

Article

Assessing Emergency Shelter Demand Using POI Data and Evacuation Simulation

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Received: 25 November 2019; Accepted: 13 January 2020; Published: 14 January 2020



Abstract: Mapping the fine-scale spatial distribution of emergency shelter demand is crucial for shelter planning during disasters. To provide shelter for people within a reasonable evacuation distance under day and night disaster scenarios, we formed an approach for examining the distribution of day and night shelter demand at the plot-scale using point of interest (POI) data, and then analyzed the supply and demand status of shelters after an evacuation simulation built in Python programming language. Taking the downtown areas of Guangzhou, China as a case study, the results show that significant differences exist in the size and spatial distribution of shelter demand in daytime and nighttime, and the total demand is 7.929 million people, which is far larger than the resident population. The average evacuation time of all 16,883 routes is 12.6 min, and after the evacuation, 558 of 888 shelters exceed their capacity to varying degrees, accounting for 62.84% of the total, indicating that the shelters cannot completely receive the potential evacuees. The method proposed in this paper provides a direct quantitative basis for the number and size of new shelter resources being planned during urban renewal activities, and form a reference for land reuse and disaster prevention space organization in future urban planning.

Keywords: emergency shelter; shelter demand assessment; point of interest; evacuation simulation; Python programming language; Guangzhou

1. Introduction

In 2018, there were 315 natural disaster events recorded with 11,804 deaths, over 68 million people affected, and US\$131.7 billion in economic losses around the world. Earthquakes were the deadliest type of disaster, accounting for 45% of deaths, followed by flooding at 24% [1]. Efforts have aimed at preventing disasters and improving resilience, and the construction of emergency shelters is an important component of these efforts [2]. Evidence from disasters indicates that emergency shelters can reduce casualties to a certain extent in the event of a disaster [3,4]. An emergency shelter is a facility where government agencies or pre-established voluntary organizations conduct assessments and provide disaster services for evacuees who do not have destinations. These facilities are able to accommodate people and provide food and water, as well as basic first aid, pet shelter (as appropriate), health support, and basic disaster services [5]. Numerous studies have made progress in areas such as shelter planning support methods, space suitability assessment, locations optimization, emergency materials and facilities allocation, and sheltering behavior and psychology [6–11]. Since the users of the shelters are citizens, a key issue during possible evacuation activity is determining the

spatial distribution of potential evacuees for emergency shelter demand, which is directly related to the rationality of shelter locations and evacuation efficiency, that is, whether all the shelters in the city can provide refuge for people at a reasonable evacuation distance and time during a disaster [8,9,12].

Mapping the regional distribution of the population is a basis for analyzing the shelter demand [13,14]. Assessing the population distribution accurately is difficult because the population is mobile, with differences in both size and distribution at different times during day and night [15]. Traditional geospatial data, such as land cover data, have been widely used to describe population distribution [16,17]. With the development of technology and the richness of data, some scholars have incorporated big data or multi-source data as the data foundation to map fine-scale population distribution. Mossoux et al. [18] proposed an inverse calibration method to reduce the errors in roof type classification for high-resolution remotely sensed data processing, and the application of this method to population distribution assessment showed its potential for producing systematic population maps, especially in areas where regular census data are unavailable. Ma et al. [19] used subway smart card data to assess hourly dynamic changes in community population distribution, which can be applied in estimating the potential number of evacuees under different disaster scenarios and to support future urban planning. To produce population distribution map at the building scale, Yao et al. [20] introduced a down-scale approach to refine spatial distribution accuracy from street level to grid level based on points of interest (POIs) and real-time social platform user densities data, and the results can guide numerous urban construction practices such as disaster prevention, policies making, and resources allocation optimization.

The estimation of shelter demand is generally obtained through a superposition analysis of potential areas affected by disasters and population distribution [7]. Using census data, Chen et al. [8] predicted the population density distribution of future urban planning at the street level based on the current population distribution, and then identified the areas that may be affected by the disaster according to a risk analysis. Finally, shelter demand is estimated by overlapping the results of the above two processes in a geographic information system (GIS). Sugimoto et al. [21] selected a tsunami caused by an earthquake as a study scenario and calculated the scale and spatial distribution of possible casualties considering the maximum inundation areas combined with factors such as the time required to seek refuge after an earthquake, the inundation depth, flow rate, and the evacuation speed. Vecere et al. [22] used ERGO-EQ and HAZUS-MH tools and set the hazard, vulnerability, and exposure of the earthquake as input parameters to estimate the number of the displaced population and shelter demand, accompanied by a comparative analysis of results and recommendations for improvement based on local conditions. Chou et al. [23] developed a disaster loss estimation system based on HAZUS (a nationally applicable standardized methodology that contains models for estimating potential losses from earthquakes, floods, and hurricanes in America) to analyze the number of potential buildings damaged and the number of homeless under different intensities of earthquake and counted by district. Due to the uncertainty of disasters, the shelter construction must meet the needs of both day and night disaster response. Based on high-resolution aerial imagery, census data, and high-precision land use data, Yu and Wen [9] used a GIS-based analytic hierarchy process to assess the need for shelters in daytime and nighttime disaster scenarios. Chen et al. [13] reported that in addition to considering the time of disaster occurrence, the demand should be differentiated according to different evacuation situations. In the case of an emergency evacuation, the demand should be the maximum number of people present during the day and night; in the case of short-term and long-term refugees, the demand is equal to the number of night residents due to having sufficient notice for organizational actions. To improve the response capability in complex disaster environments, some scholars assessed the shelter demand from the perspective of different disaster types and intensities [8,24].

To understand whether the city can provide adequate shelters and enable evacuees to take refuge nearby, an evacuation simulation is necessary [21]. Various areas, such as evacuation schemes [25], decision-making methods [26], transport modes [27], influencing factors [28], evacuation behavior [29], differences in evacuees [30], and routes selection [31] have aroused the research interest. In terms

of spatial scale, some researchers selected the entire city as the object, and some focused on specific areas within the city [32,33]. In general, few evacuation simulation studies are directly related to the emergency shelter. The key problem with simulation experiments is establishing the relationship between evacuation activities and urban environment to process complex spatial, facility, and road network data as the main parameters [34]. Yamada [35] theoretically proposed two methods of network traffic to optimize urban emergency evacuation plans when assigning each resident to a nearby shelter. The first method involves modeling the city as an undirected graph, and the evacuation plan is obtained by solving the shortest path problem on the graph; the second method considers the shelter capacity as a limitation and the problem is transformed into a minimum cost stream goal-oriented solution. Filipe and Kacprzyk [36] developed an evolutionary learning algorithm for the assignment of paths and shelters based on the assumptions of fairness and global optimality, supplemented with heuristic methods to solve the evacuation problem with limited shelter capacity. This method considers the pedestrian simulation scenario on the road network, the intersections correspond to nodes, and the street segments connecting the intersections are modeled by links. The simulation results are closely related to assumptions such as various traffic scenarios and speeds. Lee and Hong [37] chose the evacuation of different slope areas under a flood scenario as a case to calculate the possible speed and evacuation distance of evacuees when selecting the shelter locations. The results showed that the evacuation distance of five minutes on flat ground is about 120 m different from that of 15° slope areas. For a dynamic spatial allocation of urban shelters, Yu et al. [38] developed an agent-based simulation method that can estimate the evacuation time of residents from their locations to shelters and detect the congestion of evacuation routes. Yuan et al. [39] proposed a traffic evacuation simulation system based on an integrated multi-level drive decision model that generates agent behavior in a unified framework, and the agents' activities are determined by various existing behavioral models widely used in different driver simulation models. The system can support emergency managers when designing and evaluating more realistic traffic evacuation plans to produce the best evacuation scheme. With the development of emerging technologies, some scholars have begun to focus on intelligent evacuation [40–43].

Geospatial data plays a crucial role in disaster relief. Now, volunteered geographic information (VGI) and web-based crowdsourcing data are being used in the field of disaster management, and GIS have evolved from tools that were limited to situational awareness to fundamental tools supporting. The development and widespread use of online mapping, remote sensing and VGI are providing decision makers with necessary information in emergency response [44]. Traditionally, emergency managers identified the disaster response period as a blind period, where victims needed to ensure their own safety and security [45]. Due to volunteer crowdsourcing, people share real-time, time critical and location specific information whenever a disaster occurs, which can help the emergency managers to take necessary actions to reduce the disaster risk, increase the real-time awareness and predict the direction [46]. In a project of crisis mapping, the researchers used crowdsourced event data from Tweets and Facebook posts to produce the crisis map, and the practice showed that people used the map not only for situational awareness reporting including multimedia such as photos and short videos, but also for offering both help with materials and personal assistance. However, VGI and crowdsourcing are bringing dramatic changes in emergency management [47].

This study originated from the practice of emergency shelter planning in China. In the planning, we found it difficult to analyze the high-precision spatial distribution of shelter demand. In addition, the distribution of shelters was usually based on the service radius, which leads to the scientific doubt of the results. Therefore, we try to increase the quantitative basis for shelter allocation through evacuation simulation. At present, few studies focused on the above two issues at the urban scale. Using POI data, and Python programming language, we explored the distribution of shelter demand and shelter status after an evacuation simulation in the downtown areas of Guangzhou. The rest of this paper is organized as follows: Section 2 first presents an overview of the study area and a description of types of data and the data processing, and then introduces the methods of shelter demand assessment

and evacuation simulation. Section 3 provides an analysis of the size and distribution of daytime and nighttime shelter demand at the plot scale in study area, along with the distribution of evacuees and the residual capacity of shelter. Section 4 discusses the deficiencies and limitations of this study. Conclusions and directions of future work are presented in Section 5. We hope that this work can provide a direct quantitative basis for adding new resources for shelters in the process of urban renewal activities, and form a reference for land reuse and disaster prevention space organization in future urban planning.

