International Journal of
Geo-Information

MDPI

Article

Modeling the Hourly Distribution of Population at a High Spatiotemporal Resolution Using Subway Smart Card Data: A Case Study in the Central Area of Beijing

Yunjia Ma [1,2,3], Wei Xu [1,2,3,*], Xiujuan Zhao [1,2,3] and Ying Li [1,2,3]

1 Key Laboratory of Environmental Change and Natural Disaster of Ministry of Education, Beijing Normal University, Beijing 100875, China; mayj@mail.bnu.edu.cn (Y.M.); xjzhao@mail.bnu.edu.cn (X.Z.); ying.li@bnu.edu.cn (Y.L.)
2 Academy of Disaster Reduction and Emergency Management, Ministry of Civil Affairs & Ministry of Education, Beijing Normal University, Beijing 100875, China
3 Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China
* Correspondence: xuwei@bnu.edu.cn; Tel.: +86-010-5880-6695

Academic Editors: Norbert Bartelme and Wolfgang Kainz
Received: 22 February 2017; Accepted: 24 April 2017; Published: 26 April 2017

Abstract: The accurate estimation of the dynamic changes in population is a key component in effective urban planning and emergency management. We developed a model to estimate hourly dynamic changes in population at the community level based on subway smart card data. The hourly population of each community in six central districts of Beijing was calculated, followed by a study of the spatiotemporal patterns and diurnal dynamic changes of population and an exploration of the main sources and sinks of the observed human mobility. The maximum daytime population of the six central districts of Beijing was approximately 0.7 million larger than the night-time population. The administrative and commercial districts of Dongcheng and Xicheng had high values of population ratio of day to night of 1.35 and 1.22, respectively, whereas Shijingshan, a residential district, had the lowest value of 0.84. Areas with a high population ratio were mainly concentrated in Dongcheng, Xicheng, West Chaoyang, and Southeast Haidian. The daytime population distribution showed a hierarchical spatial pattern of planar centers and second scattered centers as opposed to multiple scattered centers during the night-time. This was because most people moved inward from the areas with a low–high to high–low population ratio of day to night from night-time to daytime, which can be explained by the process of commuting between residential areas and workplaces. Several distinctive phenomena (e.g., the distribution of new industrial parks, the so-called old residential areas, and colleges and universities) in the development of China are reflected by the spatiotemporal pattern of the distribution of population. The general consistency of the population ratios of day to night, population distribution, population variation of typical communities, and population mobility pattern with previous research suggests that the subway smart card data has potential in analyzing dynamic diurnal variations of urban population. This method can be easily duplicated to calculate hourly dynamic changes in population at the community level. These results can be used to estimate the potential hourly number of evacuees under different temporal scenarios of disasters and to support future urban planning in Beijing.

Keywords: population distribution; hourly; community level; innovative model; subways smart card data; Beijing

1. Introduction

Our understanding of the basic laws governing human motion remains limited due to the lack of tools to monitor the time-resolved location of individuals [1]. However, the increasing availability of 'big data' may offer a new perspective for modeling dynamic population by addressing the coupling of transportation models with population data to expand population distribution scenarios to even finer time intervals (e.g., hourly) [2]. Numerous researchers have increasingly turned to remote sensing and geospatial data to refine the spatial resolution of population density. In contrast, very few studies have been conducted on the high temporal resolution of population distribution. To make the most of big data, an innovative method is required to improve the temporal resolution. A high spatiotemporal resolution and contemporary data on population distribution is crucial in the fields of urban planning [3], disaster risk management [4,5], epidemiology [6], and environmental impact analysis [7], which require accurate definitions of population exposure.

Louis Wirth differentiated population during daytime and night-time for the first time in 1938 [8]. Up until the 1950s, the study of daytime population remained in the descriptive stage. Using a cordon count traffic survey system or an origin-destination survey system, researchers reported the phenomenon of the separation of residential and workplace locations and further explored the factors affecting the differences of population between day and night [9–12]. However, the main methods of estimating the daytime population (e.g., origin-destination matrices [13,14], estimation methods using Journey to Work census data [15], or using traffic survey data [16]) rarely considered the spatial perspective. At the beginning of the 21st century, many countries built daytime population distribution models based on census data [17–19]. For example, the US Census Bureau collected commuting data for workers at the census tract level and reported the national daytime population distribution at the county level. Unfortunately, the spatial resolution of these models was low due to the use of census blocks.

With the rapid development of population spatialization, global and regional gridded population datasets are now available. Widely used global datasets that rely on an areal weighting approach include the Gridded Population of the World and the Global Rural Urban Mapping Project. Other large-area population datasets (e.g., Landscan, the United Nations Environment Program for Latin America, Africa, and Asia, and the WorldPop, AfriPop, and AsiaPop projects) are obtained via remote sensing and geographical information system techniques that use statistical methodology and the empirical relationships between population and land use or other ancillary data to disaggregate census data to a finer spatial scale [20–23]. However, the temporal resolution of the population datasets is coarse and ignores the marked discrepancy between the spatial distribution of daytime and night-time population, especially in metropolitan regions.

Synthesizing the ideas of daytime population models and the disaggregation of census data, McPherson [4] reported a method for estimating the urban daytime population as opposed to only the night-time population using the US Census, infrastructure, and business demographic data at a 250 m pixel resolution. This was the first time that the diurnal temporal shift in population (as a result of employment) was estimated using a high-resolution population distribution. Numerous research methods, including Landscan, have been used to study the distribution of population at a high spatial resolution both during daytime and night-time to improve the accuracy of the daytime population by considering other types of population apart from workers [2,24,25]. However, as labor- and time-intensive methods, traditional remote sensing and demographic techniques are unable to account for all types of population (e.g., workers, students, tourists, and patients) in their estimation. The representation of temporal resolution can range from a simple average night-time and daytime distribution to hourly (and finer scale) frames [2].

In recent years, locational sources of big data have increasingly become available and their applications are currently the subject of much study [26]. The temporal accuracy of the distribution of population and mobility can be specified hourly using mobile phone location data [27–31]. Vehicle global positioning system trajectories [32–35], transactions of credit [36] (or bank [37]) cards and transportation cards [38–40], as well as location-based social media data [41–44] (e.g., Facebook, Twitter [45,46], and Flickr) also provide a means with which to investigate the spatiotemporal characteristics of human mobility with a particular focus on the impact of demography [47–49]. However, one significant bias of mobile phone location data used to identify population is that the estimated population is always less than the number of the registered population [27,50,51] due to the heterogeneous ownership and usage patterns of mobile phones [52–54] (e.g., low/high ownership among rural/urban communities). Thus, big data have been widely used to spatiotemporally and schematically characterize the geographical locations of human mobility rather than the estimation of population. Innovative research into the distribution of hourly population at high spatiotemporal resolution based on big data is therefore important in the solution of problems that traditional remote sensing and big data methods are unable to solve.

The main objective of this study was to develop a model for estimating the hourly dynamic changes in population at the community level based on subway big data. Using this model, the hourly population of each community in six central districts of Beijing was calculated, followed by a study of the spatiotemporal patterns and diurnal dynamic changes of population and an exploration of the main sources and sinks of the observed human mobility. The unique aspect of this study was the integrated improvement of temporal and spatial resolutions, which were expected to reach the hour and community levels, respectively. The method can be easily duplicated to calculate the hourly dynamic changes of population at the community level. These results can be used to estimate the potential hourly number of evacuees in different temporal scenarios of disasters and to provide support for future urban planning in Beijing.

