTI, while the models with network factors can explain 50% and 52% of variation (i.e., $R^2$ =0.5 and 0.52) for the PTI. The network factors have higher estimated coefficients in model 2, 4 and 6. The results suggest that the network factors play significant and important roles on PTI. Furthermore, the GTWR models can explain 79%, 93% 94% and 95% of the variation (i.e., $R^2 = 0.79$, 0.93, 0.94 and 0.95) in the PTI with a lower AIC by comparing with OLS models. This confirms that the GTWR model is more suitable than the OLS models. The OLS results show that commercial density, public service density, density of business establishment, street connectivity, population density, employee density, and total length of walkable and cyclable paths are negatively associated with the PTI. This implies that the potential public transport demand level would likely decrease if the five factors are improved. Other factors, such as residential density, intersection density, mixed land use, degree, and betweenness, are positively associated with the PTI. This suggests that the potential public transport demand level would likely increase if these six factors are improved. Figure 8 shows local t-value for the *betweenness* variable, where the grey color is area with non-statistical significant (i.e., p-value > 0.05), while the gradient color is local t-value with statistical significant (i.e., p-value <0.05). The result indicates that the significant coefficients estimated between PTI and selected variables change over time (see Figure S15-S27 in supplement).

**Table 3.** Results of OLS models.

| | | *Model 1* | *Model 2* | *Model 3* | *Model 4* | *Model 5* | *Model 6* | |
|---|---|---|---|---|---|---|---|---|
| **No.** | *Variable* | *Coef.* | *Coef.* | *Coef.* | *Coef.* | *Coef.* | *Coef.* | *VIF* |
| | Intercept | 0.26*** | 0.18*** | 0.24*** | 0.19*** | 0.37*** | 0.23*** | |
| 1 | RD | -0.23*** | -0.12*** | -0.26*** | -0.15*** | 0.37*** | −0.19*** | 2.3 |
| 2 | AD | | | | | −0.39*** | 0.03 | 1.9 |
| 3 | CD | -0.07** | -0.06*** | -0.06** | -0.07*** | −0.18*** | −0.08*** | 2.0 |
| 4 | PSD | | | | | −0.17*** | −0.19*** | 1.6 |
| 5 | DBE | | | -0.09*** | -0.06*** | −0.46*** | −0.05** | 2.1 |
| 6 | ID | | | | | −0.20*** | 0.16*** | 2.5 |
| 7 | Ent | 0.09*** | -0.05** | 0.13*** | -0.04** | 0.41*** | −0.04 | 1.5 |
| 8 | SC | -0.15*** | -0.07*** | -0.14*** | -0.06** | −0.26*** | −0.06*** | 1.1 |
| 9 | PD | -0.04** | -0.23*** | -0.10*** | -0.23** | −0.14*** | −0.14*** | 2.1 |
| 10 | ED | | | | | −0.08*** | −0.23*** | 2.3 |
| 11 | TWP | | | 0.19*** | -0.02*** | −0.19*** | −0.04** | 2.3 |
| 12 | Deg | | **0.68*****| | **0.68***** | | **0.66***** | 3.5 |
| 13 | Bet | | **-0.13***** | | **-0.12***** | | **−0.11***** | 3.3 |
| | **Adjusted $R^2$** | **0.03** | **0.50** | **0.05** | **0.50** | **0.10** | **0.52** | |
| | RSS | 167.00 | 66.01 | 163.40 | 85.73 | 154.42 | 83.10 | |
| | AIC | -1367.67 | -4032.80 | -1451.93 | -4042.09 | −1671.27 | −4159.15 | |

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.
RD: residential density; AD: administrative density; CD: commercial density; PSD: public service density; Ent: entropy; DBE: density of business establishments; ID: intersection density; SC: street connectivity; PD: population density; ED: employee density; TWP: total length of walkable and cyclable paths; Deg: network degree; Bet: betweenness