2. Materials and Methods

2.1. Study Area and Data Processing

The study area is located at the center of downtown Guangzhou (China), including the districts of Liwan, Yuexiu, Tianhe, and Haizhu (Figure 1), which are the only 4 districts of the 11 in Guangzhou with an urbanization rate of 100%. The total land area is about 279.63 km², accounting for 3.76% of the whole city. Yuexiu and Liwan are traditional old towns with small areas of 33.8 and 59.1 km², respectively. Considerable parts are newly built in Tianhe and Haizhu, which cover large areas of 96.33 and 90.4 km², respectively. According to data from the Guangzhou Municipal Bureau of Statistics, at the end of 2017, Tianhe had the largest population at 1,679,900, followed by Haizhu and Yuexiu, with 1,663,100 and 1,163,800, respectively, and Liwan had the smallest population of 950,000.

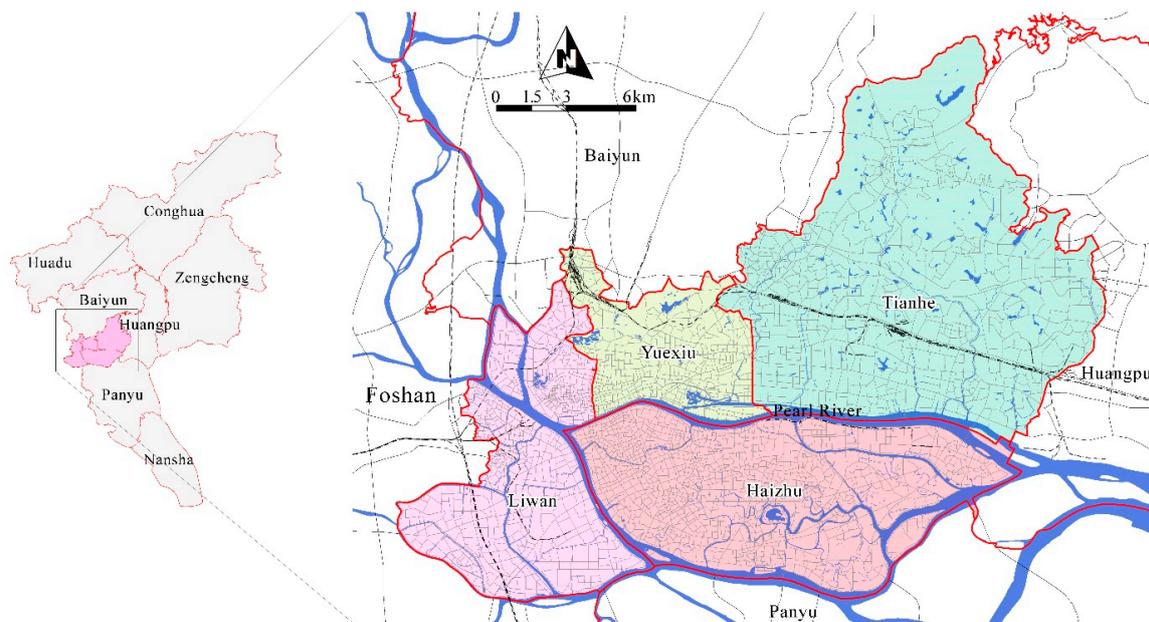


Figure 1. Study area.

In this study, the main data type used was POIs, which were collected from the Baidu Maps open platform in early 2018. The POIs data were divided into 14 categories and 524 subcategories, including catering services, scenic spots, enterprises, shopping services, transportation facilities, finance and insurance, education and culture, business housing, living services, sports and leisure, health care, government agencies, accommodation services, and public facilities, which basically cover all kinds of facilities that citizens can access. The POIs (Figure 2a) totaled 145,084, each of which contained information such as name, category, address, district, and coordinates of the facilities. Another data type is the distribution of residential quarters, apartments, and dormitories (Figure 2b) from a real estate transaction company, the data attributes included name, address, coordinates, number of buildings, number of households, and property company, for a total of 4533 pieces of

information. Official statistics of practitioners in various industries from yearbooks of Liwan, Yuexiu, Tianhe, and Haizhu were used as auxiliary data.

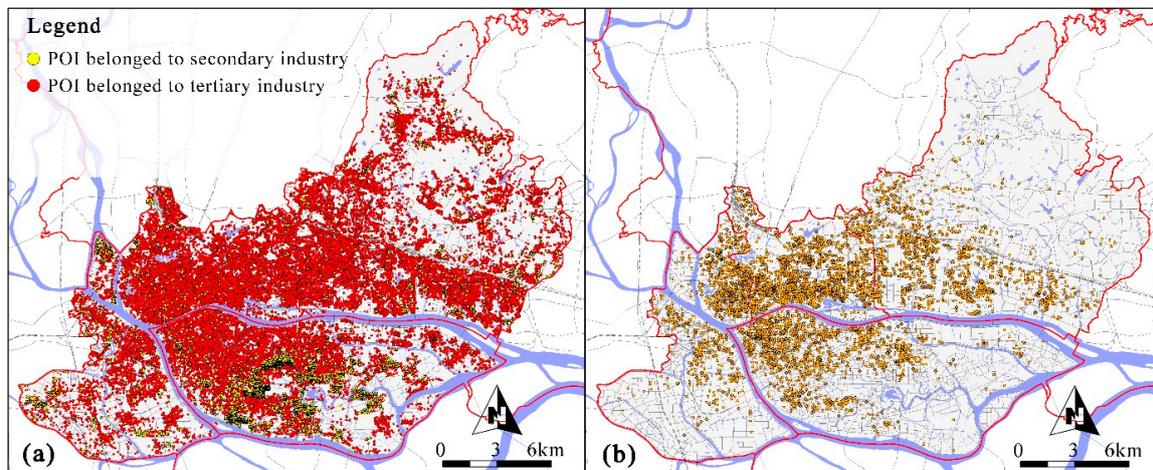


Figure 2. Data distribution of (a) points of interest (POIs) and (b) residential buildings.

To use POIs and statistics of practitioners to predict the shelter demand, that is, to represent the urban population distribution through economic activities, the classification of the two types of data must be consistent in the industry. Therefore, the POI data should be filtered and reclassified according to the official statistical caliber, and the process is completed in a GIS platform. Finally, after the reclassification, 5968 POIs belonged to secondary industry and 139,116 to tertiary industry.

2.2. Methods

2.2.1. Analysis of Shelter Demand Based on the Distribution of Day and Night Population

Population variation is a challenge in emergency shelter planning because it is directly related to whether the shelters can meet the requirements of day and night disaster relief. As the most economically active and densely populated areas in Guangzhou, large differences exist in the size and distribution of day and night population within the four districts. The location of emergency shelters should prevent potential evacuees from all-weather disasters. From the perspective of population mobility, the people who are present during the day mainly include the working population, aging population, primary and secondary school students, vocational and technical school students, college students, and inpatients in general hospitals; the mobile population during the day is mainly distributed in subway stations, bus stations, train stations, scenic spots, megamalls, and large gymnasiums. The people who are present at night are mainly the residents in residential quarters, apartments, and dormitories. Travelers in brand chain and star hotels, vocational and technical school students, college students, and inpatients in general hospitals are also present (Table 1). Due to the small mobile population at night, it was not considered in the analysis of shelter demand.

Table 1. Main groups of potential evacuees under the day and night disaster prevention objectives.

Prevention Objective	Type of Evacuee	Main Groups of Evacuees
Daytime disaster	Population present	Working population, aging population, primary and secondary school students, vocational and technical school students, college students, inpatients in general hospitals
	Mobile population	Passengers in subway stations, passengers in bus stations, passengers in train stations, tourists in scenic spots, people in megamalls, people in large gymnasiums
Nighttime disaster	Population present	Population in residential quarters, residents in apartments and dormitories, travelers in brand chain and star hotels, vocational and technical school students, college students, inpatients in general hospitals

The above mentioned unemployed population and mobile population in the analysis of shelter demand, including the people distributed in primary and secondary schools, vocational and technical schools, colleges, general hospitals, megamalls, gymnasiums, scenic spots, brand chain, and star hotels, subway stations, bus stations, and train stations, for which we used two types of data sources for population size and distribution analysis. The first was the statistical yearbook data of Guangzhou and each district, which provided the number of students in schools and the number of hospital beds. Second, as the numbers in subway stations, passenger stations, megamalls, and some other facilities cannot be accurately determined in each place, we adopted the average value of data released by government departments, institutions, or enterprises, including subway passenger flow data, passenger numbers in transit stations, tourist arrivals, etc. As the main proportion of nighttime population, the number of residents in each plot was estimated by its number of households and the average size of family households, which in study area is 2.75 people per family according to the Main Data Bulletin of 2015 National 1% Population Sampling Survey in Guangzhou released in 2016. The industrial population accounts for the vast majority of the daytime population. Its size and spatial distribution were estimated with the number of POIs in the plots and the data of employees classified by type of industry in statistical yearbooks, calculated in a GIS platform as follows:

$$P_w = \left(N_i^j \times \frac{S_j}{N^j} \right) + \left(M_i^j \times \frac{T_j}{M^j} \right) \quad (1)$$

where P_w is total number of practitioners in the secondary and tertiary industries of a certain plot i ; N_i^j is the number of POIs related to category j in the second industry of plot i ; S_j is the number of practitioners related to category j in secondary industry; N^j is the total number of POIs related to category j in second industry; M_i^j is the number of POIs related to category j in the tertiary industry of plot i ; T_j is the number of practitioners related to category j in tertiary industry; and M^j is the total number of POIs related to category j in tertiary industry.