2. Data and Method

2.1. Study Area and Datasets

This work used the six central districts of Beijing—Dongcheng, Xicheng, Chaoyang, Haidian, Shijingshan, and Fengtai—as the study area. This region is an agglomeration area for politics and culture, as well as high-tech industries and universities. The region covers an area of 1369 km^2 and the 6th National Census Data Bulletin recorded a resident population of 11.72 million in 2010. This region accounts for 8% of the area of Beijing, but concentrates approximately 61% of the total resident population of the city, and population density is about seven times the average for Beijing. The region covers 2039 communities, which corresponds to the finest administrative unit level, and has 17 subway lines with 173 subway stations (except the airport area) (Figure 1). The proportion of journeys made by subway in the central area of Beijing was 20.6% in 2013, and continues to increase [55]. This constitutes records of about 50% of all public transport services. These journeys made by subway have certain representativeness in relation to the whole origin-destination matrix of the city. The proportions of journeys made by car, taxi, bike, and others are 32.7%, 6.5%, 12.1% and 2.7%, respectively [55].

Three major types of data were used in this study (Table 1): (1) the night-time population at the community level; (2) the number of people traveling on the subway; and (3) spatial geographical data. The total population data for each community were derived from the Beijing Municipal Bureau of Civil Affairs. The number of people traveling by subway, which was provided by the Beihang Interest Group on SmartCity [56], was the average value for five consecutive working days in August 2013. The subway smart card data includes many attributes, and the hourly number of people swiping in and out at each station was used in this study. The geospatial data, including the locations of the communities and the subway stations, were provided by the Key Laboratory of Environmental Change and Natural Disaster of Ministry of Education, Beijing Normal University.

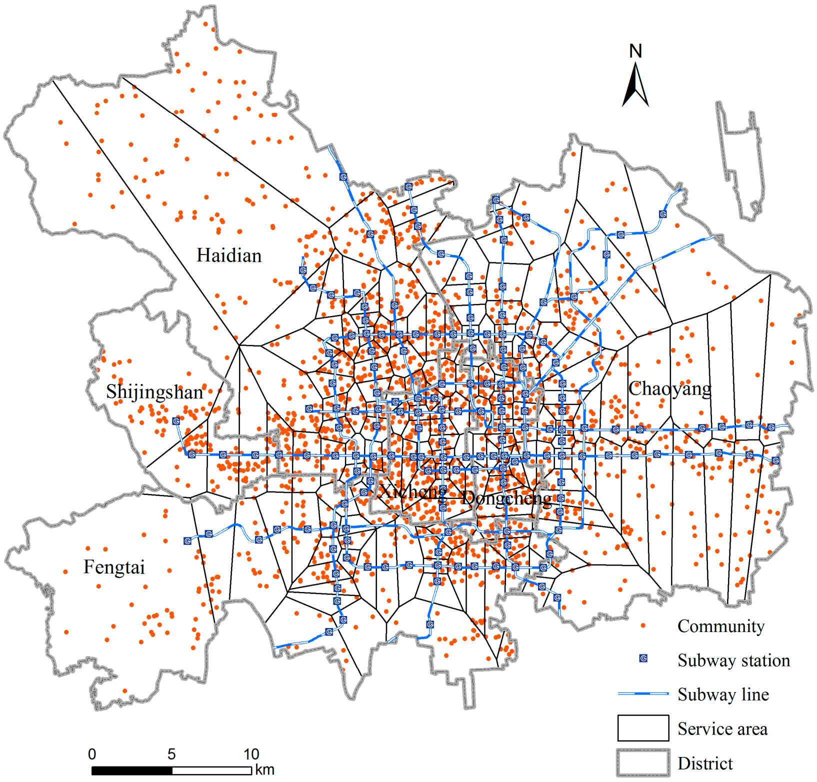

Figure 1. Catchment areas of subway stations in the central area of Beijing.

Table 1. Data used in this study.

Database	Source	Year	Data Description
Community population data	Beijing Municipal Bureau of Civil Affairs	2012	Total population
Subway smart card data	Beihang Interest Group on SmartCity	2013	Bi-hourly population flow at each subway station
Geospatial data	Key Laboratory of Environmental Change and Natural Disaster of Ministry of Education, Beijing Normal University	2014	Location of communities and subway stations

2.2. Method

Dynamic Daytime Population Estimation Model

The night-time population of an area is generally assumed to be the total resident population recorded in census data. The hourly changes in population during the daytime are more difficult to capture at a high spatial resolution than the night-time population, especially for municipalities, due to the frequent movements of the population. In some countries, the census reports the estimated daytime population at the census tract level based on simple models obtained by considering the total number of commuters moving into and out of the area (e.g., the US Census Bureau [18], Census Bureau of Japan [17], and MapInfo of Canada [57]). This is a reliable source of data for regional assessments; however, the tract unit is arguably too large to be used for emergency responses at the community level and does not address the spatial issues associated with the aggregation of data [25]. In addition, such a model does not include all the different population types leaving and moving into the area. This paper proposes a model to estimate the hourly dynamic changes in population at the community level using subway smart card data and community census data.

Despite the disadvantages of the current formulas for the estimation of the daytime population, a consensus has been reached that the daytime population can be calculated based on the night-time population in any region (Equation (1)). The population change caused by people leaving and moving into the area during the day is the key to calculating the daytime population of a region. In this paper, the change of population was calculated from the number of people swiping in and swiping out within the catchment areas of subway stations (Equations (2) and (3)):

$$DP = NP + P_m - P_l \tag{1}$$

$$P_m = \frac{PEX}{\alpha} \tag{2}$$

$$P_l = \frac{PEN}{\alpha} \tag{3}$$

where *DP* is the daytime population in the region (i.e., within the catchment area of a subway station); *NP* is the night-time total population of the communities in the region; P_m is the population moving into the region during the day, which can be calculated from the number of people swiping out from subway stations, namely *PEX*; P_l is the population leaving the region during the day, which can be calculated by the number of people swiping into subway stations, i.e., *PEN*; and α is the proportion of journeys made by subway. The value of α was set to 20.6% in this study for the preliminary exploration of the feasibility of the method. Based on this model, once the number of people swiping in and swiping out has been determined for each subway station, the hourly population of the communities within the catchment area is decreased or increased based on the weighted population. The temporal dynamics of the population at the community level can be calculated as per Equation (4):

$$P_{ik} = P_{i0} + \sum_{j=1}^{k} \frac{P_{i0}}{P} \times (P_{mj} - P_{lj}) \quad k = 1, 2, \cdots, n \tag{4}$$

where P_{ik} is the population during period k for each community i; P_{i0} is the total population of community i at night; P is the total population of the communities within the catchment area of a subway station; P_{mj} is the number of people moving into the region during period j; P_{lj} is the number of people leaving the region during period j; and the values of k represent the 20 different time periods in each working day (i.e., k = 1 for period 05:00–06:00, k = 2 for 06:00–07:00, k = 20 for the period 24:00–01:00). The catchment area of the subway station in this study was directly obtained from the Voronoi diagram in ArcGIS (Figure 1).

3. Results

3.1. Population Changes at the District Level

The hourly daytime and night-time population of all communities in the central area of Beijing can be calculated based on Equations (1)–(4). The night-time population, from 01:00 to 05:00, was provided by the community census data. Figure 2 presents the hourly changes of the total population of the six districts. The total population of the study area increased rapidly from 07:00. The peak total population of 13.83 million was reached at about noon; 0.7 million more people than the night-time population. The 0.7 million people entering from outside the region affected the overall density and population estimation with a low proportion of approximately 6% of the total population. The total population then decreased symmetrically until the evening, when the population was similar to the night-time population at 01:00 the next day. The shape of the curve and the daytime increase in population were consistent with the variations in the metropolitan population found by other researchers [11,12,16,58].