**Table 4.** Results of GTWR models.

| | | *Model 7* | *Model 8* | *Model 9* | *Model 10* | *Model 11* | *Model 12* |
|---|---|---|---|---|---|---|---|
| **No.** | *Variable* | *Mean Coef.* | *Mean Coef.* | *Mean Coef.* | *Mean Coef.* | *Mean Coef.* | *Mean Coef.* |
| | Intercept | 0.17 | 0.05 | 0.32 | 0.11 | 0. 43 | 0. 13 |
| 1 | RD | -0.44 | -0.07 | -0.45 | -0.05 | −0.76 | −0.15 |
| 2 | AD | | | | | −0.48 | −0.08 |
| 3 | CD | -0.09 | -0.03 | -0.07 | -0.01 | −0.11 | −0.02 |
| 4 | PSD | | | | | −0.52 | −0.03 |
| 5 | DBE | | | -0.05 | -0.02 | −0.44 | −0.05 |
| 6 | ID | | | | | 0.99 | −0.01 |
| 7 | Ent | 0.16 | 0.05 | 0.08 | 0.03 | 0.50 | 0.06 |
| 8 | SC | -0.06 | -0.03 | -0.10 | -0.03 | −0.41 | −0.04 |
| 9 | PD | -0.29 | -0.33 | -0.15 | -0.36 | -0.60 | −0.22 |
| 10 | ED | | | | | −1.55 | −0.54 |
| 11 | TWP | | | 0.33 | 0.05 | 0.52 | 0.07 |
| 12 | Deg | | **0.74** | | **0.71** | | **0.74** |
| 13 | Bet | | **-0.19** | | **-0.19** | | **−0.12** |
| | **Adjusted $R^2$** | **0.79** | **0.93** | **0.93** | **0.94** | **0.95** | **0.95** |
| | Bandwith | 0.005 | 0.007 | 0.004 | 0.007 | 0.005 | 0.010 |
| | AIC | -17015.43 | -15308.65 | -24807.91 | -15631.02 | −20159.17 | −14900.4 |

RD: residential density; AD: administrative density; CD: commercial density; PSD: public service density; Ent: entropy; DBE: density of business establishments; ID: intersection density; SC: street connectivity; PD: population density; ED: employee density; TWP: total length of walkable and cyclable paths; Deg: network degree; Bet: betweenness

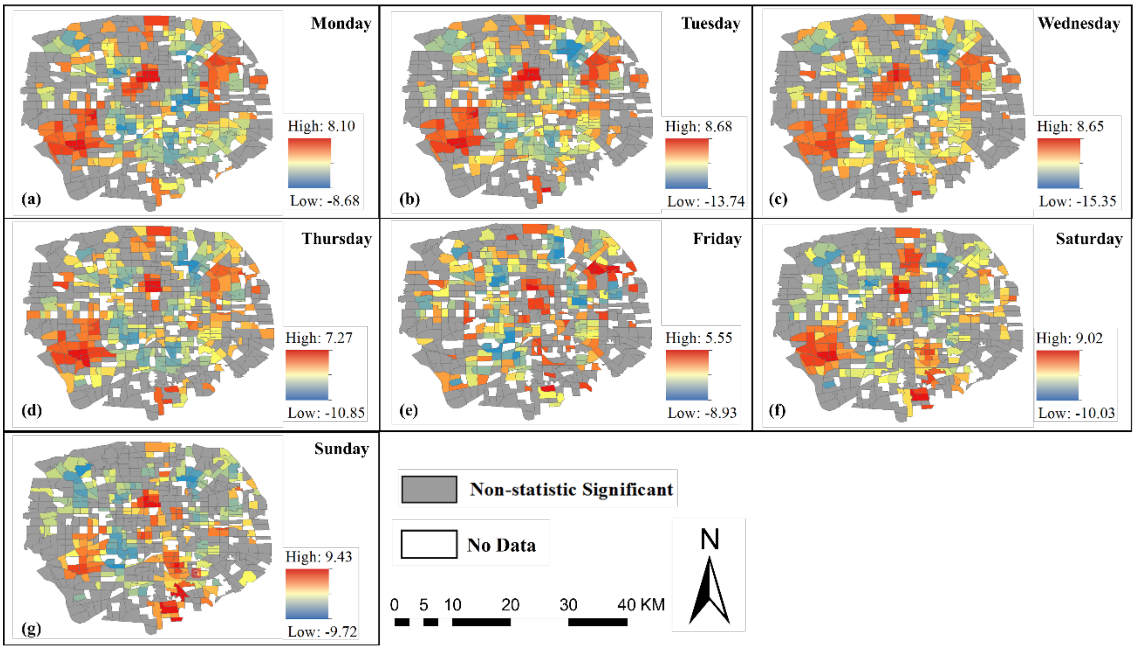



**Figure 8.** Daily patterns of the local t-value of *betweenness* for the PTI over a week.

The GTWR results further indicate that the impacts of the built environment and spatial interaction network variables on the PTI are spatially and temporally heterogeneous. The average local coefficients of the selected variables estimated by GTWR model (i.e., model 12) are visualized individually in Fig. 9. To make it simple, we only demonstrate the results based on model 12, since it covers all selected independent variables (Table 1) in this study. The average local coefficients of each factor are calculated using the total values over seven consecutive days divided by seven. Large and small coefficient values are represented in red and blue, respectively. The TAZs that have no related data are shown in white.