In general, if the continuous and efficient operation of evacuation and rescue activities after a disaster can be ensured, the shelter demand in the short-, medium-, and long-term can be predicted based on the residents [13]. From the perspective of evacuation behavior and preference, if taking refuge in officially designated shelters is necessary, staying in a familiar environment, protecting family property, and acting with family or friends are the main considerations [48–50]. These considerations indicate that providing fixed shelters with accommodation conditions to meet the shelter needs of the residents has certain rationality. However, some special circumstances may arise, such as extremely serious disasters, unstable disaster relief capabilities, and the inability to completely evacuate to the fixed shelters in the medium- and long-term in a short period of time. Therefore, all shelters with short-term accommodation conditions must be provided to the evacuees for an overnight refuge. Then,

the fixed short-term shelters will be the priority in these situations to improve the coverage level under the daytime and nighttime disaster scenarios. At this time, the shelter demand should be based on the maximum population of the plots in the day and night and can be expressed as follows:

$$Demand = \sum_{i=1}^n \text{Max} \left[Pop_{day}^i, Pop_{night}^i \right] \quad (2)$$

where *Demand* is the number of potential refugees in fixed shelters; Pop_{day}^i is the number of daytime populations in plot *i*; and Pop_{night}^i is the number of nighttime populations in plot *i*.

2.2.2. Evacuation Simulation Using Network Analysis in GIS and Python Programming Language

The balance of supply and demand in emergency shelters is important for effective disaster mitigation functions during disasters and in the evaluation of shelter service capacity. In the traditional practices of shelter planning, supply and demand are generally balanced by districts, rarely seen on streets. A problem that arises is that the probability is high that the supply and demand of certain small areas within the city may be unbalanced, and the service gap could be large. Therefore, we aimed to establish an evacuation simulation model between evacuees and shelters, and tried to simplify and implement complex and dynamic evacuation activities. In principle, the evacuation simulation solves a problem of evacuee assignment from the start to the destination, which can also be understood as a multi-objective allocation problem. The plots where the evacuees located are demand points (the starts), and the plots where the shelters are located are the destinations. Figure 3 shows that some demand points are covered by multiple available shelters; one shelter may also cover multiple demand points. For example, shelters A, B, C, D, E, F, and G, all serve more than one demand point. The objectives of the simulation model are as follows:

- (1) For the shelters that exceed their capacity, to calculate the time required when the capacity reaches the maximum.
- (2) The target shelter of each demand point and the number of evacuees evacuated from the demand point to the shelter.
- (3) For those shelters with capacity that is not exceeded, the time required when they stop receiving evacuees.
- (4) The total number of evacuees received at each shelter and the remaining number of evacuees that the shelters can still accommodate.

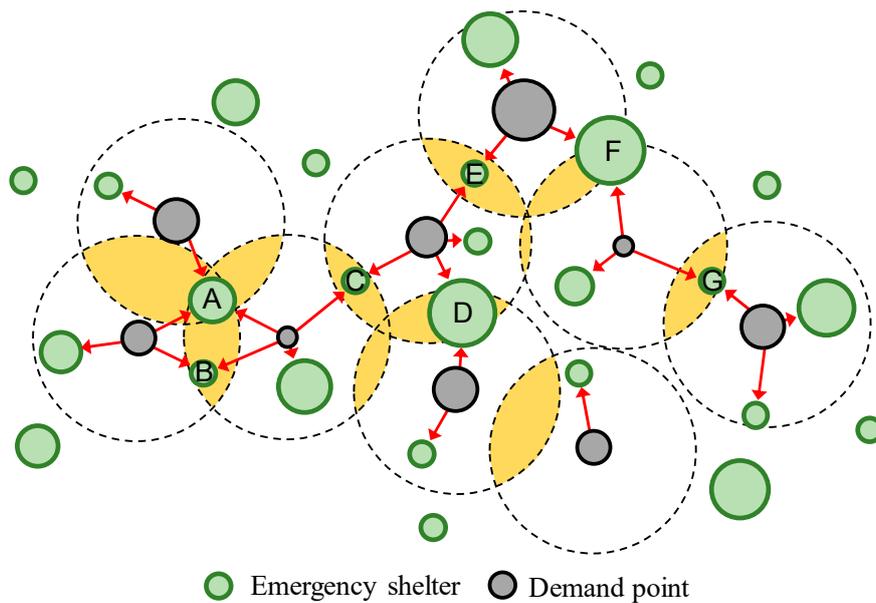


Figure 3. A brief principle map for the evacuation from demand points to surrounding shelters.

The basic considerations and parameters setting of the model are as follows:

- (1) The evacuees move along the evacuation routes, so linear distances are replaced with real distances, which is achieved by constructing a distance cost matrix model based on GIS.
- (2) In the selection of the target shelters, the general principle is to for refugees to be located nearby. The closer the shelter, the more evacuees are allocated, but not only in one shelter. In the simulation, the people to be evacuated at each demand point will be assigned to numerous designated shelters within a reasonable distance, regardless of the complex behaviors such as shelter-in-place, taking refuge in unspecified locations, and traveling to further shelters.
- (3) Evacuation road network is safe and reliable after the disaster, regardless of the unexpected blocking factors of the routes.

The effective width of the evacuation routes, the space occupied by pedestrians, and the travel speed of the evacuees during the disaster are set as follows:

According to the Chinese Code for Design of Urban Road Engineering (Revised 2016) (CJJ 37-2012), the width of urban sidewalk should be 3–5 m, and the average width is generally about 4 m. Considering the space requirements of pole facilities and green spaces (about 1 m in width), the actual available width for pedestrians is compressed. Therefore, the effective average width of evacuation routes was set to 3 m in the model.

In terms of space occupied by pedestrians, the Code for Design of Urban Road Engineering (Revised 2016) (CJJ 37-2012) indicates that the width of a group of pedestrians on the sidewalk is 0.75 m. Under non-contact conditions, the space occupied by pedestrians is approximately a circular area with a diameter of 0.6–0.92 m (average of about 0.75 m). When the average distance between the pedestrians is 1.22–1.34 m, they can move freely without disturbing others [51]. Therefore, as the evacuation routes should accommodate as many evacuees as possible and to ensure a safe evacuation (no crowding, trampling, etc.), we set the horizontal distance between the pedestrians to 0.75 m and the longitudinal distance to 1.34 m. Then, based on an effective 3 m wide route, the horizontal space can accommodate 4 people at the same time.

The walking speed of Chinese adult men and women is mostly concentrated between 1 and 1.3 m/s [51]. When a disaster occurs, the pace is generally faster. Through an evacuation experiment, Fan found that in an emergency, the average travel speed of residents from their locations to the nearby shelters is about 2.15 m/s [52]. Accordingly, the average travel speed of evacuees in the model was set to 2.15 m/s, and the differences between groups were not considered.

The evacuation simulation was achieved in three main steps:

Step 1: Using the network analysis method in ArcGIS, a network data set containing demand points, available resources for shelters, and road network was established, and then the OD cost matrix was constructed using Model Builder. The input elements were road network, demand points, and shelters; and the output elements were evacuation distances.

The result of this step represented straight paths from each demand point to each shelter point. Then, we exported the attribute table of the path matrix as a txt file and encoded it as UTF-8.

Step 2: According to the objectives, considerations, and parameter settings of the model, the results of step 1 were further processed using Python programming language. The results include key information such as the whereabouts and evacuation time of evacuees.

In this step, we mainly extracted the needed information in the txt file from step 1 for iterative calculations. All the demand points allocated evacuees to their surrounding shelters at the same time, regardless of the capacity of the shelters. The results were output as several xls format files.

Step 3: We statistically analyzed the results of step 2. Partial results (xls format files) were imported into the ArcGIS for spatial statistical analysis, and the results were further visualized as needed. The supply and demand status of shelters after the evacuation simulation are presented below.

3. Results

3.1. Distribution and Size of Shelter Demand

Figure 4 shows the distribution and size of the day and night population. The population is generally composed of residents and floating population. In addition to the working population in various industries, the people who are present during the daytime also include the elderly, primary and secondary school students, vocational and technical school students, college students, and inpatients in general hospitals, of which the number of the elderly was estimated using the proportion in the community, which is 7.9% according to the Main Data Bulletin of 2015 National 1% Population Sampling Survey in Guangzhou released in 2016; other types of population data were obtained from the statistical yearbooks of each district. During the day, the floating population includes the people distributed in passenger stations, scenic spots, megamalls, and large gymnasiums. The population at night are mainly people in residential quarters, apartments, and dormitories, and other residents, such as business travelers in brand chain and star hotels, students in vocational and technical schools, students in higher education institutions, and inpatients in general hospitals. Due to the smaller mobile populations at night, they were excluded from the analysis.

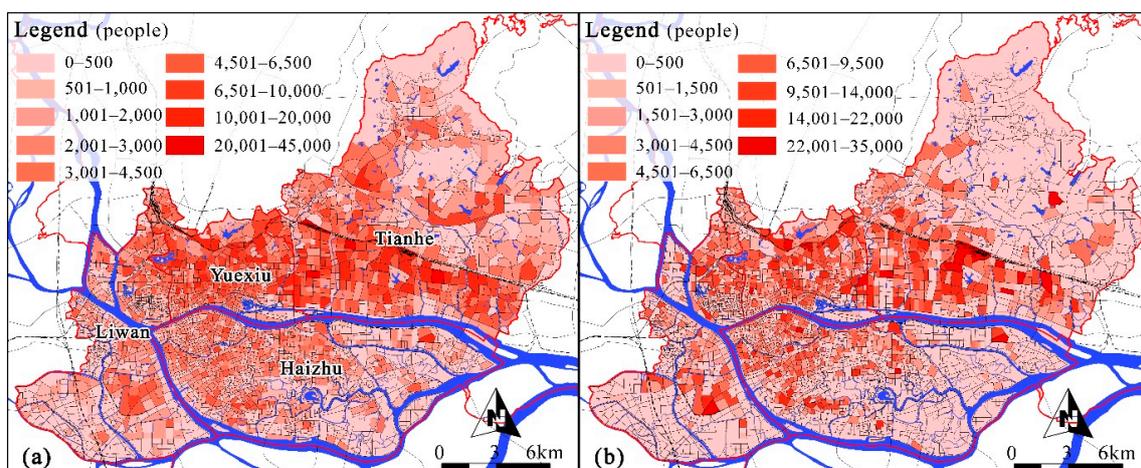


Figure 4. Population distribution and size during the (a) day and (b) night.