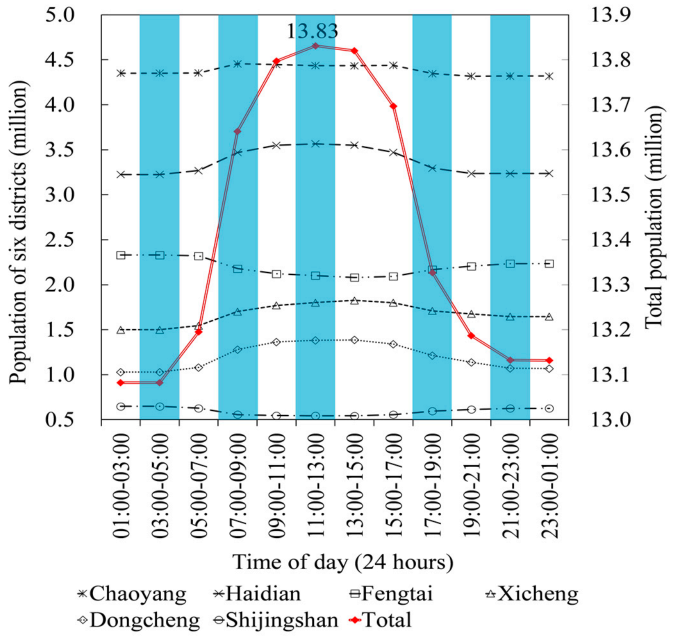

Figure 2. Bi-hourly variation of the total population in the central area of Beijing.

Table 2 presents the estimated total night-time population, the maximum daytime population, and population ratio of day to night for the six central districts of Beijing. The average ratio of the maximum daytime population to the night-time population was 1.06. Within the six districts, four had a population ratio >1. Dongcheng and Xicheng districts, which are downtown areas of Beijing, had large population ratios of 1.35 and 1.22, respectively. The ratios for Haidian and Chaoyang districts approached 1 due to a balance in the population inflow and outflow between day and night. Shijingshan and Fengtai districts had low population ratios of 0.84 and 0.89, respectively. These results are similar to those of Huang [19,59], who estimated the population ratio of day to night of the district of Beijing by dividing the working population of the economic areas by the population of the residential areas using census data in 2000.

Table 2. Population ratios of day to night in the six central districts of Beijing.

District	Function	Night-Time Population	Maximum Daytime Population	Population Ratio of Day to Night
Dongcheng	Administrative and commercial	1,029,408	1,386,270	1.35
Xicheng	Administrative and commercial	1,499,466	1,825,688	1.22
Haidian	Mixed	3,224,669	3,565,169	1.11
Chaoyang	Mixed	4,350,650	4,435,670	1.02
Fengtai	Mixed	2,329,916	2,081,075	0.89
Shijingshan	Residential	648,559	543,074	0.84
Average		13,082,668	13,836,946	1.06

3.2. Spatial Distribution of Population Ratio of Day to Night

The population ratio of day to night can adequately measure the regional level of aggregation of economy, reflecting the substitution degree of economic locations for residential locations [60]. The higher the population ratio of day to night in a region, the larger the proportion of commercial land; this ratio is lower in residential areas.

Figure 3 shows that the areas with a high population ratio were mainly concentrated in Dongcheng, Xicheng, West Chaoyang, and Southeast Haidian.

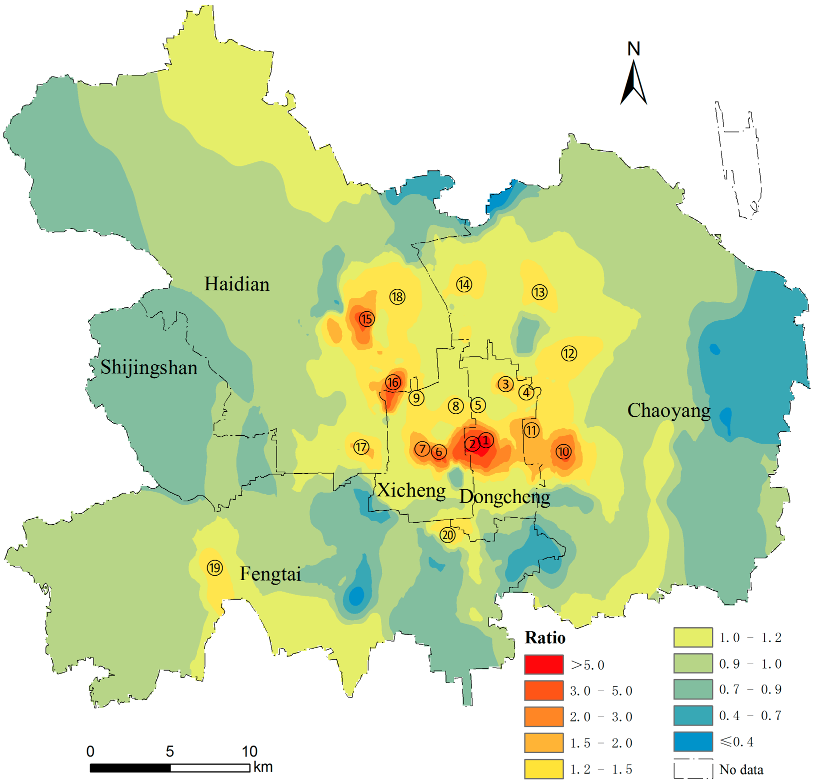

Figure 3. Spatial distribution of population ratio of day to night in the different districts of Beijing; see Table 3 for names of locations. The actual analysis units are communities; however, for a better representation, the distribution is smoothed by inverse distance-weighted interpolation.

Table 3. High value areas of population ratio of day to night.

ID	Station	District	Type	Population Ratio of Day to Night
1	Wangfujing	Dongcheng	Business area	13.80
2	Tian'anmen	Dongcheng	Tourist area	6.08
3	Yonghegong Lama Temple	Dongcheng	Tourist area	1.89
4	Dongzhimen	Dongcheng	Business area	1.51
5	Nanluoguxiang	Dongcheng	Tourist area	1.25
6	Xidan	Xicheng	Business area	4.53
7	Fuxingmen	Xicheng	Business area	2.88
8	Beihai North	Xicheng	Tourist area	1.33
9	Xizhenmen	Xicheng	Business area	1.31
10	Guomao	Chaoyang	Business area	6.56
11	Chaoyangmen	Chaoyang	Business area	1.90
12	Sanyuanqiao	Chaoyang	Business area	1.44
13	Wangjing West	Chaoyang	Business area	1.30
14	Beijing Olympic Park	Chaoyang	Tourist area	1.23
15	Zhongguancun	Haidian	Business area	3.50
16	Beijing Zoo	Haidian	Tourist area	3.54
17	Gongzhufen	Haidian	Business area	1.50
18	Wudaokou	Haidian	University area	1.28
19	Beijing Garden Expo	Fengtai	Tourist area	1.33
20	Beijing South Railway Station	Fengtai	Railway station	1.28

The population ratio of most areas was >1.0 in Dongcheng and Xicheng. The area around Wangfujing station, the most famous business center of Beijing, had a maximum value of 13.80, followed by the areas around Tian'anmen and Xidan stations with values of 6.08 and 4.53, respectively

(Table 3). The areas around the Yonghegong Lama Temple, Dongzhimen, and Fuxinmeng stations had population ratios of 1.5–3.0 and the areas around Beihai North, Nanluoguxiang, and Xizhimen stations had population ratios of 1.2–1.5. The areas around Wangfujing, Xidan, Dongzhimen, Fuxingmeng, and Xizhimen stations are typical business areas of Beijing, and those around Tian'anmen, Yonghegong Lama Temple, Beihai North, and Nanluoguxiang stations are typical tourist locations, with high population ratios of day to night.

There were also several centers with a high population ratio of day to night in Chaoyang and Haidian, which are business centers, tourist locations, or university areas. The area around Guomao station, which is the central business district of Chaoyang, had the highest value of 6.5. The area around Zhongguancun station (the high-tech business center of Beijing) and Beijing Zoo station (a typical tourist area) had values of 3.50 and 3.54, respectively. The areas around Chaoyangmen and Gongzhufen stations had values of 1.5–2.0 and the areas around Sanyuanqiao, Wangjing West, Wudaokou, and Beijing Olympic Park stations had values of 1.2–1.5. In Fengtai district, only the two areas around the Beijing Garden Expo and Beijing South Railway Station had values >1.2. The daytime population was less than the night-time population in the whole of Shijingshan district, which is a typical dormitory town.

