https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022


Natural Hazards and Earth System Sciences
Discussions

# Spatial accessibility of emergency medical services under inclement weather: A case study in Beijing, China

Yuting Zhang [a], Kai Liu [a,b]*, Xiaoyong Ni [a,b], Ming Wang [a,b], Jianchun Zheng[c], Mengting Liu[c], Dapeng Yu[d]

[a] *School of National Safety and Emergency Management, Beijing Normal University, Beijing 100875, China*

[b] *Academy of Disaster Reduction and Emergency Management, Ministry of Emergency Management & Ministry of Education, Beijing Normal University, Beijing 100875, China*

[c] *Beijing Research Center of Urban System Engineering, Beijing 100035, China*

[d] *Geography and Environment, Loughborough University, Loughborough, UK*

* Corresponding author. E-mail address: liukai@bnu.edu.cn (Kai Liu); Full postal address: School of National Security and Emergency Management, Beijing Normal University, #19 Xinjiekou Wai Ave., Beijing 100875, China.

## Abstract

The accessibility of emergency medical services (EMSs) is not only determined by the distribution of emergency medical facilities but is also very vulnerable to weather conditions. Inclement weather could affect the efficiency of the city's traffic network and further affect the response time of EMSs, which could therefore be an essential impact factor on the safety of human lives. This study proposes an EMS-accessibility quantification method based on selected indicators and explores the influence of inclement weather on EMS accessibility and identifies the hot spots that have difficulty

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022


Natural Hazards and Earth System Sciences
Open Access
Discussions

accessing timely EMSs. A case study was implemented in Beijing, which is a typical megacity in China, based on the ground-truth traffic data of the whole city in 2019. The results show that inclement weather has a general negative impact on EMS accessibility. The 15-min EMS coverage rate of the area could have a maximum reduction of 13% at the citywide scale and could reach over 40% in some suburban townships. Although on the whole, the urban area would have more traffic speed reduction, towns with lower baseline EMS accessibility is more vulnerable to inclement weather, furthermore, the proportion of elderly population in these towns is also higher than the average level of the whole city. Under the worst scenario in 2019, 12.6% of population (about 3.5 million) could not get EMS within 15 minutes, compared to 7.5% with the normal condition. This study could provide a scientific reference for city planning departments to optimize traffic under inclement weather and the site selection of emergency medical facilities.

## Keywords

Emergency medical services (EMSs), spatial accessibility, inclement weather, service area coverage

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022




## 1 Introduction

Emergency medical services (EMSs) are a pivotal part of the public health system, and the response time of EMSs is a vital factor in decreasing morbidity and improving survival (Blackwell and Kaufman, 2002). In China, the EMS system is mainly composed of prehospital emergency services and in-hospital emergency services. Prehospital emergency service refers to on-site emergency treatment, guardianship in transit, and handover with in-hospital emergency institutions. This process can be divided into two parts: the ambulances depart from the first-aid station to the scene and from the scene to the nearest hospital. The efficiency of emergency services is highly vulnerable to inclement weather conditions such as rain and snow, as inclement weather conditions reduce road capacity, increase travel time, and sometimes block roads completely(Agarwal et al., 2006; Chang et al., 2010; Cools et al., 2010; Suarez et al., 2005; Zhang and Chen, 2019), thus reducing the spatial accessibility and extending the response time of EMSs. For example, on July 21, 2012, a sudden rainstorm in Beijing led to a one-third increase in the number of calls to the emergency center, and the transfer time of ambulances was significantly prolonged, taking approximately one and a half to two hours for each evacuation during the rainstorm. On June 24, 2021, in Luoping County, Qujing City, Yunnan Province, a rainstorm caused severe waterlogging on several main roads in the city; an ambulance carrying a critically injured boy was stuck on a flooded road, and the rescuers had to use a canoe to transfer the injured boy. On August 1, 2019, in Baoji, Shaanxi Province, a rainstorm caused an ambulance to stall on waterlogging, trapping 5 doctors and patients. In the context of global climate change and rapid urbanization, extreme inclement weather events strike cities more frequently. In addition, accidents such as traffic accidents and lightning accidents are more prone to occur in inclement weather, which increases the demand for EMSs(Edwards, 1996; Ramgopal et al., 2021). It is therefore of great importance to investigate the influence of inclement weather on the spatial accessibility of EMSs.

Improving urban socio-economic equity is one of the key urban needs in a post-COVID-19 world(Moglia et al., 2021). Analysis of spatial accessibility is widely used in evaluating the equity of access to emergency services and to further optimize the distribution of emergency service sites. The spatial accessibility of EMSs is defined by the travel impedance (distance or time) between service locations and the scene (Guagliardo, 2004). A large body of research on spatial accessibility is concerned with access to hospitals (Luo and Wang, 2003; Mao and Nekorchuk, 2013; Pan et al., 2018; Wang et al., 2020; Yin et al., 2021) and first-aid stations (Hashtarkhani et al., 2020; JONES and BENTHAM, 1995; Shin and Lee, 2018), and the two-step floating catchment area (2SFCA) method is the most common method to measure the interaction between supply and demand. On that basis, traffic congestion, spatiotemporal variation, rainstorms, floods, and other factors are gradually incorporated into the spatial accessibility analysis. (Hu et al., 2020) constructed a transportation simulation model to evaluate the impact of traffic congestion on the spatial accessibility of EMSs in inner-city Shanghai. (Yu et al., 2020) analyzed the accessibility of fire and rescue service stations in England within different time radii under different flood scenarios, including the coverage of area and population. (Li et al., 2021) used FloodMap-HydroInundation2D, a hydrodynamic inundation model, to simulate flood scenarios and used the enhanced two-step floating catchment area (E2SFCA) method to measure EMS accessibility in Shanghai under a 100-year pluvial flood scenario, considering the city dynamics of population and traffic, as well as road closures caused by flood events. (Coles et al., 2017) and (Yang et al., 2020) also used

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



the FloodMap model to simulate fluvial flood events. Based on the simulation results, (Coles et al., 2017) measured the coverage of service areas for the Ambulance Service and the Fire & Rescue Service, and (Yang et al., 2020) proposed a multi-coverage optimal location model for EMS facilities. (Green et al., 2017) used TUFLOW, which is also a hydrodynamic inundation model, to generate a citywide surface water inundation scenario in Leicester, UK, and quantified the accessibility and evaluated the service coverage of the ambulance and fire and rescue services. (Albano et al., 2014) used the MIKE FLOOD model to simulate flood events in the Puglia region in southern Italy and analyzed the routes of emergency travel activities. (Rizeei et al., 2019) used a pluvial flooding probability model to predict PF-prone areas and optimized the configuration of the emergency response center (ERC). (Andersson and Stålhult, 2014)used network analysis methods to generate the shortest paths from hospitals to various administrative areas in Manila, Philippines, and evaluated the impact of different flood events on these paths.