On the whole, nighttime is more pronounced than daytime in terms of population size differences and imbalances between plots. Table 2 shows that the population in Liwan is the lowest during the day, indicating that its number of employees is small; the populations in Tianhe, Haizhu, and Yuexiu are large and relatively close, reflecting that little differences exist in the number of employees in each district. In terms of nighttime population, Haizhu has the largest and Liwan has the lowest, which is directly related to the number of residents. Judging from the change in the day and night populations, Haizhu has the largest difference, reaching 460,000, indicating that its population is regionally mobile, and the differences in the other districts were not obvious. From the perspective of the number of plots with a large population, the plots during the day is 1,305, which is significantly higher than the 785 at night, demonstrating the importance of shelters to meet the needs of disaster prevention in both day and night.

Table 2. Statistics of daytime and nighttime population (pop.) of districts and plots.

Districts	Daytime Pop.	Nighttime Pop.	Pop. by Maximum Value	Plots with a Daytime Max Pop.	Plots with a Nighttime Max Pop.
Haizhu	1,387,269	1,846,491	2,363,008		
Liwan	716,957	1,029,398	1,263,100		
Tianhe	1,844,425	1,638,609	2,389,968	1305	785
Yuexiu	1,484,732	1,4734,81	1,912,937		

Figure 5 shows the change in the day and night time population of the plots (the number of people in the daytime minus the number at nighttime). In terms of the intensity of the change, the population changes in Haizhu, Liwan, and Tianhe are greater, whereas the day and night population in Yuexiu is basically the same. In terms of the extreme value of the change, the population in partial plots in Tianhe varies considerably between day and night. After a frequency statistical analysis of the change value, we found that the majority of the plots had a change value between 0 to 2000, followed by the plots with a change value between -2000 to 0 ; the remaining plots with an obvious change value were those distributed between -4000 to -2000 , 2000 to 4000 , and -6000 to -4000 .

Although the overall size of the nighttime population is larger than that during the daytime, the detailed statistics of each district show that the number of plots with a maximum population during the daytime is larger than at night (Table 3). There are 284, 45, 92, and 99 more plots with a higher population in the daytime in Haizhu, Liwan, Tianhe, and Yuexiu, respectively, which are mainly distributed in commercial, business, and office areas. Therefore, these plots must be considered as key area during the shelter planning. If the nighttime population is used for shelter demand, the shelter locations in such areas will not be able to provide enough space for the surrounding evacuees when a disaster hits during the daytime, which again reflects the necessity of evaluating the shelter demand based on the comprehensive requirements of day and night disaster relief.

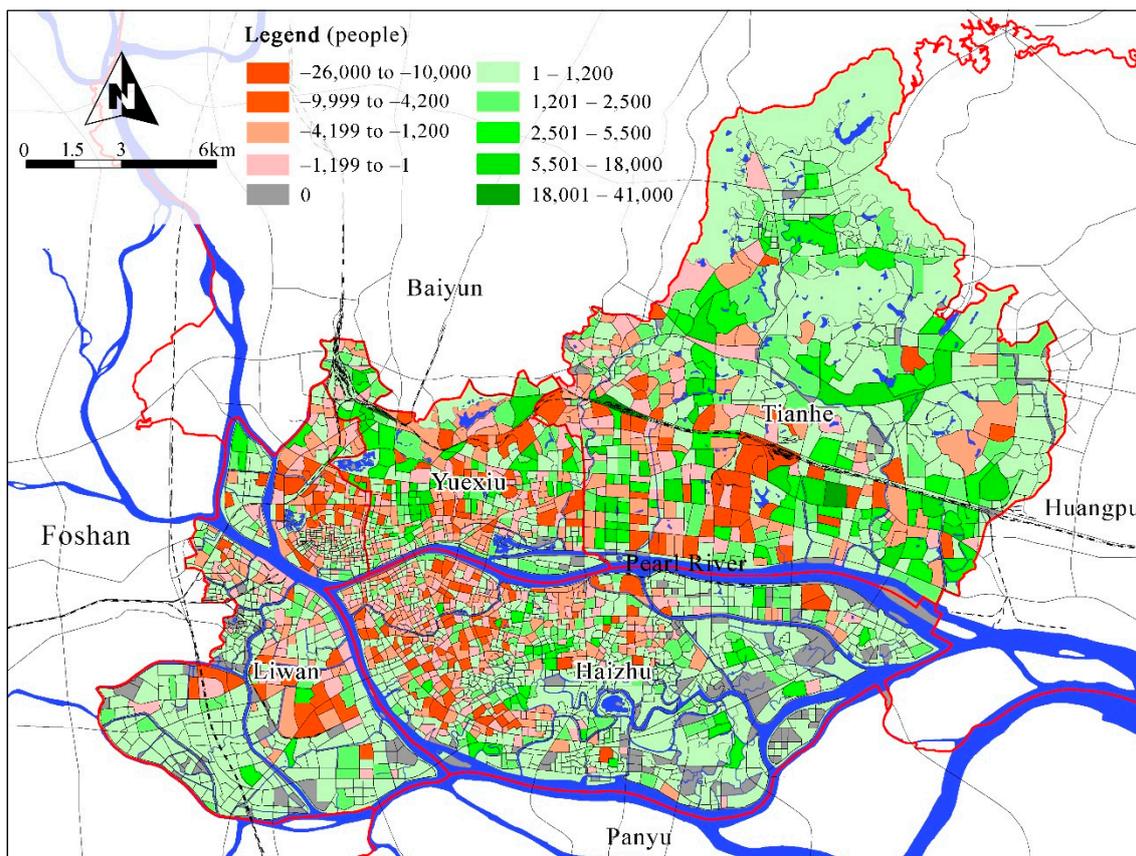


Figure 5. The population change of the plots between day and night.

Table 3. The number of plots with a maximum population and the population change by district.

District	Plots with a Daytime Max Pop.	Pop. Increase over Nighttime	Plots with a Nighttime Max Pop.	Pop. Increase over Daytime	Plots with Equal Pop.
Haizhu	660	439,916	376	971,618	129
Liwan	178	84,243	133	281,746	25
Tianhe	226	414,680	134	438,864	47
Yuexiu	241	347,016	142	387,043	43

To provide shelter for evacuees both during the day and at night, the shelter demand was determined by applying the high values of the day and night population in the plots, and the final distribution of shelter demand is shown in Figure 6. The total demand is about 7.93 million people, including in Haizhu, Liwan, Tianhe, and Yuexiu, with a 2.36, 1.26, 2.39, and 1.91 million, respectively. The total demand is 2.45 million higher than the resident population (5.48 million) in the study area, which indicates that the population has a strong regional mobility, and a serious gap exists between shelter capacity and potential number of evacuees. Figure 6 shows that the shelter demands in Tianhe and Yuexiu, which have plentiful urban service functions, are significantly higher than the other two districts. In the old urban areas, due to the weakening of functions and the reduction of employment positions, the demand is lower than in newly developed areas.

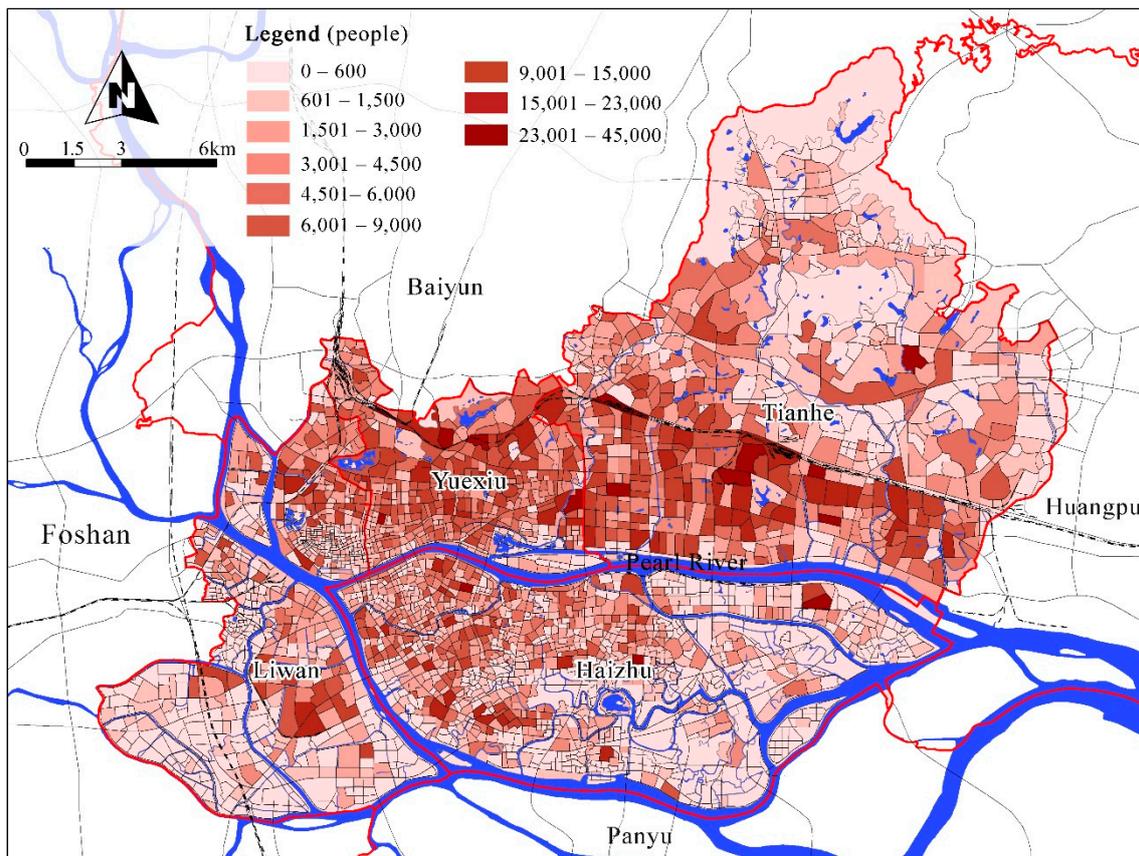


Figure 6. Distribution and size of shelter demand based on day and night disaster relief.