The central area of Beijing can be divided into four types of areas based on the different combinations of population density during daytime and night-time: (1) high in both daytime/night-time (HH); (2) high/low in daytime/night-time (HL); (3) low/high in daytime/night-time (LH); and (4) low both in daytime and night-time (LL). This was further supported by the temporal and spatial structure of the dynamic population distribution. Both the daytime and night-time population aggregate in industrial parks, parts of the business centers with residential land, railway stations, and university districts, which have the functions of working, living, and education. The communities with a large difference between a high daytime population and low night-time population were mainly distributed in business centers and tourist areas. Parts of the suburban and downtown areas are usually referred to as dormitory towns, including Shijingshan district, the east of Fengtai district, the east of Chaoyang district, the northeast of Haidian district, and the so-called old residential area of downtown Beijing. These areas have low values for the spatial distribution of the population ratio of day to night with many residential communities. The LL areas were mainly distributed in the northwest of Haidian district and west of Fengtai district, which have large areas of farmland and mountains.

3.3. Temporal and Spatial Structure of the Dynamic Population Distribution

Understanding the variation in urban population during the daytime and night-time could help us better understand the mechanisms of city evolution [24]. Figure 4 shows the population density maps of the study area for five typical periods of 03:00–05:00 (night-time), 07:00–09:00 (morning peak), 11:00–13:00 (daytime maximum value), 17:00–19:00 (evening peak), and 21:00–23:00 (close to night-time) based on the hourly change of total population given in Figure 2. Overall, the distribution of population density in the six central districts showed a significant pattern of downtown-suburban-outer suburban, with a population density >25,000, 10,000–25,000, and <10,000 people/km^2, respectively, from the center to the outer areas during both daytime and night-time. The daytime population spread significantly inward from the suburbs and outer suburbs to the downtown areas, especially from 07:00 to 09:00. In contrast, the urban crowds dispersed during the evening peak period as people returned to the residential areas. Table 4 suggests that the modes of the number of communities and area percentages of communities for different population densities in five time periods showed regular changes as positive feedback of the mobility of population. The number of communities and percentage of community areas increased around areas of population density >100,000 people/km^2 and 50,000–100,000 people/km^2 in the morning and decreased symmetrically in the afternoon. The modes of change in the rest areas showed opposite trends.

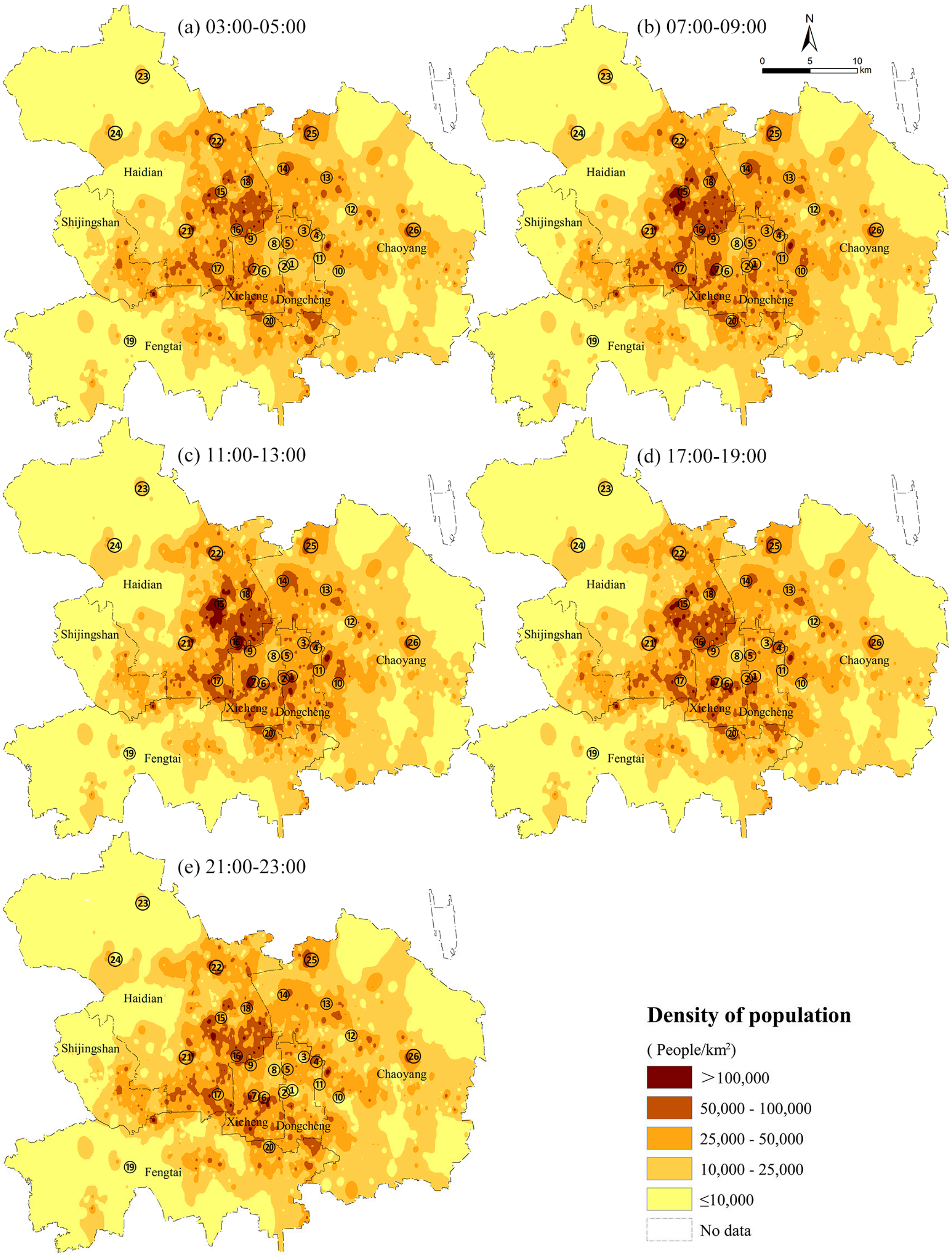

Figure 4. Spatial distribution of the dynamic population in the central area of Beijing. To make the spatial distribution clear, the IDW method was adopted. 21, Shijicheng; 22, Shangdi Information Industry Park; 23, Yongfeng High-tech Industrial Base; 24, Wenquan Science & Technology Park; 25, Laiguangying Culture Creative Industry Park; and 26, Dongba business area. No. 1 to No. 20 are the same as shown in Figure 3.

Table 4. Community number and area percentage (%) for different population densities in specific time periods.

Population Density of Community (People/km^2)	03:00–05:00	07:00–09:00	11:00–13:00	17:00–19:00	21:00–23:00	Mode of Change
≤10,000	534/73.96	532/73.95	537/74.62	539/74.64	536/73.81	Not obvious
10,000–25,000	555/15.77	533/15.15	526/14.52	553/14.80	553/15.67	↘↗
25,000–50,000	582/7.97	545/7.87	547/7.69	543/7.64	564/7.78	↘↗
50,000–100,000	314/2.13	353/2.75	338/2.74	336/2.65	324/2.49	↗↘
>100,000	54/0.17	76/0.28	91/0.43	68/0.27	62/0.25	↗↘

Note: ↘ means the decrease of population, and ↗ means the increase of population.

Turning to the central areas of the city, which have a high level of urbanization, there are obvious differences between the daytime and night-time population distributions. Figure 4c shows that there were several significant agglomeration centers for the daytime population, mainly located in the business area, tourist area, the university and college area in Haidian district, and some of the railway stations (e.g., Beijing South Railway Station). Similarly, there were centers of population agglomeration in the suburbs, mostly in industrial parks (Figure 4, locations 22–26). Overall, the daytime population distribution of the central area of Beijing has a hierarchical spatial pattern of planar center–second scattered center, which results from spatial planning, e.g., the location of industrial parks in the suburbs. This kind of industrial agglomeration is beneficial in driving regional economy, and also in the relocation of urban population to the suburbs.