The majority of the existing studies mainly focus on the accessibility of EMSs in waterlogging scenarios by assuming that roads are impassable when the flooded water depth reaches a specific depth. The latter can directly cause road interruptions and reduce the accessibility of EMSs. However, in addition to waterlogging, inclement weather, such as light rainfall and snowfall, could also affect the velocity and capacity of road traffic and further have a significant impact on the accessibility of EMSs. Due to insufficient recorded traffic data, relatively few studies have been performed to analyze road access capacity according to actual traffic speed variation. Therefore, this study could fill the research gap from an empirical research perspective.

This study focuses on the impact of inclement weather on EMS response intervals, that is, the time from its dispatch to arrival at the scene and the time from the scene to

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



arrival at the hospital. We first explore the impact of inclement weather on traffic and EMS accessibility based on ground-truth traffic data for the whole year. Then, we evaluate EMS accessibility under the worst scenario of the year and evaluate the urban-rural disparities in the distribution of emergency medical facilities, considering the difference in population and road network distribution between urban and suburban areas, quantifying the inequity of public service, which is of great importance for optimizing the site selection of emergency medical facilities in order to reduce the inequality across the society (Mohsenizadeh et al., 2020). This study could help guide EMS construction planning in cities, get prepared for extreme weather conditions, solve the contradiction between the demand and supply of public EMSs, and finally assist the decision-making of the corresponding government departments.

## 2 Study area and dataset

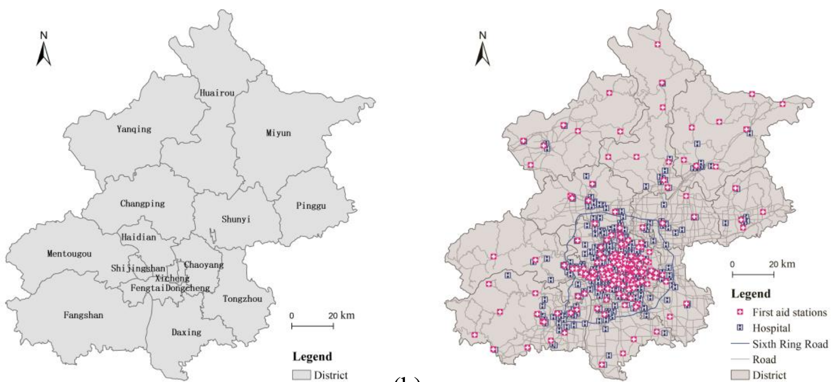
### 2.1 Study area

Beijing, the capital of China, is located in the northern part of the North China Plain, with a total area of 16,410.54 square kilometers (Figure 1a). According to the seventh national census (http://www.stats.gov.cn/tjsj/tjgb/rkpcgb/), Beijing has a population of 21.89 million. As one of the largest metropolises in the world, Beijing has a monsoon-driven humid continental climate, with an average annual precipitation of approximately 600 mm, 80% of which is concentrated from June to September (Song et al., 2014). The terrain of Beijing is high in the northwest and low in the southeast, which is conducive to the formation of heavy rain and triggers strong convective weather. Beijing has a typical monocentric urban structure, and the area within the Six Ring Road is generally recognized as the urban core area. It is obvious that the density

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



of transportation network and medical facilities in the urban area of Beijing are much higher than those in the suburbs (Figure 1b). In recent years, with the accelerating process of urbanization in Beijing, the problem of urban rainstorms and waterlogging has become increasingly prominent, and the range of urban waterlogging has been continuously expanded (Wang et al., 2021), which has a serious impact on the efficiency of traffic operation. For example, on July 21, 2012, Beijing was attacked by a rainstorm, with the average cumulative rainfall reaching 170 mm, which caused 1.6 million people to be affected, 79 people to die, more than 10,000 houses to collapse, and 63 roads to be seriously flooded, and the economic loss reached 116. 200 million yuan(Wang et al., 2013).




(a) (b)

**Figure 1.** (a) Administrative division of Beijing and (b) EMS facility locations in Beijing

**2.2 Dataset**

The data involved in this paper mainly include traffic data, meteorological data, EMS data, and demographic data. Based on traffic data and meteorological data, we could build a topology road network with travel time as impendence under inclement

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



weather conditions and corresponding normal weather conditions. Combining the topology road network with medical facility locations and the distribution of the population, we could further analyze the spatial accessibility of EMSs.

**2.1 Traffic and road network data**

The traffic data of Beijing are obtained from the Beijing Municipal Commission of Transport. The data span is from January 1, 2019, to December 31, 2019, including the average traffic speed (m/s) of each road section, updated every 2 min. The road network data contain 71,188 nodes and 81,523 edges, which can basically cover all the main roads in the whole Beijing area.

**2.2 Meteorological data**

The meteorological data utilized in this paper are TRMM precipitation data obtained from NASA (https://gpm.nasa.gov/data/directory), with a spatial resolution of 0.1° (approximately 10 km) and a temporal resolution of 30 minutes. The whole city of Beijing is covered by 175 grids.

**2.3 Medical facilities data**

The medical facilities mentioned in this paper mainly refer to two categories. One is the first-aid stations, and the other is hospitals, as shown in Figure 1b. The locations of these first-aid stations were obtained from the distribution map of first-aid stations published on the official website of the Beijing Emergency Center (https://www.beijing120.com/channel/184), including 72 stations in the downtown area and 98 stations in the suburbs. The hospital point data were extracted from the online map point of interest (POI) data of Beijing in 2019. After coordinate correction and

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022




deduplication, it contains a total of 630 general hospitals, 76 of which are third-level grade-A hospitals.

### 2.4 Demographic data

The demographic data of 2019 were obtained from WorldPop (https://www.worldpop.org/) with a spatial resolution of 100 meters. The data records are in a form of population size.

## 3 Methodology

Figure 2 gives the methodology of this study. We first divide the weather conditions into two categories, inclement weather conditions and normal weather conditions, according to precipitation data. Second, the time impedance of each road section is analyzed based on the road network and traffic speed for both inclement and normal weather conditions, and the respective coverage rate of first-aid stations and the shortest travel time to hospitals are calculated. Finally, the spatial accessibility to the population is calculated, and hot spots are identified.