3.2. Evacuation Simulation

The built-up areas and regions with mature functions and concentrated population in the four districts were further selected as the target area for a simulation, with a total area of 177.92 km². To construct a basic database, the plots with evacuees and the available resources for shelters were converted into points. The demand points include the size information of evacuees, and the effective shelter area information was contained in the shelter points.

The first step in the OD cost matrix analysis in ArcGIS generates evacuation routes information between the starting point and the destination, including route name, starting point (demand point) ID, destination (shelter) ID, route ranking, route distance, and linear distance, as shown in Table 4. The “Location” in front of the “Route name” represents the starting point, and the latter “Location” represents the destination. Since the results cover all the routes from each demand point to each shelter and the evacuation simulation needs quick and available routes within a reasonable distance for the evacuees, the results need to be filtered according to the actual evacuation distance. The Chinese Code for Design of Disasters Mitigation Emergency Congregate Shelter (GB51143-2015) stipulates that the evacuation distance of short-term fixed shelters should be within 1000 m. In an evacuation experiment, Fan found that the evacuation distance should not exceed 200 m of the distance proposed in the code [52]. The evacuation simulation describes a point-to-point evacuation state, where the people to be evacuated are concentrated at the demand point, and the shelter is also simplified as a point. As a certain distance exists from the starting point and the destination to the boundary of the plot, the filtering criteria for the route distance in Table 4 was set to 1200 m.

Table 4. Information of evacuation routes calculated by OD cost matrix.

Route Name	Starting Point ID	Destination ID	Route Ranking	Route Distance (m)	Linear Distance (m)
Location 1–Location 861	1	861	1	320.40	246.81
Location 1–Location 66	1	66	2	933.21	658.76
Location 1–Location 799	1	799	3	1068.95	661.61
Location 1–Location 65	1	65	4	1135.32	814.81
Location 2–Location 861	2	861	1	438.97	192.91
Location 2–Location 66	2	66	2	814.63	490.30
Location 2–Location 65	2	65	3	1016.74	663.83
Location 3–Location 861	3	861	1	440.03	227.25
Location 3–Location 799	3	799	2	1005.58	560.61
Location 3–Location 66	3	66	3	1052.84	643.36
Location 4–Location 868	4	868	1	406.36	312.54
Location 4–Location 66	4	66	2	973.37	603.14
Location 4–Location 869	4	869	3	1038.25	902.07
...

Table 4 provides evacuation routes for the simulation, including which target shelters are available around the demand point and the shortest path to these shelters. Then, the evacuation simulation model constructed by the Python programming language performs a calculation of evacuee assignment and evacuation time by calling the path information. Table 5 presents the information after evacuation, including route ranking, route length, number of people evacuated along each route, and the required evacuation time. Under normal circumstances, several shelters are available around a demand point, and the number of refugees evacuated to these shelters and the time required are different, mainly related to the length of evacuation route and the number of evacuees. Statistics showed that the average evacuation time of all 16,883 routes is about 12.6 min, and the shortest evacuation time is within 1 min. However, due to a large number of people in some plots, the evacuation time along a few routes is more than 3 h, which indicates that a large gap exists in shelter locations around some demand points. In general, the evacuation time of most routes is between 6 and 15 min (Figure 7).

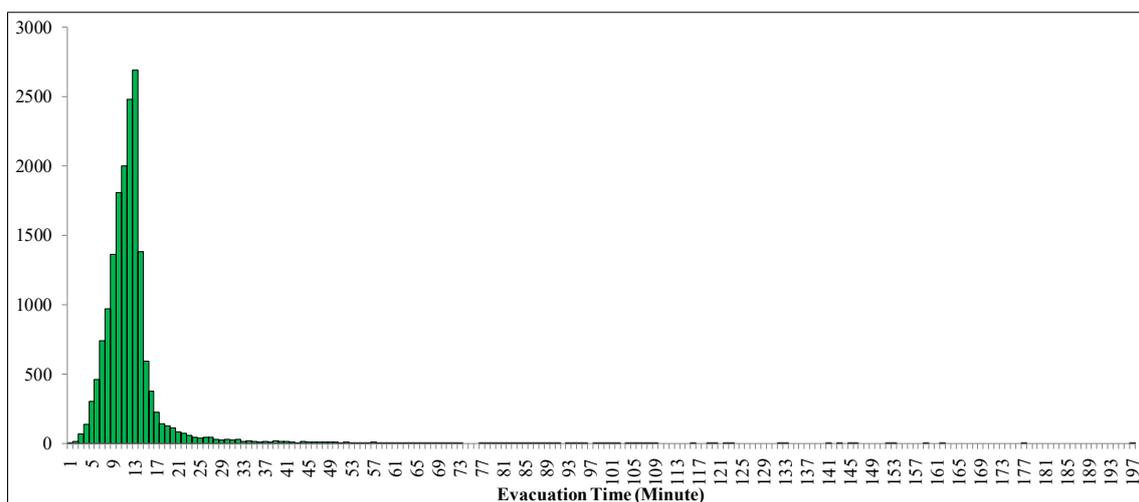
**Figure 7.** The frequency distribution of evacuation time required for all routes.

Table 5. The number (N.) of evacuees along each route and the evacuation time required.

Route Name	Demand Point ID	Shelter Point ID	Route Ranking	Route Length (m)	N. of Evacuees (Individual)	Evacuation Time (min)
...
D766-S1042	766	1042	2	880.34	65	10.32
D766-S399	766	399	3	881.69	60	10.27
D766-S84	766	84	4	883.60	55	10.25
D766-S589	766	589	5	908.74	49	10.50
D766-S1043	766	1043	6	917.58	45	10.57
D766-S83	766	83	7	952.23	40	10.92
D766-S1054	766	1054	8	965.63	37	11.03
D766-S85	766	85	9	1039.05	32	11.78
D766-S106	766	106	10	1043.55	30	11.83
D766-S104	766	104	11	1057.58	27	11.95
D766-S986	766	986	12	1113.06	24	12.57
D766-S1053	766	1053	13	1115.04	23	12.55
D766-S103	766	103	14	1130.78	21	12.73
D767-S1043	767	1043	1	420.80	10,709	93.92
D767-S85	767	85	2	454.16	2,663	27.22
D767-S986	767	986	3	562.54	1,824	21.45
D767-S1042	767	1042	4	589.83	1,527	19.25
D767-S88	767	88	5	736.29	1,081	17.18
D767-S588	767	588	6	737.41	978	16.33
D767-S589	767	589	7	1028.90	636	16.70
D767-S591	767	591	8	1040.90	587	16.43
D767-S89	767	89	9	1080.21	528	16.37
...

Each shelter has a maximum capacity. The simulation results showed how many people were evacuated from each demand point to the shelters nearby. The sum of people evacuated to the same shelter through the numerous evacuation routes is the final number of evacuees accepted by the shelter. Compared with the capacity of the shelter, whether the shelter can accommodate more people or whether it has exceeded its capacity and the specific amount by which this number is exceeded can be determined. Table 6 shows the evacuee and capacity information of several typical available resources for shelters after evacuation simulation. According to statistics, 558 out of 888 shelters exceed their capacity to varying degrees, accounting for 62.84% of the total, which also reflects that too few shelters exist within a reasonable distance around many demand points when a serious disaster occurs.

Table 6. Comparison between the number (N.) of evacuees accepted in each shelter and the capacity.

Shelter Point ID	Type of Resource	Effective Area (m ²)	N. of Evacuees Accepted (Individual)	Maximum Capacity	Residual Capacity
...
186	school playground	6949	230	3475	3245
187	school playground	4490	6203	2245	-3959
188	school playground	12,824	3626	6412	2786
189	school playground	3085	1555	1542	-13
190	school playground	9472	4034	4736	702
...
407	square	3809	3983	1905	-2079
408	square	2207	11,577	1103	-10,473
409	square	2283	75	1142	1066
410	square	2659	64	1330	1266
411	square	4136	70	2068	1999
...
609	green space	11,410	877	5705	4828
610	green space	2937	12,351	1469	-10,882
611	green space	8288	1485	4144	2659
612	green space	14,800	1051	7400	6348
613	green space	32,117	1713	16,058	14,345
...

Table 6 was input to ArcGIS using the shelter point ID to visualize the spatial distribution of evacuees accepted at each shelter after evacuation, as shown in Figure 8. The colored dots are the shelters that accepted the evacuees in the simulation, and the different colors indicate that different numbers of evacuees that are accommodated. The distribution of evacuees has several characteristics. First, due to the fewer available resources for shelters in the old urban areas in Liwan, Yuexiu, and Haizhu, the yellow and red dots are many, indicating that the average number of evacuees in the shelters is large. Second, more green dots along the main rivers shows that fewer people take refuge here, which may be caused by the low population density at the riverside and having more green spaces. Third, many green spots are visible in the newly built areas of Eastern Haizhu and Tianhe, showing the lack of pressure on receiving evacuees because urban planners designed more parks and other green spaces in the new areas and considered the issue of service distance, so shelters can provide better coverage for the potential evacuees.