In contrast, the population distribution at night shows a scattered pattern in the central urbanized area, which is different from the planar agglomeration pattern seen during the daytime. Figure 4 shows that the distribution of the night-time population spreads significantly outward from the downtown area to the suburbs and outer suburbs, reflecting the pattern of commuting. Parts of the outer suburb area that aggregate the night-time population, such as Shijingshan district, are usually referred to as commuter or dormitory towns in urban planning and urban geography as the residents in these areas usually work elsewhere during the daytime. Most industrial parks in the suburbs have a high density of night-time population as they have a self-contained residential area in addition to being workplaces of the resident population. There were also some agglomerations of night-time population in the downtown area, mostly the staff dormitory areas of colleges and universities and the so-called old residential area. To summarize, the night-time population distribution of the central district in Beijing shows a scattered spatial pattern of multiple centers resulting from the unique spatial planning system in China, such as areas of college and university accommodation and the so-called old residential areas.

3.4. Population Variation of Typical Communities

With the development of industrial and residential suburbanization in Chinese cities, the locations of urban population workplaces are now clearly different from the locations of residential areas [60]. Typical communities in residential, business, tourist, and university areas were selected to analyze the hourly changes of population (Figure 5). The four curves for the residential communities (Figure 5a) were obtained from Caofang station in Chaoyang, Fenzhongsi station in Fengtai, Yuxin station in Haidian, and Pingguoyuan station in Shijingshan. There are many universities within the catchment area of Wudaokou station, including the China University of Geosciences, the Beijing Language and Culture University, the Beijing Forestry University, and the China University of Mining and Technology. The University of Science and Technology Beijing is one of the universities within the catchment area of Xitucheng station. The population movements during daytime and night-time are summarized in the following sections.

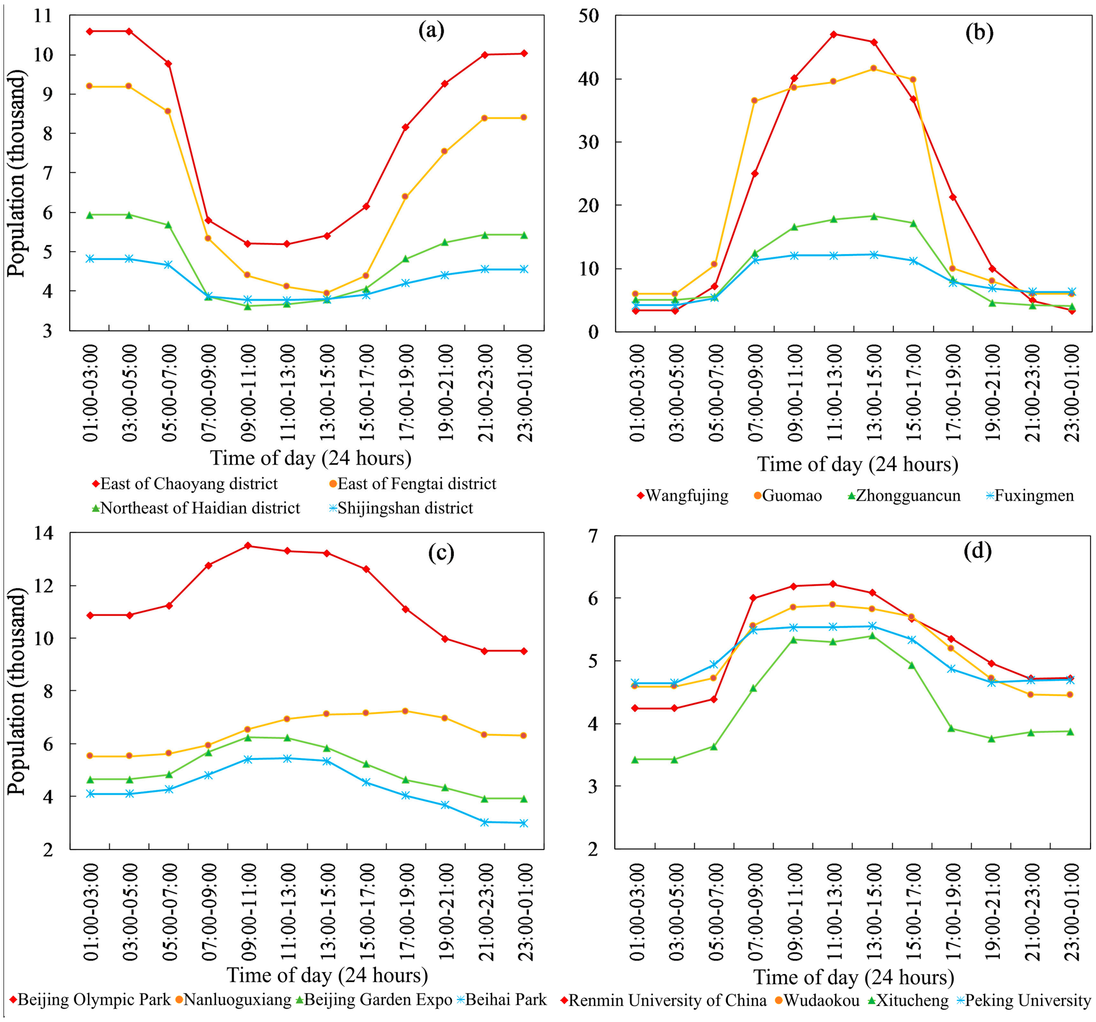

Figure 5. Population variations of typical communities. The average population of all communities within the catchment area of the corresponding subway station was used to derive the population variation of (**a**) residential communities; (**b**) commercial communities; (**c**) communities in the tourist areas; and (**d**) the university communities.

3.4.1. Residential Areas

Residential communities are extensively distributed in the outer suburbs, including Shijingshan, East Fengtai, East Chaoyang, and Northeast Haidian, as a result of the large proportion of residential land. Based on maps of the dynamic population and the population ratio of day to night distribution, the daytime population is less than the night-time population in these residential communities and is located in the low-value zone for the population ratio of day to night. The population of residential communities, which shows a tide-like variation falling and rising over a 24-h period, can be represented by a U-shaped curve. A decrease in the population is observed during the morning peak when thousands of people leave home to travel to their workplace. The population shows an inverse trend during the evening peak.

3.4.2. Business Areas

With high values of the population ratio of day to night, commercial communities are major workplaces and experience an influx of population during the daytime; the most typical areas of which are Wangfujing, Guomao, Zhongguancun, and Fuxingmen. The change of population in commercial communities is the opposite of that in residential communities, with an inverted U-shaped curve, especially in Guomao, where the increased population is maintained until the evening peak period. The activity of commuting between the workplace and residential areas makes a significant contribution to the difference in the population between the residential and commercial communities. The source and sink of the complementary population distribution can be explored for these different communities based on the population variation curve

3.4.3. Tourist Areas

The population starts to gradually increase after 07:00 and reaches its peak at noon, when it may be several thousand higher than the night-time population. There is a subsequent decrease of the population after 13:00 in some communities located near parks such as the Beijing Olympic Park, the Beijing Garden Expo, and Beihai Park. However, the population continually increases until 21:00 and then subsequently decreases in some tourist areas, e.g., Nanluoguoxiang, due to alternative attractions during the night-time.

3.4.4. University Areas

Communities located near universities have common features with both the business and tourist districts. On average, the population of each community increases by about 1000 people in the morning with the arrival of faculty workers and tourists. People return home after work or tourist activities in a symmetrical manner.

3.4.5. Summary of Population Mobility

From night-time to daytime, most people spread inward from the residential communities in Shijingshan, the east of Fengtai, the east of Chaoyang, and the northeast of Haidian, as well as from the so-called old residential areas, to the business, tourist, or university areas. The population flows within the communities of industrial parks in the suburbs. These industrial parks also absorb people from the downtown areas as the population ratio of day to night is >1 during the daytime. All these spatial processes are reversed from daytime to night-time.

4. Discussion

The method would not work well for locations with fewer stations, but it can be extended to a large spatial scale using railway transportation and high-speed rail. Furthermore, it would be more suitable for metropolitan regions (e.g., London and most of cities of Japan) with many subway stations and a high proportion of journeys made by subway.