The spatial patterns in Fig. 9 clearly demonstrate how different factors contribute unevenly to the level of public transport demand across space. For each of the factors, the different colors in the study area indicate the uneven contribution of the same factor to the PTI. Compared with previous studies, the findings provide a quantitative way to measure the spatially heterogeneous impact of the built environment and spatial interaction of passenger flows on public transport demand. For example, the Summer Palace, a large and famous national park located in the northwestern part of the study area, has significant positive association with administrative density and public service density. However, the street connectivity has a negative influence on the PTI in the Summer Palace TAZ. In this sense, if the policy makers or practitioners need to increase the use of the public transport system, these results provide important guidance; in particular, they show that the selection of which factors need to be investigated must consider spatial diversity to what extent.

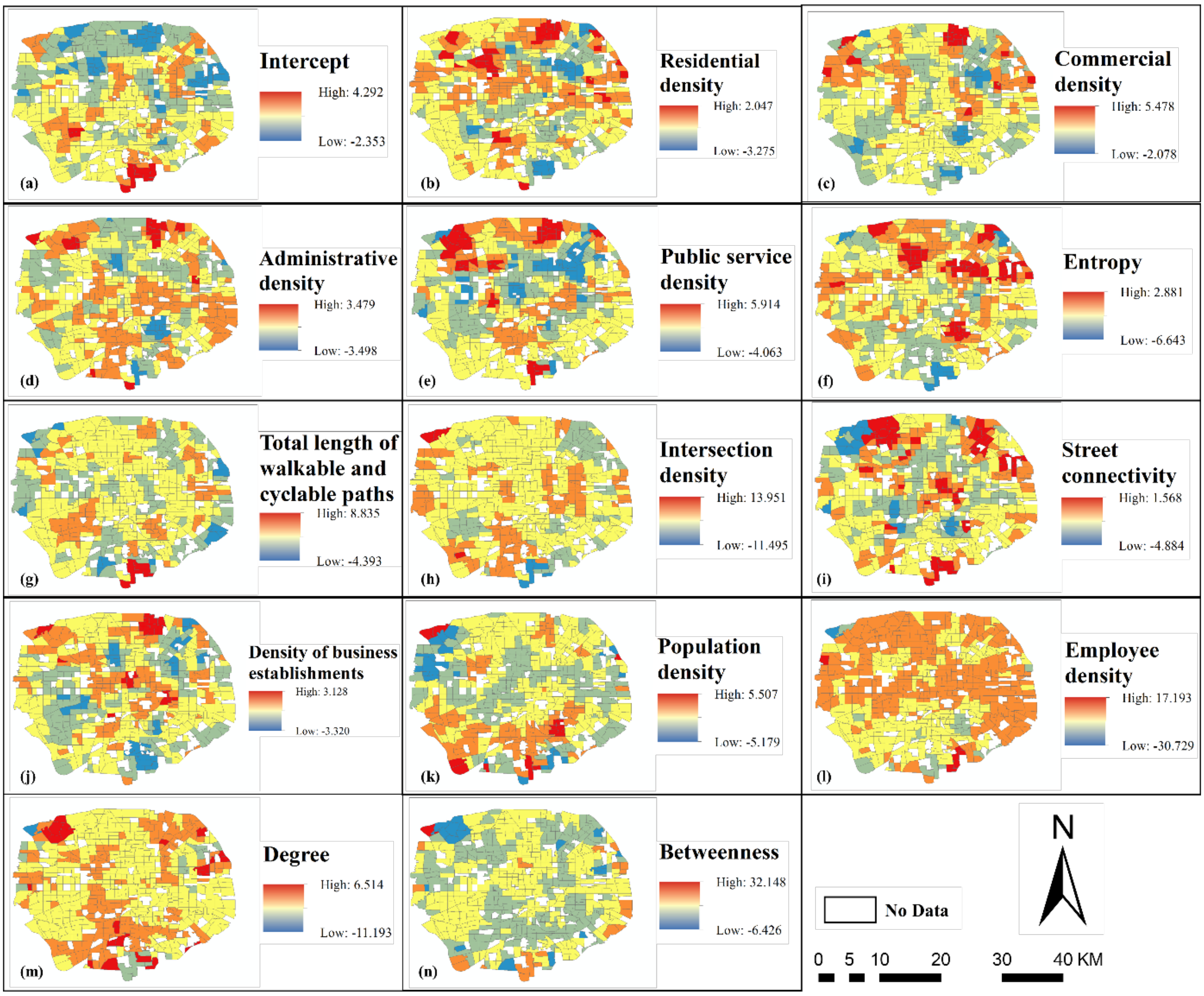



**Figure 9.** Average local coefficients of the eleven factors with the PTI of each TAZ in Beijing.

Fig. 10 shows the spatial patterns of the local coefficients of one centrality measure, i.e., betweenness, with the PTI over one week on a daily basis. The differences between any two days can be clearly observed, particularly between weekdays and weekends. For example, the spatial distributions on Wednesday (Fig. 10c) and Friday (Fig. 10f) differ significantly. These results show that the same factor can influence a location differently at different times, and demonstrate the temporal heterogeneity of the influence of different factors on the PTI. They also demonstrate a quantitative method for measuring the heterogeneous impact of these factors. However, it is challenging to simultaneously consider spatial and temporal heterogeneity when trying to identify when, where, and which factors should be modified to improve the relationship between the built environment and public transport demand.