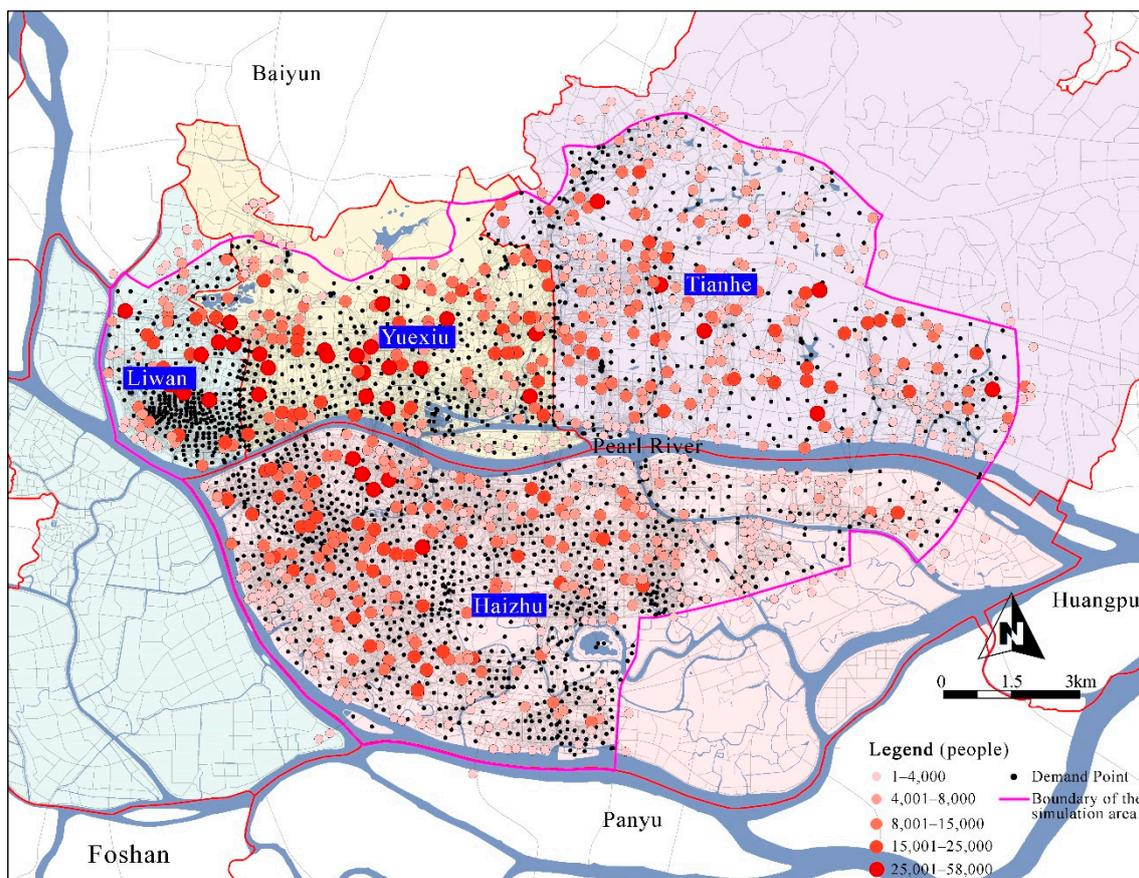


Figure 8. Distribution of evacuees accepted in shelters after the simulation.

The final state of shelters is shown in Figure 9 after the evacuation is completed. A red dot indicates that the number of people evacuated to the shelter has exceeded the maximum capacity, also indicating that the shelter demand will not be met at the time of the disaster; conversely, the green dot indicates that these shelters are large in size and can accept more people for refuge. On the whole, a serious imbalance exists in the distribution and size of shelters in the four districts, especially in Liwan, Yuexiu, and Haizhu. More red dots in the central and western regions of the simulated area show that these places are facing a serious shelter supply shortage mainly because these places are traditional old urban areas. A possible solution is to add new resources for shelters in combination with future urban renewal activities. In the eastern region, including Tianhe and the eastern part of Haizhu, many shelters have excess capacity, which increases the flexibility of these shelters to receive potential evacuees when disasters occur.

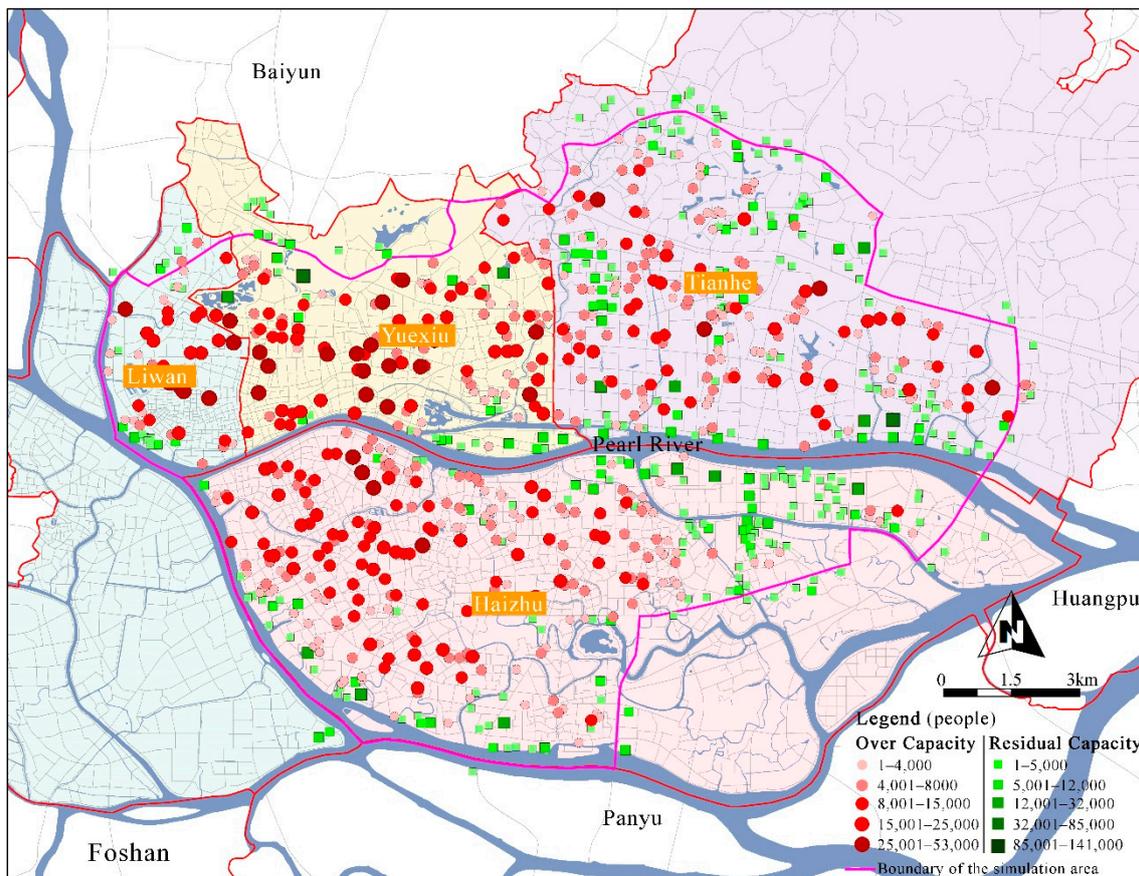


Figure 9. The final state of shelters after the evacuation simulation.

Additional statistics were used to analyze the supply and demand for shelters in each district, as shown in Table 7. In terms of the shelters that exceeded their capacity, Haizhu is the largest with 1.62 million people, mainly concentrated in the old urban areas in the west, followed by Yuexiu, Tianhe, then Liwan. Haizhu provides the largest effective shelter area, but given the uneven distribution of the resources for shelters, the capacity of shelters varies in different areas. In general, the shelters in central and western regions exceed capacity, whereas the eastern shelters have residual capacity due to their larger average size. Shelters in Tianhe can accommodate more people for refuge, with 890,000 people, followed by Haizhu and Yuexiu. Tianhe and the eastern part of Haizhu, as newly developed areas, have more green space coverage, so the shelters in these areas also have larger residual capacity. The residual capacity in Tianhe is distributed outside the core central business district (CBD), and that of Haizhu is mainly distributed in the eastern part. Overall, many shelters exist in each area that either exceed or do not exceed the maximum capacity, indicating that the imbalance between supply and demand of shelters within the districts is widespread. In the future, new resources should be added near the over-capacity shelters, or the capacity of the existing shelters should be increased.

Table 7. The final state of shelter capacity in each district after the simulation.

District	N. of Shelters	Effective Area (m ²)	N. of Evacuees Accepted	Maximum Capacity	Residual Capacity	Over Capacity (Yes or No)
Haizhu	226	882,687	2,065,598	441,344	−1,624,255	Yes
	142	2,110,444	192,003	1,055,222	863,219	No
Liwan	40	192,273	570,817	96,136	−474,681	Yes
	18	222,897	25,214	111,448	86,235	No
Tianhe	174	728,743	1,502,922	364,372	−1,138,550	Yes
	135	2,213,960	217,979	1,106,980	889,001	No
Yuexiu	118	566,513	1,660,877	283,257	−1,377,620	Yes
	35	1,189,411	897,53	594,705	504,952	No

4. Discussion

In the field of disaster relief, accurate determination of population spatial distribution is challenging. In shelter demand analysis, we assessed the distribution of daytime and nighttime population using POI and residential building data with household information. Residents compose the majority of the night population, and the mobile population is so small that we evaluated the nighttime population distribution using only the residential building data with a relatively acceptable error. The working people are the main proportion of daytime population, but the mobile population and other unemployed people also represent a large proportion. In the calculation, combined with the official statistics of practitioners, a mean value method was used to estimate the population size of each POI, and then we totaled the population size in each plot according to the POIs contained in the plot. For the same type of POI, the scale differences between individual POIs may be large, so the population size they represent should differ, resulting in large errors in some plots. However, for the downtown areas of a mega city such as Guangzhou, with a huge and mobile population, the data and methods that can be used to map the population distribution with high precision are limited. In terms of the difficulty of data acquisition, POIs are relatively easy to obtain at the technical level. Although certain errors exist in the data, POIs provide meaningful data to analyze the distribution of the urban daytime population. In the future, to improve the reliability of the results, high-precision spatial-temporal analysis of shelter demand should be conducted with the help of mobile phone signal data or social platform data.