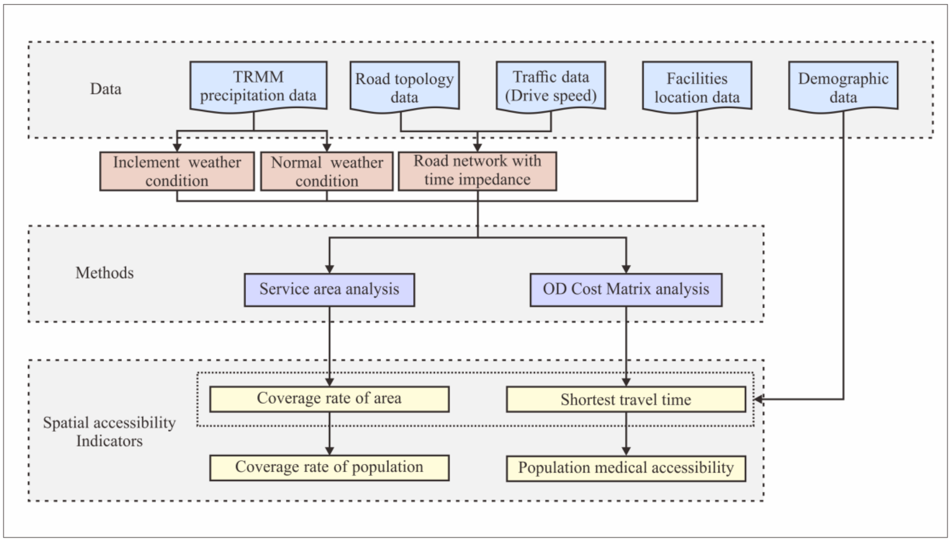



**Figure 2**. Methodology of this study

### 3.1 Fluctuation of traffic speed under inclement weather

For each weekday with precipitation, the traffic speed data of the selected period are extracted and averaged. To avoid the inherent temporal variations of traffic speed resulting from the day-of-week effects, holiday effects (Cools et al., 2007), season, and other non-meteorological related factors, we introduce baseline days for inclement weather days in this study to calculate the traffic speed fluctuation. For a given precipitation day, we search for the same day of week in the 2 weeks forward and backward to obtain the corresponding baseline days without precipitation. Only nonholidays without precipitation events are selected as baseline days; otherwise, we would continue to look forward or backward until 4 baseline days are found. The average speed data of the four baseline days in the selected period were then averaged as the baseline speed for the given precipitation day, and the traffic speed reduction rate was calculated by eq. (1):

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



$$r_c = \frac{v_p - \frac{\sum_{j=0}^{m} v_{d_j}}{m}}{\frac{\sum_{j=0}^{m} v_{d_j}}{m}} \quad (1)$$

where $r_c$ is the traffic speed reduction rate of the precipitation day to its corresponding baseline days; $v_p$ is the traffic speed of the given precipitation day; $v_{d_j}$ is the traffic speed of a baseline day, and m is the number of baseline days. In this case, $m$ equals 4.

The average traffic speed reduction rate is obtained by averaging the reduction rates of all roads with reduced speed in the city.

## 3.2 Analysis of coverage rate

### 3.2.1 The coverage rate of area

A service area is a region that encompasses all roads that are accessible within a specified impedance. Either distance or time can be used as impedance. In this study, the time needed to pass through the road is calculated by the length of each road divided by its corresponding traffic speed, and the service area analysis is carried out with time as the impedance. The core idea of the service area analysis function is to generate service area polygons by setting each first-aid station as the starting point and the traveling time as the driving radius. Under the inclement weather conditions and their corresponding baseline conditions, the service area analysis of the 15-minute arrival time was carried out. The total area of the obtained service area polygon is calculated to obtain the EMS coverage. The coverage rate of area is calculated by eq. (2):

$$r_a = \frac{\sum A_s}{A} \times 100\% \qquad (2)$$

In eq. (2), $r_a$ is the coverage rate of the area; $A$ is the total area of the city, and $A_s$ is the area of the service area.

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



### 3.2.2 The coverage rate of population

To analyze the matching degree between the EMS coverage and the population distribution and identify the hot spots whose EMS coverage of the population is most affected in inclement weather, we downscaled the calculation to the township scale. Based on the grid population data of WorldPop and the coverage areas of EMSs under different scenarios analyzed by service areas, we calculated the coverage rates of EMSs of the population for each township. In each scenario, the polygon of service area obtained from the result of service area analysis is used to mask the population grid, and the covered population divided by the total population is the population coverage of the township (eq. (3)).

$$r_p = \frac{\sum P_s}{P} \times 100\% \qquad (3)$$

In eq. (3), $r_p$ is the coverage rate of the population; P is the total population of the township, and $P_s$ is the population that is covered by the service area.

### 3.3 The spatial accessibility to hospitals

The spatial accessibility to hospitals is quantified by two indicators: the shortest travel time and the population medical accessibility index. The shortest travel time is calculated by the OD cost matrix analysis method, which can find and measure the minimum cost path from multiple starting points to single or multiple destinations in the network. In this study, we calculate the minimum travel time $od_i$ required for each population grid centroid to reach the nearest hospital. To reduce the calculation cost, the population grid data with 100 m resolution are aggregated and converted into 1000 m resolution.

The population medical accessibility index is introduced to quantify the cumulative

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



travel time for each population grid based on its population size, which is the number of potential users of EMSs. It is defined in this study by the shortest travel time of each population grid to the nearest hospital multiplied by its population. For each population grid centroid $i$, its population medical accessibility index (*PA*) is calculated by eq.(4):

$$PA = od_i \times P_i \qquad (4)$$

In eq. (4), $od_i$ is the minimum travel time, $P_i$ is the population of the grid.

## 4 Results

Based on the characteristics of morning and evening rush traffic flow on weekdays, the diurnal variation in traffic can be divided into four phases: morning rush hours (7:00-9:00), daily regular hours (9:00-17:00), evening rush hours (17:00-19:00), and evening regular hours (19:00-22:00). We compared EMS coverage at different periods of the day, and the results show that the period of morning rush hours has the most significant negative impact on the accessibility of EMSs. Taking the average 15-minute coverage of the area of all Mondays in November as an example, in the whole city, the coverage rate of EMSs is 38.72% in morning rush hours, and during the remaining periods, the coverage rate is approximately 40% (±0.3%); within the extent of the Sixth Ring Road, the coverage rate is 77.37% in morning rush hours, and during the remaining periods, the coverage rate is approximately 83% (±0.6%). Therefore, the accessibility of EMSs during the morning rush period deserves more attention. Hence, our subsequent analysis is mainly concentrated on the morning rush period.