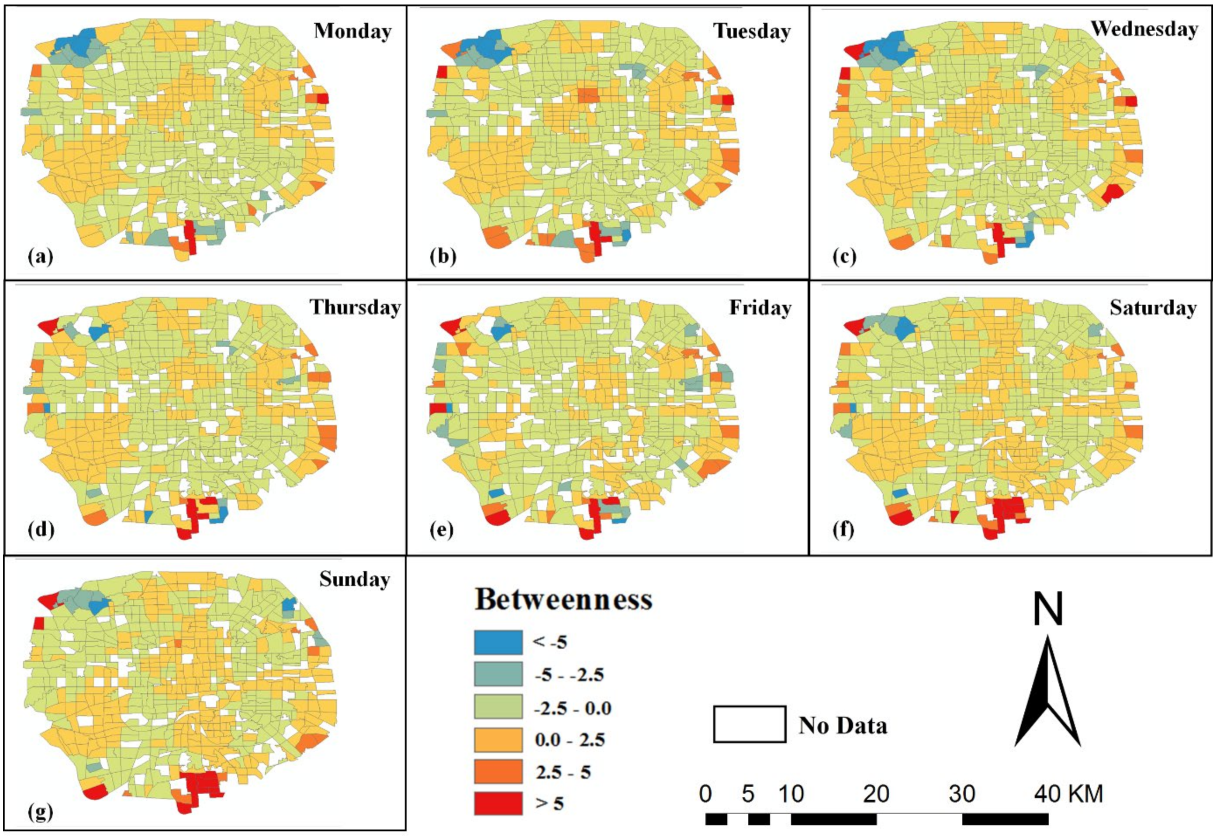



**Figure 10.** Daily patterns of the local coefficients of *betweenness* for the PTI over a week.

In previous studies, the most widely used methods for inferring the relationship between the built environment and public transport have been the linear regression method (Sung & Oh, 2011; Zhang et al., 2017) and the geographically weighted regression method (Jun et al., 2015); however, very few studies have combined both spatial and temporal analysis using the GTWR method, except Ma et al. (2018). Compared to Ma et al. (2018), the PTI proposed in this paper is a better proxy for public transport demand. The spatial interaction network structure reflects the human perception of the built environment, especially when comparing urban and non-urban areas (Van, Derudder & Witlox, 2013). The use of a spatial interaction network therefore enables our framework to capture the urban dynamics of the transport system. In our results, some of the averaged factor coefficients, i.e., the positive influence of population density, employment density, and street development, are in agreement with existing studies (e.g., Zhang et al., 2017, Yu et al., 2019). However, our results indicate that land use diversity and residential density are negatively related to public transit demand, which contradicts these two studies. This may be due to the different case study areas. Furthermore, the betweenness centrality of the spatial interaction network is found to be significantly related to the public transport demand in this study. This suggests that it is important to consider interactions as basic features in the evaluations of public transport systems (Batty, 2013).

## 6. Conclusion

The impact of the built environment on public transport is usually evaluated using local environmental factors, which tends to oversimplify or even neglect the time dimension and the spatial interactions between different built environments. The built environmental factors are heterogeneous in nature, which means that a factor may have a different degree of influence in different places and times. Furthermore, the spatial-interaction network also matters when evaluate the heterogeneous impacts of the built environment on public transport system. This study proposes an improved framework to estimate the influence of the built environment on public transport demand; it uses the geographically and temporally weighted regression (GTWR) model. A public transit index (PTI) is first proposed as the proxy for public transport demand and estimated using mobile phone data and SCD in Beijing, China. Higher PTI values in a region are indicative of more public transport use in the area. A TAZ-based spatially embedded network is generated to consider the interactions between the TAZs, and two variables of the network are investigated as factors that influence the use of public