The population characteristics from the developed dynamic population estimation model based on obtained subway smart card data are very similar to the results from previous works, e.g., the population ratios of day to night from Huang [19,59], population distribution from Qi et al. [24], and the population variation of typical communities and population mobility from Long et al. [61]. However, the mobility patterns of those taking the subway are different to those travelling via other modes of transportation. Furthermore, these differences have an impact on the final population estimates, which is the main source of error in this method. Therefore, to validate the model results, the estimated night-time and daytime population were compared to results from other methods, respectively. Future works for disaster risk assessment are also discussed. The dynamics of the population at the community level should be suitable for future rapid risk assessment, evacuation planning and relief delivery.

4.1. Evaluation for the Night-Time Population

The evaluation of models is an important aspect of research. Conducting a field survey to determine a population count per community from a statistically significant sample is an appropriate validation technique, but is extremely expensive and beyond the scope of this study. Although not entirely satisfactory, we used night-time census community data as an alternative in which to evaluate our derived dynamic population model. As the comparison does not utilize field-collected data, it was not a complete validation, but more of an indicator of the general performance of the model.

Error analysis indicated that the model performed well for night-time population at the community level. Figure 6 shows the counted census population versus the estimated night-time population from 21:00–23:00. During the night-time, the model accurately captured the population counts for the night-time residential population with a correlation coefficient of 0.92, and the median relative error for the communities was low at 4.4%. The estimated total night-time population was only 0.18% more than the population counted by the census data.

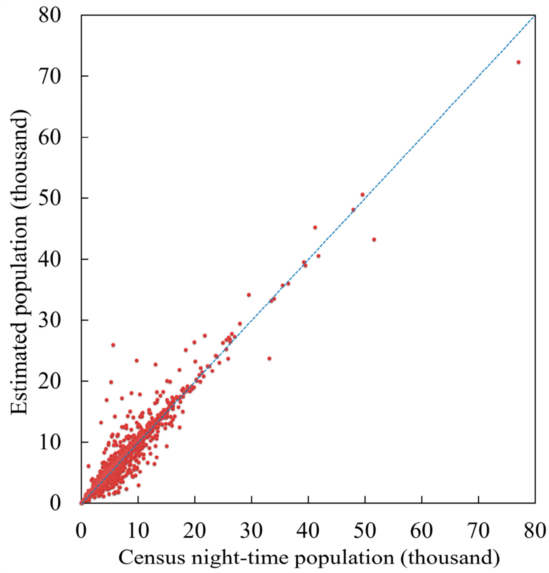

Figure 6. Census night-time population compared with the estimated night-time population based on the dynamic population model at the community level.

However, there were substantial over- and under-predictions of population in Figure 6 due to the error of the method. The over-predictions of population were mainly located in downtown areas, mostly in transport hub and tourist areas. In contrast, the under-predictions of population were mainly located in suburban areas, especially in residential areas. The main reason was that people would take the subway as their first choice as they needed to arrive at the office on time, and would prefer taking a bus or another way home when there was no time stress.

4.2. Evaluation for the Daytime Population

Figure 7a shows the statistical daytime population based on a relationship model from Qi et al. [24], and Figure 7b shows the estimated daytime population from 11:00–13:00 with the model developed in this study. There are very good spatial consistencies between the two maps, both for the spatial pattern with high values in the southeast and low values in the northwest, and for the nine high population density areas.

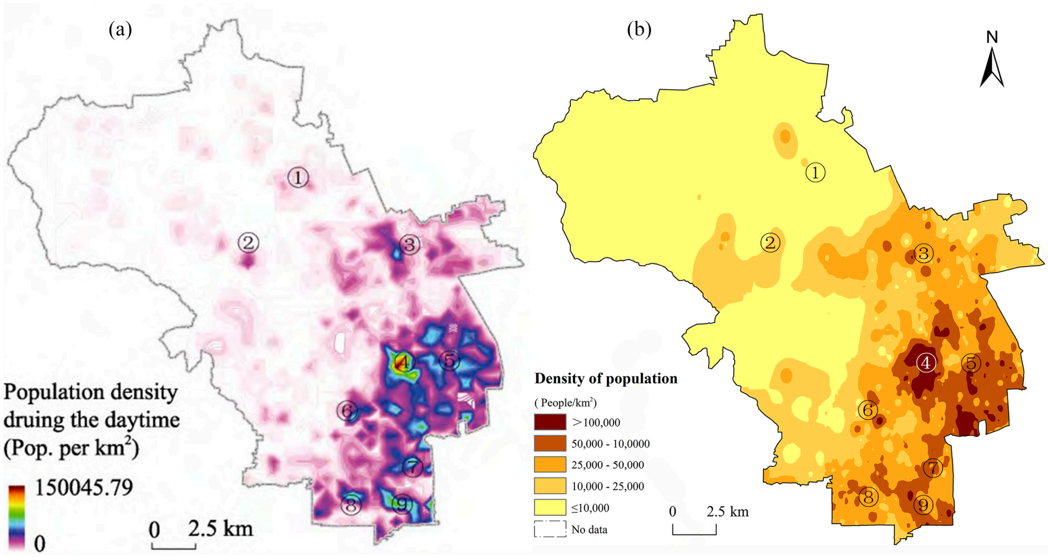

Figure 7. Comparison of the results of the daytime population distribution between the (**a**) methods of reference [24]; and (**b**) this paper. 1, Yongfeng High-tech Industrial Base; 2, Wenquan Science & Technology Park; 3, Shangdi Information Industry Park; 4, Zhongguancun; 5, University area; 6, Shijicheng; 7, Ganjiakou; 8, Wukesong; 9, Gongzhufen.

4.3. Future Work

The dynamics of the population on a detailed timescale could serve as a valuable information source [62] and is regarded as important [63] for disaster risk assessment. While population data is organized by coarse administrative units or census blocks, spatially finer data at the community level is more valuable for better planning in disaster risk management. Furthermore, the finer data could be applied to estimate the number of evacuees under different temporal disaster scenarios to better plan preparedness and mitigation based on the community dynamic population modeled by subway smart card data. It could become an integral part of regional security through emergency preparedness and response, including rapid risk assessment, modified evacuation planning and relief delivery.

5. Conclusions

Using community attribute data and data obtained from a subway fare smart card, our model significantly improved the temporal and spatial resolutions of the population distribution at the hour and community levels, respectively. This study was carried out in cooperation with relevant government departments and research institutes, and consisted of an empirical case study in six central districts of Beijing. The main conclusions are as follows.

Utilizing the increasing availability of big data, including subway fare smart card data, we focused on an hourly population distribution model to extend the existing paradigm of traditional remote sensing and earlier big data method through an innovative subway big data modeling approach. The maximum number of people in the central area of Beijing was 13.83 million during the daytime (based on the model value), approximately 0.7 million greater than the night-time population. The general consistency of the population ratios of day to night, population distribution, population variation of typical communities, and population mobility patterns with previous research suggests that subway smart card data have potential in analyzing the dynamic diurnal variations of an urban population.

The spatial structure of the population distribution during daytime was significantly different from that during the night. The daytime population distribution of the central area of Beijing has a hierarchical spatial pattern of planar centers and second scattered centers. However, the night-time population distribution shows a scattered spatial pattern of multiple centers, which is affected by the unique spatial planning in China, such as the location of the so-called old residential areas, the accommodation for colleges and universities in downtown areas, and industrial parks in suburbs.

As a modern city, Beijing has a population mobility pattern similar to many large cities worldwide. From night-time to daytime, most people spread inward from the LH areas to the HL areas, which reflects commuting between the residential areas and the workplace. In contrast, the night-time population spread significantly outward from the downtown area to the suburbs and outer suburbs, forming dormitory towns. A knowledge of the spatial structure of the population density and the population mobility pattern would provide useful insights in the rapid assessment of risk in disaster-prone urban regions in this age of big data.