The TRMM grid precipitation data of Beijing during morning rush hours in 2019 provided the accumulated precipitation and the spatial distribution of precipitation. In this study, we set a rule that if the precipitation of more than 10 grids in Beijing is

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



greater than 1.5 mm, it is considered a precipitation event. The average precipitation of the whole city on each date is averaged by the precipitation of all grids. In 2019, 19 working days of rainfall and 3 working days of snowfall were selected.

### 4.1 Impact of inclement weather on the traffic and EMSs coverage

#### 4.1.1 The correlation between precipitation and traffic speed

Figure 3 shows the relationship between average precipitation during morning rush hours in the city and the average traffic speed reduction rate of all roads that have speed loss in the city on weekdays. The negative values indicate that the traffic speed decreases in inclement weather conditions. We could see that the average traffic speed would decrease 10%~15% on most precipitation days. The average speed decreases most on July 1st, July 9th, September 10th and December 16th, reached 18%~25%. July 1st (Party's Day) and September 10th (Teachers Day) are special days in China and the traffic speed is affected by both the inclement weather and traffic control or more traffic. December 16th was a snowy day with a precipitation of 0.13 mm/2h, and snowfall has a greater impact on traffic than a rainfall with the same precipitation (Agarwal et al., 2005).

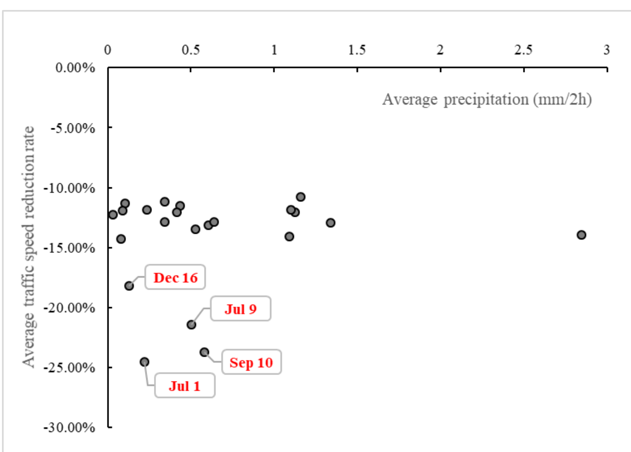


**Figure 3.** The correlation between average precipitation and average traffic speed reduction rate

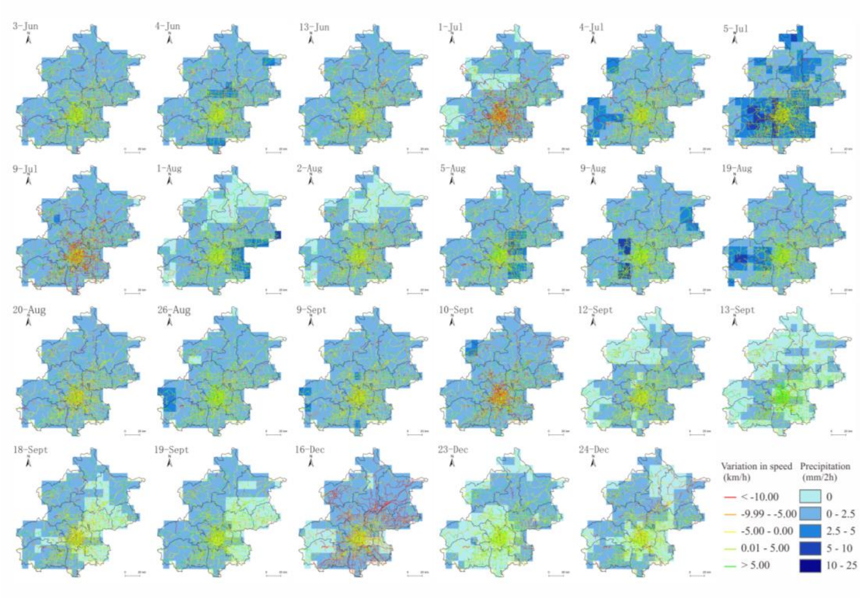



**Figure 4.** Variation in drive speed and distribution of precipitation on selected precipitation days

### 4.1.2 The correlation between precipitation and EMSs coverage rate

The change in the coverage rate of EMSs was calculated by subtracting the coverage rate under the inclement weather condition from that under the corresponding baseline condition. Figure 5 shows the correlation between the average precipitation during morning rush hours and the relative change values of the EMS coverage rate of the area. The negative values indicate that the coverage of EMSs decreases in inclement weather conditions. Consistent with the pattern of the traffic speed reduction, the worst loss of coverage rate also occurred on three rainy days: 1$^{st}$ July (Mon), 9$^{th}$ July (Tue), and 10$^{th}$ September (Tue), and one snowy day: 16$^{th}$ December (Mon), in which the 15-minute EMS coverage rate reduce by 4.6%, 5.6%, 4.2% and 13.3%. Combined with the spatial distribution of precipitation and traffic variation (Figure 4) to analyze, the snowfall on December 16$^{th}$ caused a large traffic speed reduction of the suburban roads, which

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022


Natural Hazards and Earth System Sciences
Open Access
Discussions

leaded to a significant reduction in overall EMS coverage. Therefore, we chose these four days as the worst weather scenario of the year and analysis the spatial differences of medical accessibility in the whole city.

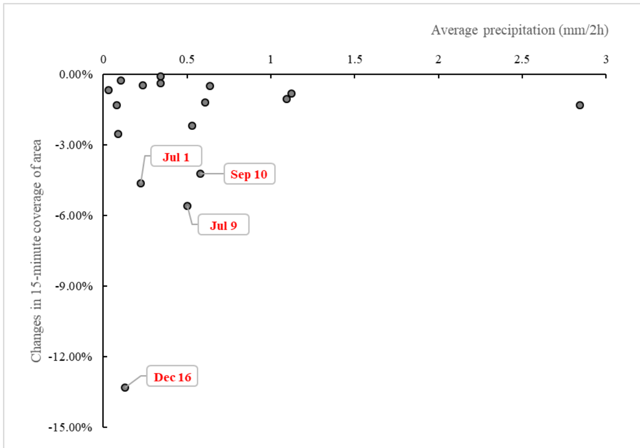



**Figure 5**. The correlation between the average precipitation and the relative change of the EMS coverage rate of the area

### 4.2 The spatial distribution of EMS accessibility under the worst scenario

#### 4.2.1 EMSs coverage rate of population

We calculated the 15-minute EMS coverage rate of the population under the four most severely affected inclement weather conditions of 1st July, 9th July, 10th September, and 16th December and their corresponding baseline conditions at the township scale in Beijing. The results demonstrate that most parts of downtown areas, including Dongcheng District, Xicheng District, Haidian District, and Chaoyang District, could have 90%–100% population coverage of EMSs, regardless of the weather conditions. In the large area of suburbs, the coverage rate of the population varied from lower than 30% to 90%. Under inclement weather conditions, the coverage rate in some towns in the suburbs would drop sharply, with the worst townships having a 40% reduction. The

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022




reason behind this difference is that the distribution of first-aid stations in Beijing is similar to the distribution of the road network, which is dense in the central urban area and sparse in the suburbs.