transport. In addition, a series of local factors of the built environment that have been used in previous studies are included in the analyses. Both the OLS and GTWR models are applied to identify the spatiotemporal heterogeneous patterns of the uneven contribution of each factor in each TAZ across space and time. The results indicate that the GTWR model has an average adjusted $R^2$ of 0.94, whereas that of the OLS model is lower (i.e., 0.03 to 0.50). The lower AIC of the GTWR model indicates that it is more suitable than the OLS. This work makes two main contributions: first, a large volume of human mobility data and spatial interaction-based network analysis are used to evaluate public transport; second, the results provide solid evidence for future public transport policy design by taking into account the spatial interactions. For instance, if a factor negatively contributes to public transport demand in a given area and time, future public transport development may need to avoid investigating this factor. Specifically, an improvement in commercial density, street connectivity, population density, employee density, and closeness may reduce the impacts of public transport policy, whereas increasing the residential density, intersection density, mixedness of land use, eigenvector, degree, and betweenness may have the opposite effect. More importantly, the factors of spatial interactions significantly contribute to the heterogeneous impacts on public transport, which means the future public transport policy may need to consider not only the environmental factors, but also the global interactions with the public transport system. In summary, the proposed framework provides a new way to dynamically evaluate public transport, and sheds new light on how to use public transport policy to facilitate sustainable urban development.

Nevertheless, this paper also has several limitations. One limitation is represented by using a PTI as an approximation of the potential public transport demand level in the regression model. Although some examples in the current literature use this index to reflect the impacts of public transport policy, we are aware that our assumption may be prone to error in relation to the non-ideal representativeness of the PTI. Because of the subjectivity of the public transport policy evaluation, it is also not possible to include all of the factors that can impact public transport. Hence, future work should focus on investigating the factors that can better reflect the impact of public transport. Finally, it is worth pointing out that the OLS and GTWR models selected for this study allow for negative coefficients, which in this particular case might seem like a counterintuitive result. In the future, we intend to rescale the regression to tackle the issue of the model producing unrealistic numbers.

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