Several distinctive phenomena in the development of China were reflected by the spatiotemporal characteristics of the population distribution in the central area of Beijing. Many industrial parks in the suburbs had a high density of both daytime and night-time population as they have self-contained residential areas. This type of industrial agglomeration is beneficial in driving regional economies, and also in the relocation of urban population to the suburbs. Many people living in the city center in the so-called old residential areas are local citizens who have inherited houses in this area, or simply enjoy living in older properties. Students and faculty staff usually live in colleges and universities, which result in a high population density during both daytime and night-time. A slight increase of the population during the daytime may be attributed to the arrival of faculty staff and tourists.

Acknowledgments: This study was funded by the National Key Research and Development Program of China (No.2016YFA0602404), the Program of Introducing Talent to Universities (No.B08008) and the National Natural Science Foundation of China (No.41201547). The subway fare smart card data were provided by Beihang Interest Group on SmartCity, and we are grateful for their permission to use it in this paper. We also thank the Beijing Municipal Bureau of Civil Affairs for providing access to community population data.

Author Contributions: Wei Xu conceived the ideas; Yunjia Ma analyzed the data and results; Yunjia Ma, Xiujuan Zhao and Wei Xu wrote the paper. Ying Li reviewed the manuscript and provided comments.

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

References

1. Gonzalez, M.C.; Hidalgo, C.A.; Barabasi, A. Understanding individual human mobility patterns. *Nature* **2008**, *453*, 779–782. [CrossRef] [PubMed]
2. Bhaduri, B.; Bright, E.; Coleman, P.; Urban, M.L. LandScan USA: A high-resolution geospatial and temporal modeling approach for population distribution and dynamics. *GeoJournal* **2007**, *69*, 103–117. [CrossRef]
3. Yu, C.; Chang, H. Personalized location-based recommendation services for tour planning in mobile tourism applications. In Proceedings of the International Conference on Electronic Commerce and Web Technologies, Linz, Austria, 1–4 September 2009; pp. 38–49.
4. McPherson, T.N.; Brown, M. Estimating daytime and nighttime population distributions in US cities for emergency response activities. In Proceedings of the Symposium on Planning, Nowcasting, and Forecasting in the Urban Zone, Seattle, WA, USA, 10–12 January 2004.
5. Aubrecht, C.; Freire, S.; Neuhold, C.; Curtis, A.; Steinnocher, K. Introducing a temporal component in spatial vulnerability analysis. *Disaster Adv.* **2012**, *5*, 48–53.
6. Eubank, S.; Guclu, H.; Kumar, V.A.; Marathe, M.V.; Srinivasan, A.; Toroczkai, Z.; Wang, N. Modelling disease outbreaks in realistic urban social networks. *Nature* **2004**, *429*, 180–184. [CrossRef] [PubMed]
7. Gariazzo, C.; Pelliccioni, A.; Bolignano, A. A dynamic urban air pollution population exposure assessment study using model and population density data derived by mobile phone traffic. *Atmos. Environ.* **2016**, *131*, 289–300. [CrossRef]
8. Wirth, L. Urbanism as a way of life. *Am. J. Soc.* **1938**, *44*, 1–24. [CrossRef]
9. Breese, G.W. *The Daytime Population of the Central Business District of Chicago: With Particular Reference to the Factor of Transportation*; University of Chicago Press: Chicago, IL, USA, 1949.
10. Quinn, J.A.; Breese, G.W. The daytime population of the central business district of Chicago. *Am. Soc. Rev.* **1950**, *15*, 827–828. [CrossRef]

11. Foley, D.L. The daily movement of population into central business districts. *Am. Soc. Rev.* **1952**, *17*, 538–543. [CrossRef]
12. Foley, D.L. Urban daytime population: A field for demographic-ecological analysis. *Soc. Forces* **1954**, *32*, 323–330. [CrossRef]
13. Akkerman, A. The urban household pattern of daytime population change. *Ann. Reg. Sci.* **1995**, *29*, 1–16. [CrossRef] [PubMed]
14. Akkerman, A.; Hwang-Kurylyk, Y.W. The origin-destination matrix as an indicator of intrahousehold travel allocation. *Transp. Plan Techn.* **2004**, *27*, 285–314. [CrossRef]
15. Fulton, P.N. Estimating the daytime population with the urban transportation planning package. *Transp. Res. Rec.* **1984**, *981*, 25–27.
16. Roddis, S.M.; Richardson, A.J. Construction of daytime activity profiles from household travel survey data. *Transp. Res. Rec. J. Transp. Res. Board* **1998**, *1625*, 102–108. [CrossRef]
17. Statistics Bureau Home Page/Daytime Population. Available online: http://www.stat.go.jp/english/data/kokusei/2000/jutsu1/00/01.htm (accessed on 22 March 2016).
18. Bhaduri, B. *Population Distribution during the Day*; Springer: Berlin, Germany, 2008; pp. 880–885.
19. Huang, R. The regional structure of Beijing. *Chin. J. Popul. Sci.* **2003**, *5*, 49–55.
20. Langford, M.; Harvey, J.T. The use of remotely sensed data for spatial disaggregation of published census population counts. In Proceedings of the IEEE/ISPRS Joint Workshop on Remote Sensing and Data Fusion over Urban Areas, Roma, Italy, 8–9 November 2001.
21. Harvey, J.T. Population estimation models based on individual TM pixels. *Photogramm. Eng. Remote Sens.* **2002**, *68*, 1181–1192.
22. Yue, T.X.; Wang, Y.A.; Chen, S.P.; Liu, J.Y.; Qiu, D.S.; Deng, X.Z.; Liu, M.L.; Tian, Y.Z. Numerical simulation of population distribution in China. *Popul. Environ.* **2003**, *25*, 141–163. [CrossRef]
23. Yue, T.X.; Wang, Y.A.; Liu, J.Y.; Chen, S.P.; Qiu, D.S.; Deng, X.Z.; Liu, M.L.; Tian, Y.Z.; Su, B.P. Surface modelling of human population distribution in China. *Ecol. Model* **2005**, *181*, 461–478. [CrossRef]
24. Qi, W.; Liu, S.; Gao, X.; Zhao, M. Modeling the spatial distribution of urban population during the daytime and at night based on land use: A case study in Beijing, China. *J. Geogr. Sci.* **2015**, *25*, 756–768. [CrossRef]
25. Sleeter, R.; Wood, N. Estimating daytime and nighttime population density for coastal communities in Oregon. In Proceedings of the Urban and Regional Information Systems Association Annual Conference, Vancouver, BC, Canada, 26–29 September 2006.
26. Ahas, R.; Mark, Ü. Location based services—New challenges for planning and public administration? *Futures* **2005**, *37*, 547–561. [CrossRef]
27. Mao, X.; Xu, R.; Li, X.; Wang, Y.; Li, C.; Zeng, B.; He, Y.; Liu, J. Fine grid dynamic features of population distribution in Shenzhen. *Acta Geogr. Sin.* **2010**, *65*, 443–453.
28. de Montjoye, Y.; Hidalgo, C.A.; Verleysen, M.; Blondel, V.D. Unique in the crowd: The privacy bounds of human mobility. *Sci. Rep.* **2013**, *3*, 1376. [CrossRef] [PubMed]
29. Wesolowski, A.; Buckee, C.O.; Pindolia, D.K.; Eagle, N.; Smith, D.L.; Garcia, A.J.; Tatem, A.J. The use of census migration data to approximate human movement patterns across temporal scales. *PLoS ONE* **2013**, *8*, e52971. [CrossRef] [PubMed]
30. Yang, X.; Fang, Z.; Xu, Y.; Shaw, S.; Zhao, Z.; Yin, L.; Zhang, T.; Lin, Y. Understanding spatiotemporal patterns of human convergence and divergence using mobile phone location data. *ISPRS Int. J. Geoinf.* **2016**, *5*, 177. [CrossRef]
31. Lu, S.; Fang, Z.; Zhang, X.; Shaw, S.; Yin, L.; Zhao, Z.; Yang, X. Understanding the representativeness of mobile phone location data in characterizing human mobility indicators. *ISPRS Int. J. Geoinf.* **2017**, *6*, 7. [CrossRef]
32. Yuan, J.; Zheng, Y.; Xie, X. Discovering regions of different functions in a city using human mobility and POIs. In Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, New York, NY, USA, 12–16 August 2012.
33. Tang, J.; Liu, F.; Wang, Y.; Wang, H. Uncovering urban human mobility from large scale taxi GPS data. *Phys. Stat. Mech. Appl.* **2015**, *438*, 140–153. [CrossRef]