To illustrate the impact of inclement weather on the EMS coverage rate of the population more clearly, Figure 6 shows the change in the EMS coverage rate of the population in townships in inclement weather relative to normal weather on the four days. The results identify several townships in the outer suburbs (Miyun, Huairou, Pinggu and Yanqing districts) that would experience the most severe decrease in population coverage under inclement weather conditions, with a maximum reduction of more than 40%. These areas are hot spots that need to draw attention in EMS construction planning. Compared with other districts in inner suburbs, such as Shunyi, Daxing, and Tongzhou, these areas are farther away from the city center and have less distribution of medical facilities and sparser road networks and more vulnerable to inclement weather, and these areas are also regions with a relatively higher proportion of the elderly population over the age of 80 in the total population. The average proportion of the elderly is 1.88% in the whole city, 1.37% in the inner suburbs and 2.04% in the outer suburbs. On December 16$^{th}$, 12.6% of population (3.5 million) could not get EMS within 15 minutes, compared to 7.5% with the baseline condition.

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



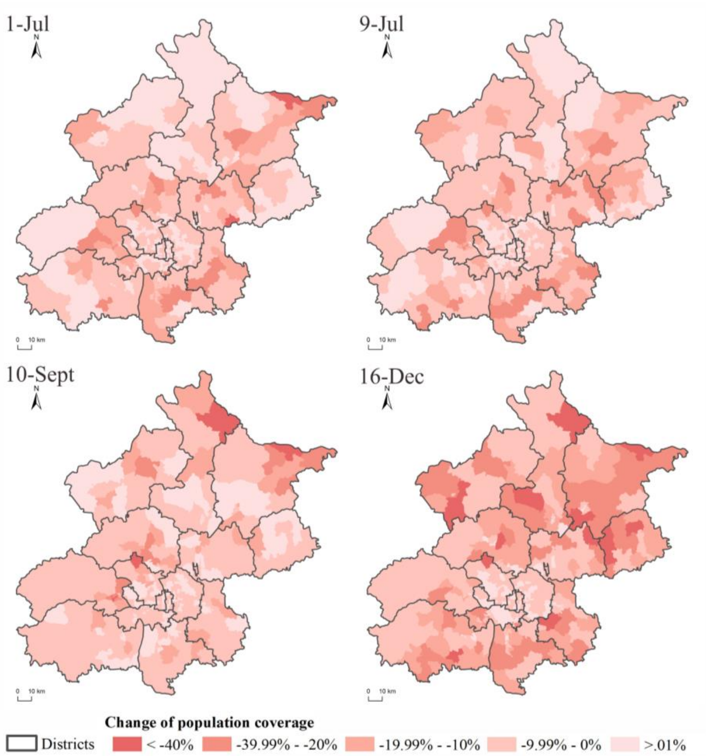
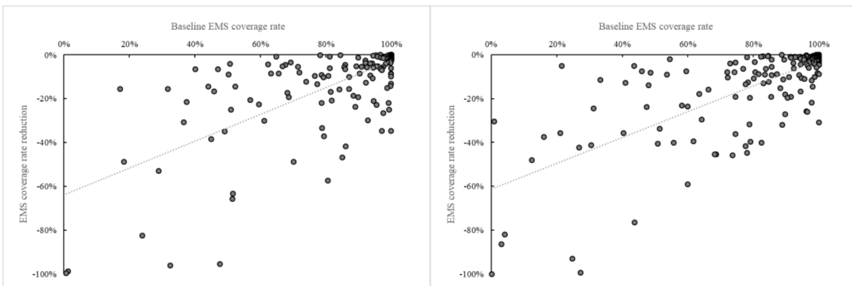
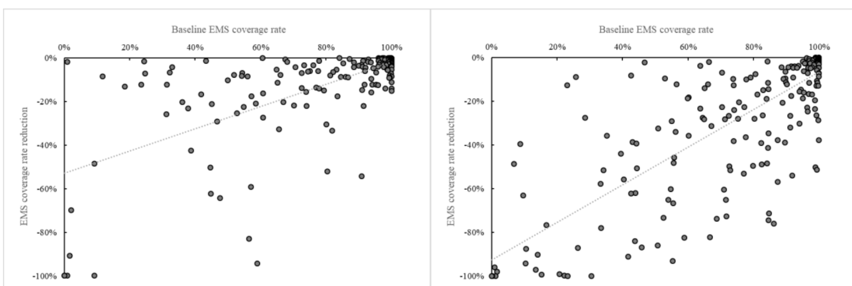



**Figure 6.** The change in EMS coverage rate of the population in townships in inclement weather relative to normal weather on 1st July, 9th July, 10th September, and 16th December

Figure 7 shows the correlation between the baseline EMS coverage rate of the population of each township and its reduction under inclement weather. The results reveal that the population of the towns with low baseline EMS coverage rate would lose more EMS coverage under inclement weather, especially on snowy day. The average traffic speed reduction in the urban area (within the Sixth Ring road) was -26.64%, -23.27%, -25.20% and -15.77% on 1st July, 9th July, 10th September, and 16th December, while that in the suburban area (outside the Sixth Ring Road) was -19.59%, -19.08%, -17.27% and -23.21%. The reason why that suburban area would become more vulnerable under inclement weather is that combined with the traffic speed reduction and the EMS coverage reduction, although the urban area has more traffic speed loss on rainy days, the suburban area still experiences more EMS coverage loss, and once the inclement weather affects the traffic on some road, the urban areas still have many other roads than can bypass, but not in suburbs; on snowy days, the suburban area has more traffic speed reduction, and with the sparser road network, the EMS coverage in the suburban area would shrink much more than rainy days.