In the evacuation simulation in this study, we assumed that the shelter demand in each plot was concentrated in the geometric center of the plot and shelters were set as points. Therefore, the simulation became a simplified point-to-point multi-objective allocation problem. In reality, a certain distance exists between the two types of points and the boundary of the plot. Because the spatial scale cannot contain roads within the plot, the perpendicular line from the point to the boundary is set as this distance. These perpendiculars also play a role in evacuation routes; the simulation did not consider the micro traffic environment of the plot. If attempting to perfect an evacuation plan, people should take refuge from their locations along the real routes, and the results will provide accurate evacuation distance and required time information, but the data used in this study cannot accurately identify the location of people. In addition, we assumed that the people in each plot are located in the geometric center and were ready for an evacuation, without considering distance and time factors for the evacuation from the interior of the building to the outdoor site, which may result in an underestimation of the evacuation time to varying degrees. The aim of this study was to investigate whether the supply and demand of shelters on the spatial scale of the main urban area can maintain a balance within a reasonable evacuation distance, so addressing the problem of building evacuation at the microscopic level was beyond the scope of this study.

In the setting of the simulation environment, establishing an urban environment model would be ideal if the variables of the evacuation process are as close as possible to the real disaster situation, especially for the traffic environment. The evacuation simulation requires route information. In data processing, to conduct the simulation, we transformed the original complex double-line road network into a single-line network without considering the signal lights. Due to the large spatial scale of the

case area, the processed road network neither contained all the branches and lanes nor the roads inside the plots, which decreased the precision of the length of the evacuation route, thereby decreasing the precision of the evacuation time results. A hypothetical condition for the evacuation route network is that the post-disaster roads are intact and the evacuation network is still stable and reliable. Due to insufficient data, we did not assess the reliability of the road network. Therefore, the simulation is an idealized evacuation scheme. In the next step, the unexpected interruption of routes, the reliability of the route network, and the difference in route capacity should be evaluated using traffic environment modeling. A feasible solution would be to use traffic big data and consider environmental variables to formulate evacuation plans under different traffic scenarios.

The diverse behaviors and psychology of people experiencing disaster may directly impact the evacuation process and results. In the event of a disaster, based on individual preference or actual conditions, staying at home, taking refuge in situ, traveling to a further shelter, and staying with family or friends are alternative options. In terms of transportation mode, people may choose to evacuate on foot or by public transportation. We aimed to judge the supply and demand for urban shelters through a quantitative evacuation simulation, and to provide a basis for ensuring shelters provide adequate coverage to the surrounding population via the gradual and continuous pre-disaster preparation. This preparation process does not need to distinguish complex behaviors and psychology, so the simulation did not consider them as influencing factors as a walking scenario evacuation. As a possible consequence, in actual evacuation activities, people may tend to concentrate in some of the shelters because of certain behavioral preferences, so an organized evacuation and temporary emergency plans are particularly important. In addition, we did not differentiate evacuation groups such as children, the young and middle-aged, and the elderly. These groups have different needs and abilities during disasters, which directly affect evacuation behavior, the transportation model, and evacuation time, thereby impacting the simulation results as well. Studying small- or medium-scale regions based on more data types and evacuation behavior experiments is necessary.

In any case, the assumptions we set in the simulation become uncertain factors that affect the reliability of the results. The number of evacuees and evacuation time in the results cannot represent the actual situation in disasters, resulting in limited applications in practice. In pre-disaster preparations, we can tell urban planning professionals where there are gaps in shelters, so that we can increase the available shelter resources in future planning, but we cannot give an accurate area. In a possible emergency evacuation, the emergency managers can judge where evacuation risk may exist based on the results of evacuation simulation. In this way, emergency resources can be targeted in the decision-making process. However, the results cannot exactly tell the managers how long the evacuation will be completed and how many people need to be evacuated, because the real evacuation depends on many factors, as assumed and simplified in this study.

5. Conclusions

Using data of POIs, residential buildings, and industry employee statistics, we assessed the shelter demand and post-evacuation shelter status in the downtown areas of Guangzhou, including Liwan, Yuexiu, Tianhe, and Haizhu. In the analysis of shelter demand and based on the daytime and nighttime disaster response needs, the population distributed in each plot between day and night was defined as the number of potential evacuees. We found significant differences in the size and spatial distribution of shelter demand in daytime and nighttime, and the demand is unevenly distributed within the area. Haizhu, Liwan, and Tianhe had dramatic day–night demand changes. During the day, the demand is mainly distributed in Yuexiu and Tianhe, which have mature urban functions and numerous enterprises. At night, the demand is mainly concentrated in the plots with residential buildings, with the demand in other plots being obviously less. The total shelter demand for day and night refuging was about 7.929 million people, which is 2.454 million more than the resident population. The evacuation simulation showed that the average evacuation time of all 16,883 routes was 12.6 min, and some were more than three hours due to the huge number of people located at the

demand points. After the evacuation, 558 of 888 shelters exceeded their capacity to varying degrees. In terms of shelter capacity, Haizhu had the largest over-capacity of 1.62 million people. Conversely, for the residual capacity, shelters that did not exceed the capacity in Tianhe can accommodate another 890,000 people, which was the highest amount. The results indicated that the supply and demand of shelters in the study area was unbalanced and the distribution was uneven, preventing the shelters from completely covering the potential evacuees. Our findings provide a direct quantitative basis to guide the amount and size of new shelter resources during urban renewal activities, and being a reference for land reuse and disaster prevention space organization in future urban planning.

In future research, improving the accuracy of shelter demand assessment based on more data types is necessary. During disasters, numerous complex variables affect evacuation, such as unexpected interruption of roads, physical obstacles, secondary disasters, and human behavior and psychology, which have been difficult to quantify in related practices and research fields. The next step in evacuation simulation is to set environmental variables as close as possible to the post-disaster conditions for small- or medium-scale areas. In addition, we established a database containing demand points, emergency shelters, and evacuation routes information. Therefore, building a decision-making system and management platform for shelter planning will be another research direction.

Author Contributions: Conceptualization, Yao Fang and Wei Chen; Data curation, Wei Chen, Qing Zhai, Wei Wang and Yijie Zhang; Methodology, Wei Chen, Yao Fang, and Yijie Zhang; Programming, Wei Chen and Yijie Zhang; Writing—original draft preparation, Wei Chen and Yao Fang; Writing—review and editing, Wei Chen and Wei Wang; Visualization, Wei Chen and Wei Wang; Supervision, Yao Fang and Qing Zhai; Project administration, Yao Fang; Funding acquisition, Yao Fang and Qing Zhai. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Natural Science Foundation of China (Grant No. 41601139) and the Natural Science Foundation of Jiangsu Province (Grant No. BK20160892).

Acknowledgments: We thank the editor and anonymous referees who read the paper and provided helpful comments for improvements.

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

References

1. UNDRR. Natural Disasters 2018. Available online: <https://reliefweb.int/sites/reliefweb.int/files/resources/CREDNaturalDisaster2018.pdf> (accessed on 15 August 2019).
2. Davis, I. What have we learned from 40 years' experience of Disaster Shelter? *Environ. Hazards* **2011**, *10*, 193–212. [[CrossRef](#)]
3. Kilci, F.; Kara, B.Y.; Bozkaya, B. Locating temporary shelter areas after an earthquake: A case for Turkey. *Eur. J. Oper. Res.* **2015**, *243*, 323–332. [[CrossRef](#)]
4. Nigg, J.M.; Barnshaw, J.; Torres, M.R. Hurricane Katrina and the flooding of new orleans: Emergent issues in sheltering and temporary housing. *ANNALS Am. Acad. Polit. Soc. Sci.* **2016**, *604*, 113–128. [[CrossRef](#)]
5. FEMA. Planning Considerations: Evacuation and Shelter-in-Place. Available online: https://www.fema.gov/media-library-data/1533580334064--72e9356ed35b726b1a25f4a8c3372c9d/DRAFT_Planning_Considerations_Evacuation_and_Shelter-in-Place_201808.pdf (accessed on 26 August 2019).
6. Pérez-Galarce, F.; Canales, L.J.; Vergara, C.; Candia-Véjar, A. An optimization model for the location of disaster refuges. *Socio Econ. Plan. Sci.* **2017**, *59*, 56–66. [[CrossRef](#)]
7. Chen, W.; Zhai, G.; Fan, C.; Jin, W.; Xie, Y. A planning framework based on system theory and GIS for urban emergency shelter system: A case of Guangzhou, China. *Hum. Ecol. Risk Assess.* **2017**, *23*, 441–456. [[CrossRef](#)]
8. Chen, W.; Zhai, G.; Ren, C.; Shi, Y.; Zhang, J. Urban resources selection and allocation for emergency shelters: In a multi-hazard environment. *Int. J. Environ. Res. Public Health* **2018**, *15*, 1261. [[CrossRef](#)] [[PubMed](#)]
9. Yu, J.; Wen, J. Multi-criteria satisfaction assessment of the spatial distribution of urban emergency shelters based on high-precision population estimation. *Int. J. Disaster Risk Sci.* **2016**, *7*, 413–429. [[CrossRef](#)]
10. Uster, H.; Dalal, J. Strategic emergency preparedness network design integrating supply and demand sides in a multi-objective approach. *IISE Trans.* **2017**, *49*, 395–413. [[CrossRef](#)]