34. Vazquez-Prokopec, G.M.; Bisanzio, D.; Stoddard, S.T.; Paz-Soldan, V.; Morrison, A.C.; Elder, J.P.; Ramirez-Paredes, J.; Halsey, E.S.; Kochel, T.J.; Scott, T.W. Using GPS technology to quantify human mobility, dynamic contacts and infectious disease dynamics in a resource-poor urban environment. *PLoS ONE* **2013**, *8*, e58802. [CrossRef] [PubMed]
35. Zhang, F.; Zhu, X.; Guo, W.; Ye, X.; Hu, T.; Huang, L. Analyzing urban human mobility patterns through a thematic model at a finer scale. *ISPRS Int. J. Geoinf.* **2016**, *5*, 78. [CrossRef]
36. Lenormand, M.; Louail, T.; Cantú-Ros, O.G.; Picornell, M.; Herranz, R.; Arias, J.M.; Barthelemy, M.; Miguel, M.S.; Ramasco, J.J. Corrigendum: Influence of sociodemographic characteristics on human mobility. *Sci. Rep.* **2015**, *5*. [CrossRef] [PubMed]
37. Sobolevsky, S.; Sitko, I.; Tachet Des Combes, R.; Hawelka, B.; Murillo Arias, J.; Ratti, C. Money on the move: Big data of bank card transactions as the new proxy for human mobility patterns and regional delineation. The case of residents and foreign visitors in spain. In Proceedings of the 2014 IEEE International Congress on Big Data, Anchorage, AK, USA, 27 June–2 July 2014.
38. Hasan, S.; Schneider, C.M.; Ukkusuri, S.V.; González, M.C. Spatiotemporal patterns of urban human mobility. *J. Stat. Phys.* **2013**, *151*, 304–318. [CrossRef]
39. Roth, C.; Kang, S.M.; Batty, M.; Barthélemy, M. Structure of urban movements: Polycentric activity and entangled hierarchical flows. *PLoS ONE* **2011**, *6*, e15923. [CrossRef] [PubMed]
40. Gong, Y.; Lin, Y.; Duan, Z. Exploring the spatiotemporal structure of dynamic urban space using metro smart card records. *Comput. Environ. Urban Syst.* **2017**, *64*, 169–183. [CrossRef]
41. McKenzie, G.; Janowicz, K. Where is also about time: A location-distortion model to improve reverse geocoding using behavior-driven temporal semantic signatures. *Comput. Environ. Urban Syst.* **2015**, *54*, 1–13. [CrossRef]
42. McKenzie, G.; Janowicz, K.; Gao, S.; Gong, L. How where is when? On the regional variability and resolution of geosocial temporal signatures for points of interest. *Comput. Environ. Urban Syst.* **2015**, *54*, 336–346. [CrossRef]
43. Wu, L.; Zhi, Y.; Sui, Z.; Liu, Y. Intra-urban human mobility and activity transition: Evidence from social media check-in data. *PLoS ONE* **2014**, *9*, e97010. [CrossRef] [PubMed]
44. Jurdak, R.; Zhao, K.; Liu, J.; AbouJaoude, M.; Cameron, M.; Newth, D. Understanding human mobility from Twitter. *PLoS ONE* **2015**, *10*, e131469. [CrossRef] [PubMed]
45. Yin, J.; Du, Z. Exploring multi-scale spatiotemporal twitter user mobility patterns with a visual-analytics approach. *ISPRS Int. J. Geoinf.* **2016**, *5*, 187. [CrossRef]
46. Li, Y.; Li, Q.; Shan, J. Discover patterns and mobility of Twitter users—A study of four US college cities. *ISPRS Int. J. Geoinf.* **2017**, *6*, 42. [CrossRef]
47. Luo, F.; Cao, G.; Mulligan, K.; Li, X. Explore spatiotemporal and demographic characteristics of human mobility via Twitter: A case study of Chicago. *Appl. Geogr.* **2015**, *70*, 11–25. [CrossRef]
48. Cheng, Z.; Caverlee, J.; Lee, K.; Sui, D.Z. Exploring millions of footprints in location sharing services. *ICWSM* **2011**, *2011*, 81–88.
49. Li, L.; Goodchild, M.F.; Xu, B. Spatial, temporal, and socioeconomic patterns in the use of Twitter and Flickr. Cartogr. *Geogr. Inf. Sci.* **2013**, *40*, 61–77. [CrossRef]
50. Arai, A.; Fan, Z.; Matekenya, D.; Shibasaki, R. Comparative perspective of human behavior patterns to uncover ownership bias among mobile phone users. *ISPRS Int. J. Geoinf.* **2016**, *5*, 85. [CrossRef]
51. Kang, C.; Liu, Y.; Ma, X.; Wu, L. Towards estimating urban population distributions from mobile call data. *J. Urban Technol.* **2012**, *19*, 3–21. [CrossRef]
52. Wesolowski, A.; Eagle, N.; Noor, A.M.; Snow, R.W.; Buckee, C.O. Heterogeneous mobile phone ownership and usage patterns in Kenya. *PLoS ONE* **2012**, *7*, e35319. [CrossRef] [PubMed]
53. Wesolowski, A.; Eagle, N.; Noor, A.M.; Snow, R.W.; Buckee, C.O. The impact of biases in mobile phone ownership on estimates of human mobility. *J. R. Soc. Interf.* **2013**, *10*, 20120986. [CrossRef] [PubMed]
54. Deville, P.; Linard, C.; Martin, S.; Gilbert, M.; Stevens, F.R.; Gaughan, A.E.; Blondel, V.D.; Tatem, A.J. Dynamic population mapping using mobile phone data. *Proc. Natl. Acad. Sci. USA* **2014**, *111*, 15888–15893. [CrossRef] [PubMed]
55. The Traffic Trip Proporion of Public Transportation of Beijing in 2013. Available online: http://www.baogaochina.com/News/2014--02/2013NianBeiJingDeGongGongJiaoTon.html (accessed on 17 April 2016).

56. Beihang Interest Group on SmartCity (BIGSCity). Available online: http://www.smartcity-buaa.org/ (accessed on 6 April 2016).
57. Mapinfo Daytime Population Canada. Available online: http://www.pitneybowes.com/us/location-intelligence/gis-data-sets/daytime-population-canada.html (accessed on 24 May 2016).
58. Menzler, F. An estimate of the day-time population of London. *J. Town Plan. Inst.* **1952**, *38*, 116–120.
59. Huang, R. Population redistribution in the context of urbanization in Beijing since 1980s. *Popul. Res.* **2005**, *29*, 19–27.
60. Kang, W. *On the Character of Downtown Daytime Population and Its' Impacts on Regional Development: A Case Study in Luwan District, Shanghai*; East China Normal University: Shanghai, China, 2006.
61. Long, Y.; Zhang, Y.; Cui, C. Identifying commuting pattern of Beijing using bus smart card data. *Acta Geogr. Sin.* **2012**, *67*, 1339–1352.
62. Miyazaki, H.; Nagai, M.; Shibasaki, R. Reviews of geospatial information technology and collaborative data delivery for disaster risk management. *ISPRS Int. J. Geoinf.* **2015**, *4*, 1936–1964. [CrossRef]
63. Freire, S.; Aubrecht, C. Integratig population dynamics into mapping human exposure to seismic hazard. *Nat. Hazards Earth Sys. Sci.* **2012**, *12*, 3533–3543. [CrossRef]