(a) (b)




(c) (d)

**Figure 7.** The correlation between the baseline EMS coverage rate of population and its reduction percentage in inclement weather. (a) 1st July, (b) 9th July, (c) 10th September, and (d) 16th December

### 4.2.2 The accessibility to hospitals

Figure 8 shows the increased travel time from each population grid to the nearest hospital under the four inclement weather conditions of 1st July, 9th July, 10th September,

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



and 16th December relative to the baseline condition. The value indicates the impact of inclement weather on accessibility to hospitals. The situation is slightly different on rainy days and snowy days. On rainy days, the shortest time to reach the nearest hospital generally could increase by 0–10 minutes in most parts of Beijing due to slower traffic speed on the roads caused by rain. Although in some small parts of suburban areas, the shortest time to the nearest hospital would be slightly shortened on indicating that the traffic will be smoother in some areas when it rains, which may be due to the reduction of traffic demand (Maze et al., 2006). While on 16th December, affected by snow, the whole city's road traffic generally slowed down, and the travel time to the nearest hospital increased by 10–40 minutes. The western part of Mentougou District and a small part of the northern Yanqing District were the most affected, with the time needed to reach the nearest hospital prolonged by more than 30 minutes, up to 45 minutes. In Huairou district, the eastern part of Yanqing district, and the northern part of Miyun district, the travel time was also prolonged by 11–30 minutes.

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



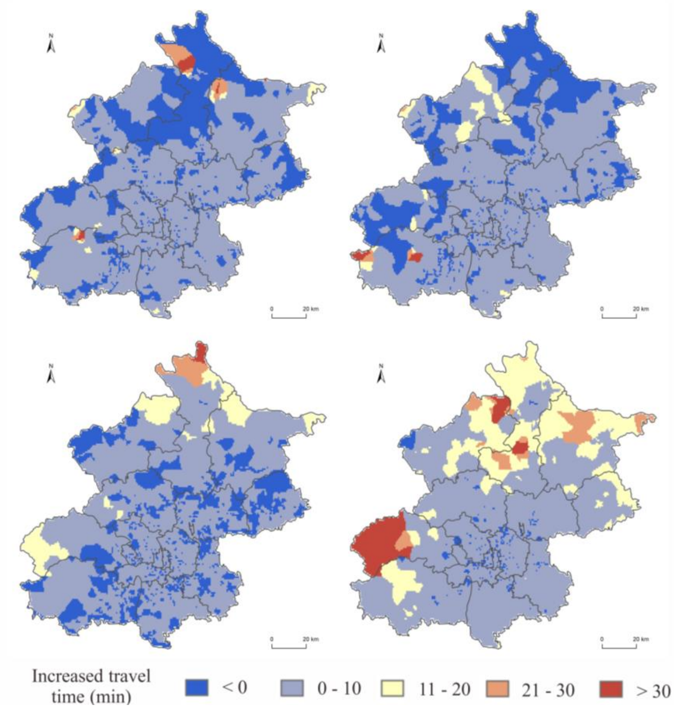
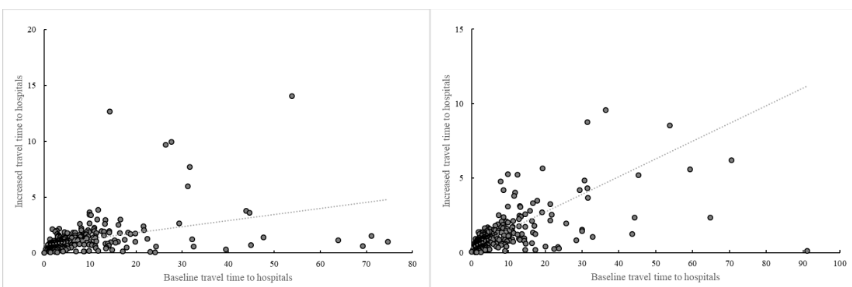




**Figure 8**. Increased travel time to hospitals on 1st July, 9th July, 10th September, and 16th December

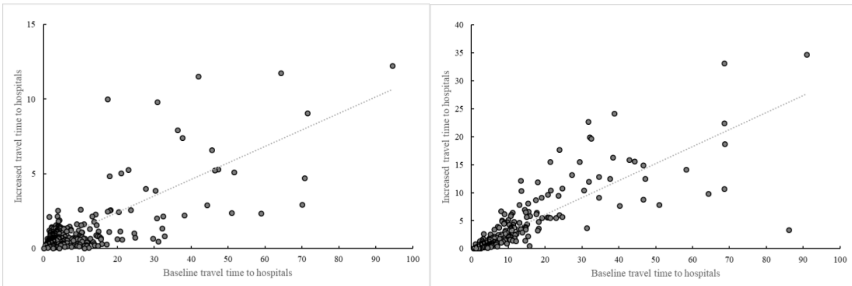
We did a zonal statistic of the average baseline travel time to hospital and the average increased travel time to hospitals to each town, and the correlation between the two indicators shown in Figure 9 indicate the similar pattern with the EMS coverage, which is the towns with low baseline accessibility to hospitals would also more affected by inclement weather.



https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



(a) (b)




(c) (d)

**Figure 9.** The correlation between the baseline travel time to hospitals and the increased travel time in inclement weather. (a) 1st July, (b) 9th July, (c) 10th September, and (d) 16th December

Overlaying the demographic grid data, the size of the population affected by a delay of over 10 minutes would be 0.02 million on 1st July, 0.03 million on 9th July, 0.05 million on 10th September, and 0.3 million on 16th December.

Figure 10 shows the change in the population medical accessibility index under inclement weather conditions on 1st July, 9th July, 10th September, and 16th December, relative to the baseline conditions. The results show that on three rainy days, 1st July, 9th July, and 10th September, within the Six Ring Road extent, the population medical accessibility index increased significantly under inclement weather, which means that, although the travel time would not increase much in urban areas, due to the high population density, the cumulative delay time for total potential demand would be significant. In the suburbs, the population medical accessibility index would increase slightly or even decrease, especially in some areas of Huairou, Yanqing, and Miyun districts, which means that, although the travel time would increase greatly, due to its low population density, the cumulative delay time for total potential demand would not be serious. However, due to the influence of snowfall on 16th December, the population

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



medical accessibility index in the whole city was slightly or moderately increased, and there were almost no regions where the population medical accessibility index was decreased, which means snowfall would cause an even cumulation of delay time for total potential demand across the whole city, both urban and suburban.