11. Paul, B.K. Factors affecting evacuation behavior: The case of 2007 cyclone Sidr, Bangladesh. *Prof. Geogr.* **2012**, *64*, 401–414. [[CrossRef](#)]
12. Tenerelli, P.; Gallego, J.F.; Ehrlich, D. Population density modelling in support of disaster risk assessment. *Int. J. Disaster Risk Reduct.* **2015**, *13*, 334–341. [[CrossRef](#)]
13. Chen, Z.; Chen, X.; Li, Q.; Chen, J. The temporal hierarchy of shelters: A hierarchical location model for earthquake-shelter planning. *Int. J. Geogr. Inf. Sci.* **2013**, *27*, 1612–1630. [[CrossRef](#)]
14. Masuya, A.; Dewan, A.; Corner, R.J. Population evacuation: Evaluating spatial distribution of flood shelters and vulnerable residential units in Dhaka with geographic information systems. *Nat. Hazards* **2015**, *78*, 1859–1882. [[CrossRef](#)]
15. Dmowska, A. Dasymetric modelling of population distribution—Large data approach. *Quaest. Geogr.* **2019**, *38*, 15–27. [[CrossRef](#)]
16. Briggs, D.J.; Gulliver, J.; Fecht, D.; Vienneau, D.M. Dasymetric modelling of small-area population distribution using land cover and light emissions data. *Remote Sens. Environ.* **2007**, *108*, 451–466. [[CrossRef](#)]
17. Mao, Y.; Ye, A.; Xu, J. Using land use data to estimate the population distribution of China in 2000. *Gisci. Remote Sens.* **2012**, *49*, 822–853. [[CrossRef](#)]
18. Mossoux, S.; Kervyn, M.; Soulé, H.; Canters, F. Mapping population distribution from high resolution remotely sensed imagery in a data poor setting. *Remote Sens.* **2018**, *10*, 1409. [[CrossRef](#)]
19. Ma, Y.; Xu, W.; Zhao, X.; Li, Y. 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. *ISPRS Int. Geo Inf.* **2017**, *6*, 128. [[CrossRef](#)]
20. Yao, Y.; Liu, X.; Li, X.; Zhang, J.; Liang, Z.; Mai, K.; Zhang, Y. Mapping fine-scale population distributions at the building level by integrating multisource geospatial big data. *Int. J. Geogr. Inf. Sci.* **2017**, *31*, 1220–1244. [[CrossRef](#)]
21. Sugimoto, T.; Murakami, H.; Kozuki, Y.; Nishikawa, K.; Shimada, T. A human damage prediction method for tsunami disasters incorporating evacuation activities. *Nat. Hazards* **2003**, *29*, 587–602. [[CrossRef](#)]
22. Vecere, A.; Monteiro, R.; Ammann, W.J.; Giovanazzi, S.; Melo Santos, R.H. Predictive models for post disaster shelter needs assessment. *Int. J. Disaster Risk Sci.* **2017**, *21*, 44–62. [[CrossRef](#)]
23. Chou, J.; Ou, Y.; Cheng, M.; Cheng, M.; Lee, C. Emergency shelter capacity estimation by earthquake damage analysis. *Nat. Hazards* **2013**, *65*, 2031–2061. [[CrossRef](#)]
24. Chou, J.; Lee, C. Integrating the geographic information system and predictive data mining techniques to model effects of compound disasters in Taipei. *Nat. Hazards* **2014**, *70*, 1385–1415. [[CrossRef](#)]
25. Na, H.S.; Banerjee, A. A disaster evacuation network model for transporting multiple priority evacuees. *IIE Trans.* **2015**, *47*, 1287–1299. [[CrossRef](#)]
26. McGinty, M.D.; Burke, T.A.; Resnick, B.; Barnett, D.J.; Smith, K.C.; Rutkow, L. Decision processes and determinants of hospital evacuation and shelter-in-place during hurricane Sandy. *J. Public Health Manag. Pract.* **2017**, *23*, 29–36. [[CrossRef](#)] [[PubMed](#)]
27. Swamy, R.; Kang, J.E.; Batta, R.; Chung, Y. Hurricane evacuation planning using public transportation. *Socio-Econ. Plan. Sci.* **2017**, *59*, 43–55. [[CrossRef](#)]
28. Lee, D.; Yoon, S.; Park, E.; Kim, Y.; Yoon, D.K. Factors contributing to disaster evacuation: The case of South Korea. *Sustainability* **2018**, *10*, 3818. [[CrossRef](#)]
29. Yang, X.; Jeff Ban, X.; Mitchell, J. Modeling multimodal transportation network emergency evacuation considering evacuees' cooperative behavior. *Transp. Res. Procedia* **2017**, *23*, 1038–1058. [[CrossRef](#)]
30. McGuire, L.C.; Ford, E.S.; Okoro, C.A. Natural disasters and older US adults with disabilities: Implications for evacuation. *Disasters* **2007**, *31*, 49–56. [[CrossRef](#)]
31. Bayram, V.; Yaman, H. Shelter location and evacuation route assignment under uncertainty: A benders decomposition approach. *Transp. Sci.* **2018**, *52*, 416–436. [[CrossRef](#)]
32. Shen, Y.; Wang, Q.; Yan, W.; Wang, J. A transportation-location problem model for pedestrian evacuation in chemical industrial parks disasters. *J. Loss Prev. Process Ind.* **2015**, *33*, 29–38. [[CrossRef](#)]
33. León, J.; March, A. An urban form response to disaster vulnerability: Improving tsunami evacuation in Iquique, Chile. *Environ. Plan. B Urban Anal. City Sci.* **2016**, *43*. [[CrossRef](#)]
34. Zhou, T.; Wang, D.; Zong, D.; He, X. The Study of the responsibility space regionalization of emergency shelters in the urban center and the evaluation of evacuation road based on microscope computer simulation: A Case of Chongqing Three Gorges Square Area. *Disaster Adv.* **2012**, *5*, 230–236.

35. Yamada, T. A network flow approach to a city emergency evacuation planning. *Int. J. Syst. Sci.* **1996**, *27*, 931–936. [[CrossRef](#)]
36. Flotterod, G.; Lammel, G. Evacuation simulation with limited capacity sinks: An evolutionary approach to solve the shelter allocation and capacity assignment problem in a multi-agent evacuation simulation. In Proceedings of the International Conference on Evolutionary Computation (ICEC 2010), Valencia, Spain, 24–26 October 2010.
37. Lee, J.; Hong, W. Estimating evacuation speed by slope of evacuation path for assessment of adequate shelter location in water disasters. *Asia Life Sci.* **2015**, *12*, 435–446.
38. Yu, J.; Wen, J.; Jiang, Y. Agent-based evacuation simulation for spatial allocation assessment of urban shelters. In Proceedings of the International Conference on Intelligent Earth Observing and Applications (IEOAs), Guilin, China, 23–24 October 2015.
39. Yuan, S.; Chun, S.A.; Spinelli, B.; Liu, Y.; Zhang, H.; Adam, N.R. Traffic evacuation simulation based on multi-level driving decision model. *Transp. Res. Part C Emerg. Technol.* **2017**, *78*, 129–149. [[CrossRef](#)]
40. Yabe, T.; Tsubouchi, K.; Sudo, A.; Sekimoto, Y. A framework for evacuation hotspot detection after large scale disasters using location data from smartphones: Case study of Kumamoto earthquake. In Proceedings of the 24th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM SIGSPATIAL GIS), San Francisco, CA, USA, 31 October–3 November 2016.
41. Xu, X.; Zhang, L.; Sotiriadis, S.; Asimakopoulou, E.; Li, M.; Bessis, N. CLOTHO: A Large-Scale Internet of Things-Based Crowd Evacuation Planning System for Disaster Management. *IEEE Internet Things J.* **2018**, *5*, 3559–3568. [[CrossRef](#)]
42. Zhang, P.; Liu, Y.; Yang, R.; Zhang, H.; Gong, Z.L. Improving urban traffic evacuation capability in emergency response by using smart phones. In *Lecture Notes in Computer Science*; Springer INT Publishing AG: Cham, Switzerland, 2016; pp. 241–252.
43. Yu, J.; Zhang, C.; Wen, J.; Li, W.; Liu, R.; Xu, H. Integrating multi-agent evacuation simulation and multi-criteria evaluation for spatial allocation of urban emergency shelters. *Int. J. Geogr. Inf. Sci.* **2018**, *32*, 1884–1910. [[CrossRef](#)]
44. Martin, R.S.; Painho, M. Geospatial preparedness: Empirical study of alternative sources of information for the humanitarian community. *J. Homel. Secur. Emerg. Manag.* **2019**, *16*, 20180046. [[CrossRef](#)]
45. Givoni, M. Between micro mappers and missing maps: Digital humanitarianism and the politics of material participation in disaster response. *Environ. Plan. D Soc. Space* **2016**, *34*, 1025–1043. [[CrossRef](#)]
46. Kankanamge, N.; Yigitcanlar, T.; Goonetilleke, A.; Kamruzzaman, M. Can volunteer crowdsourcing reduce disaster risk? A systematic review of the literature. *Int. J. Disaster Risk Reduct.* **2019**, *35*, 101097. [[CrossRef](#)]
47. Panek, J.; Marek, L.; Paszto, V.; Valuch, J. The Crisis Map of the Czech Republic: The nationwide deployment of an Ushahidi application for disasters. *Disasters* **2017**, *41*, 649–671. [[CrossRef](#)] [[PubMed](#)]
48. Adeola, F.O. Katrina cataclysm does duration of residency and prior experience affect impacts, evacuation, and adaptation behavior among survivors? *Environ. Behav.* **2009**, *41*, 459–489. [[CrossRef](#)]
49. Dombroski, M.; Fischhoff, B.; Fischbeck, P. Predicting emergency evacuation and sheltering behavior: A structured analytical approach. *Risk Anal.* **2006**, *26*, 1675–1688. [[CrossRef](#)] [[PubMed](#)]
50. Parlak, A.I.; Lambert, J.H.; Guterbock, T.M.; Clements, J.L. Population behavioral scenarios influencing radiological disaster preparedness and planning. *Accid. Anal. Prev.* **2012**, *48*, 353–362. [[CrossRef](#)]
51. Xu, D.; Tang, Y. *Urban Road and Transportation Planning*; China Architecture & Building Press: Beijing, China, 2007; ISBN 7112075955. (In Chinese)
52. Fan, C. The Integrated Framework for Emergency Shelter Planning for Muti-hazard Risks. Ph.D. Thesis, Nanjing University, Nanjing, China, 2016. (In Chinese).