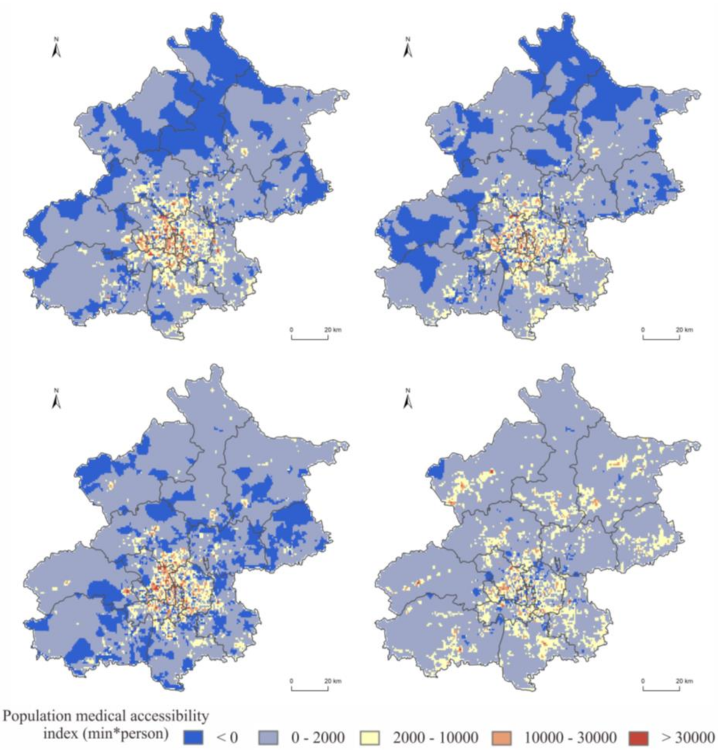



**Figure 10**. The change in the population medical accessibility index on 1st July, 9th July, 10th September, and 16th December

## 5 Conclusions and discussion

This study evaluates the spatial accessibility of EMSs in Beijing under different weather conditions in 2019 based on city-scale ground truth traffic data updated every 2 minutes. The spatial accessibility of EMSs was quantified by the coverage rate of the first-aid stations' service area, the coverage rate of first-aid stations' service population,

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022




the shortest travel time to the nearest hospital, and the population medical accessibility index. This study aims to reveal the impact of inclement weather on EMS accessibility and identify hot spots with difficulties in accessing EMSs. The conclusions are as follows:

First, the results show that inclement weather, such as rainfall and snowfall, could have a negative impact on the accessibility of EMSs overall. Precipitation reduces the driving speed of vehicles on the road, thus reducing EMS coverage. In severe cases, the EMS coverage rate of the area can be reduced by more than 10%.

Second, the EMSs accessibility is more affected by inclement weather in places with low baseline accessibility to EMSs. And the results reveal a serious rural-urban disparity in emergency medical facilities distribution in Beijing: The EMSs accessibility of population in some townships of the outer suburbs is very low and would also greatly reduce under inclement weather.

To the best of the authors' knowledge, this study provides a first attempt to analyze the spatial accessibility of EMSs under inclement weather based on city-scale ground truth traffic data and meteorological data, where the former is usually difficult to obtain due to data management requirements in cities. The results from this study provide a scientific reference for city planning departments in Beijing to optimize the site selection of emergency service facilities and get prepared for traffic dispersion on inclement weather. The relevant methods mentioned in this paper can also be popularized and easily applied to other cities once traffic data or empirical formulas regarding the impact of inclement weather on road traffic can be obtained.

However due to the data limitation, we could only analyze the EMS accessibility in 2019, and the precipitation intensity in this year was not quite high. Under such precipitation conditions, the EMSs accessibility has been affected to a certain extent, and we could guess how difficult would it be to get timely EMS under even more extreme inclement weather condition. So, the future studies should take the risk of extreme precipitation event into account.

## Data availability

All raw data can be provided by the corresponding authors upon request.

## Author contributions

YZ, and KL planned the research; JZ, ML provided the traffic data; YZ analyzed the data and wrote the manuscript draft; KL, XN, MW, and DY reviewed and edited the manuscript.

## Competing interests

The authors declare that they have no conflict of interest.

## Acknowledgments

The study is supported by the Major Program of National Natural Science Foundation of China (No. 72091512) and National Natural Science Foundation of China (41771538). The financial support is highly appreciated.

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022



# References:

Agarwal, M., Maze, T. H., and Souleyrette, R.: Impacts of weather on urban freeway traffic flow characteristics and facility capacity. Proceedings of the 2005 mid-continent transportation research symposium,2005.

Agarwal, M., Maze, T. H., and Souleyrette, R.: The weather and its impact on urban freeway traffic operations. Proceedings of the 85nd annual meeting of the Transportation Research Board, Washington DC,2006.

Albano, R., Sole, A., Adamowski, J., and Mancusi, L.: A GIS-based model to estimate flood consequences and the degree of accessibility and operability of strategic emergency response structures in urban areas, NAT HAZARD EARTH SYS, 14, 2847-2865, http://doi.org/10.5194/nhess-14-2847-2014, 2014.

Andersson, S., and Stålhult, S.: Hospitals exposed to flooding in Manila City, Philippines: GIS analyses of alternative emergency routes and allocation of emergency service and temporary medical centre.,2014.

Blackwell, T. H., and Kaufman, J. S.: Response time effectiveness: Comparison of response time and survival in an urban emergency medical services system, ACAD EMERG MED, 9, 288-295, http://doi.org/10.1111/j.1553-2712.2002.tb01321.x, 2002.

Chang, H., Lafrenz, M., Jung, I., Figliozzi, M., Platman, D., and Pederson, C.: Potential Impacts of Climate Change on Flood-Induced Travel Disruptions: A Case Study of Portland, Oregon, USA, ANN ASSOC AM GEOGR, 100, 938-952, http://doi.org/10.1080/00045608.2010.497110, 2010.

Coles, D., Yu, D., Wilby, R. L., Green, D., and Herring, Z.: Beyond 'flood hotspots': Modelling emergency service accessibility during flooding in York, UK, J HYDROL, 546, 419-436, http://doi.org/10.1016/j.jhydrol.2016.12.013, 2017.

Cools, M., Moons, E., and Wets, G.: Assessing the Impact of Weather on Traffic Intensity, WEATHER CLIM SOC, 2, 60-68, http://doi.org/10.1175/2009WCAS1014.1, 2010.

Cools, M., Moons, E., and Wets, G.: Investigating effect of holidays on daily traffic counts - Time series approach, TRANSPORT RES REC, 22-31, http://doi.org/10.3141/2019-04, 2007.

Edwards, J. B.: Weather-related road accidents in England and Wales: a spatial analysis, J TRANSP GEOGR, 4, 201-212,1996.

Green, D., Yu, D., Pattison, I., Wilby, R., Bosher, L., Patel, R., Thompson, P., Trowell, K., Draycon, J., Halse, M., Yang, L., and Ryley, T.: City-scale accessibility of emergency responders operating during flood events, NAT HAZARD EARTH SYS, 17, 1-16, http://doi.org/10.5194/nhess-17-1-2017, 2017.

Guagliardo, M. F.: Spatial accessibility of primary care: concepts, methods and challenges., INT J HEALTH GEOGR, 3, 3,2004.

Hashtarkhani, S., Kiani, B., Bergquist, R., Bagheri, N., VafaeiNejad, R., and Tara, M.: An age-integrated approach to improve measurement of potential spatial accessibility to emergency medical services for urban areas, INT J HEALTH PLAN M, 35, 788-798, http://doi.org/10.1002/hpm.2960, 2020.

Hu, W., Tan, J., Li, M., Wang, J., and Wang, F.: Impact of traffic on the spatiotemporal variations of spatial accessibility of emergency medical services in inner-city Shanghai, ENVIRON PLAN B-URBAN, 47, 841-854, http://doi.org/10.1177/2399808318809711, 2020.

JONES, A. P., and BENTHAM, G.: EMERGENCY MEDICAL-SERVICE ACCESSIBILITY AND

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022


Natural Hazards and Earth System Sciences
Discussions

OUTCOME FROM ROAD TRAFFIC ACCIDENTS, PUBLIC HEALTH, 109, 169-177, http://doi.org/10.1016/S0033-3506(05)80049-6, 1995.

Li, M., Kwan, M., Chen, J., Wang, J., Yin, J., and Yu, D.: Measuring emergency medical service (EMS) accessibility with the effect of city dynamics in a 100-year pluvial flood scenario, CITIES, 117, http://doi.org/10.1016/j.cities.2021.103314, 2021.

Luo, W., and Wang, F. H.: Measures of spatial accessibility to health care in a GIS environment: synthesis and a case study in the Chicago region, ENVIRONMENT AND PLANNING B-PLANNING & DESIGN, 30, 865-884, http://doi.org/10.1068/b29120, 2003.

Mao, L., and Nekorchuk, D.: Measuring spatial accessibility to healthcare for populations with multiple transportation modes, HEALTH PLACE, 24, 115-122, http://doi.org/10.1016/j.healthplace.2013.08.008, 2013.

Maze, T. H., Agarwal, M., and Burchett, G.: Whether weather matters to traffic demand, traffic safety, and traffic operations and flow. TRANSPORTATION RESEARCH RECORD-SERIES, 2006.

Moglia, M., Frantzeskaki, N., Newton, P., Pineda-Pinto, M., Witheridge, J., Cook, S., and Glackin, S.: Accelerating a green recovery of cities: Lessons from a scoping review and a proposal for mission-oriented recovery towards post-pandemic urban resilience, Developments in the Built Environment, 7, 100052,2021.

Mohsenizadeh, M., Tural, M. K., and Kentel, E.: Municipal solid waste management with cost minimization and emission control objectives: A case study of Ankara, SUSTAIN CITIES SOC, 52, http://doi.org/10.1016/j.scs.2019.101807, 2020.

Pan, X., Kwan, M., Yang, L., Zhou, S., Zuo, Z., and Wan, B.: Evaluating the Accessibility of Healthcare Facilities Using an Integrated Catchment Area Approach, INT J ENV RES PUB HE, 15, http://doi.org/10.3390/ijerph15092051, 2018.

Ramgopal, S., Siripong, N., Salcido, D. D., and Martin-Gill, C.: Weather and temporal models for emergency medical services: An assessment of generalizability, AM J EMERG MED, 45, 221-226, http://doi.org/10.1016/j.ajem.2020.08.033, 2021.

Rizeei, H. M., Pradhan, B., and Saharkhiz, M. A.: Allocation of emergency response centres in response to pluvial flooding-prone demand points using integrated multiple layer perceptron and maximum coverage location problem models, INT J DISAST RISK RE, 38, http://doi.org/10.1016/j.ijdrr.2019.101205, 2019.

Shin, K., and Lee, T.: Improving the measurement of the Korean emergency medical System's spatial accessibility, APPL GEOGR, 100, 30-38, http://doi.org/10.1016/j.apgeog.2018.08.009, 2018.

Song, X., Zhang, J., AghaKouchak, A., Sen Roy, S., Xuan, Y., Wang, G., He, R., Wang, X., and Liu, C.: Rapid urbanization and changes in spatiotemporal characteristics of precipitation in Beijing metropolitan area, J GEOPHYS RES-ATMOS, 119, 11250-11271, http://doi.org/10.1002/2014JD022084, 2014.

Suarez, P., Anderson, W., Mahal, V., and Lakshmanan, T. R.: Impacts of flooding and climate change on urban transportation: A systemwide performance assessment of the Boston Metro Area, TRANSPORT RES D-TR E, 10, 231-244, http://doi.org/10.1016/j.trd.2005.04.007, 2005.

Wang, J., Du, F., Huang, J., and Liu, Y.: Access to hospitals: Potential vs. observed, CITIES, 100, http://doi.org/10.1016/j.cities.2020.102671, 2020.

Wang, K., Wang, L., Wei, Y., and Ye, M.: Beijing storm of July 21, 2012: observations and reflections,

https://doi.org/10.5194/nhess-2022-218
Preprint. Discussion started: 6 September 2022


NAT HAZARDS, 67, 969-974, http://doi.org/10.1007/s11069-013-0601-6, 2013.

Wang, Y., Zhai, J., and Song, L.: Waterlogging risk assessment of the Beijing-Tianjin-Hebei urban agglomeration in the past 60 years, THEOR APPL CLIMATOL, 145, 1039-1051, http://doi.org/10.1007/s00704-021-03670-5, 2021.

Yang, Y., Yin, J., Ye, M., She, D., and Yu, J.: Multi-coverage optimal location model for emergency medical service (EMS) facilities under various disaster scenarios: a case study of urban fluvial floods in the Minhang district of Shanghai, China, NAT HAZARD EARTH SYS, 20, 181-195, http://doi.org/10.5194/nhess-20-181-2020, 2020.

Yin, J., Yu, D., and Liao, B.: A city-scale assessment of emergency response accessibility to vulnerable populations and facilities under normal and pluvial flood conditions for Shanghai, China, ENVIRON PLAN B-URBAN, 48, 2239-2253, http://doi.org/10.1177/2399808320971304, 2021.

Yu, D., Yin, J., Wilby, R. L., Lane, S. N., Aerts, J. C. J. H., Lin, N., Liu, M., Yuan, H., Chen, J., Prudhomme, C., Guan, M., Baruch, A., Johnson, C. W. D., Tule, X., Yu, L., and Xu, S.: Disruption of emergency response to vulnerable populations during floods, NATURE SUSTAINABILITY, 3, 728, http://doi.org/10.1038/s41893-020-0516-7, 2020.

Zhang, X., and Chen, M.: Quantifying the Impact of Weather Events on Travel Time and Reliability, J ADV TRANSPORT, http://doi.org/10.1155/2019/8203081, 2019.