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 influenced by 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, explores the influence of inclement weather on EMSs accessibility, and identifies the hotspots that have difficulty 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 EMSs accessibility. Under inclement weather scenario, the area in the city that could get EMSs within 15 minutes would decrease by 13% compared to normal scenario (the average state of weekdays without precipitation), while in some suburban townships, the population that could get 15-min EMSs would decrease by 40%. We found that snowfall has a greater impact on the accessibility of EMSs than rainfall. Although on the whole, the urban area would have more traffic speed reduction, towns in suburban with lower baseline EMSs accessibility are more vulnerable to inclement weather. Under the worst scenario in 2019, 12.6% of population (about 3.5 million) could not get EMSs 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

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. The efficiency of emergency services is highly vulnerable to inclement weather conditions such as rain, snow, frog, etc. The reason why inclement weather conditions would reduce the efficiency of emergency services is that inclement weather conditions would reduce road capacity, increase transfer time, and sometimes block roads completely (Agarwal et al., 2006; Chang et al., 2013; Cools et al., 2010; Suarez et al., 2005; Zhang and Chen, 2019), which leads to the reduction of spatial accessibility and delay of response time. 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). For example, on July 21, 2012, Beijing was hit by a rainstorm, with the average cumulative rainfall reaching 170 mm, caused 63 roads to be seriously flooded. This rainfall event 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 1.5~2 hours for each evacuation during the rainstorm. Usually, the transfer time wouldn't be more than 1 hour. (Wang et al., 2013; Beijing Evening,2012) On February 6, 2022, in Cleveland, US, an ambulance got stuck in the snow causing a long delay getting the patient to the hospital (Fox 8 News, 2022). On August 3, 2021, in Chattogram, Bangladesh, a daily rainfall of 190.6 mm caused many

67   ambulances with patients stuck in different areas of the city (Business Standard, 2021).

68   In the context of global climate change and rapid urbanization, extreme inclement

69   weather events strike cities more frequently (Huber and Gulledge, 2011; Stott, 2016;

70   Stott et al., 2016), the problem of urban rainstorms and waterlogging (the phenomenon

71   of a stagnant water disaster in an urban area due to heavy rainfall or continuous

72   precipitation) has become increasingly prominent. It is therefore of great importance to

73   investigate the influence of inclement weather on the spatial accessibility of EMSs.

74   The spatial accessibility of EMSs is defined by the travel impedance (distance or

75   time) between service locations and the scene (Guagliardo, 2004). A large body of

76   research on spatial accessibility is concerned with access to hospitals (Luo and Wang,

77   2003; Mao and Nekorchuk, 2013; Pan et al., 2018; Yang et al., 2020; Yin et al., 2021)

78   and first-aid stations (Hashtarkhani et al., 2020; Jones and Bentham, 1995; Shin and

79   Lee, 2018). To measure the EMSs accessibility, the two-step floating catchment area

80   (2SFCA) method is one of the common methods (Chen and Jia, 2019; Kanuganti et al.,

81   2016; Li et al., 2021; Luo and Qi, 2009). The 2SFCA method considers accessibility to

82   be mediated by not only the distance decay but also the interactions between supply

83   and demand (Chen and Jia, 2019), which is more suitable for normal scenarios. While

84   in the studies focusing on the influence of inclement weather on EMSs, people are more

85   concerned about the transportation situation, instead of the interaction between supply

86   and demand. The coverage analysis method (Coles et al., 2017; Green et al., 2017; Yu

87   et al., 2020) or shortest path analysis method (Albano et al., 2014; Andersson and

88   Stålhult, 2014) are more widely used. These methods could better characterize the

89   reduction of accessibility caused by the road service degradation. For example, Yu et

90   al. (2020) analyzed the accessibility of emergency service in England and identified

91   vulnerability hotspots by quantifying the EMSs coverage of area and population within

92 different time radii under different flood scenarios; Coles et al. (2017) measured the

93 travel time and service area coverage of EMSs in York, UK under flood scenarios by

94 using FloodMap-HydroInundation2D to model flood inundation; Yin et al. (2021)

95 assessed the vulnerability of EMSs to surface water flooding in Shanghai, China by

96 quantifying accessibility in terms of service area, population coverage and response

97 time. They simulated urban waterlogging scenarios under different rainfall intensities

98 and set traffic speed based on recorded average traffic speed under normal conditions,

99 which didn't consider the traffic speed variations induced by precipitation. Andersson

100 and Stålhult (2014) used network analysis methods to generate the shortest paths from

101 hospitals to various administrative areas in Manila, Philippines, and evaluated the

102 impact of different flood events on these paths. Most of these studies assumed that roads

103 are impassable or traffic speed has a certain degree of reduction when the flooded water

104 depth reaches a specific depth, and further evaluated the impact of rainstorm on EMSs

105 accessibility. Due to insufficient recorded traffic data, relatively few studies have been

106 performed to analyze the impact of road access capacity on EMSs accessibility

107 according to actual traffic speed variation.

108   In this study, we explore the impact of inclement weather on traffic and EMS

109 accessibility based on ground-truth traffic data. Beijing which is the capital of China is

110 used as a case study. The reductions in EMSs accessibility of Beijing under inclement

111 weathers in 2019 are quantified, and the urban-rural disparities in the distribution of

112 emergency medical facilities are further analyzed. Our study provides an approach for

113 evaluating the effectiveness and fairness of EMSs based on ground-truth traffic data,

114 and the results can not only provide reference for the optimization of EMSs in Beijing,

115 but also provide reference cases for other cities, which has a great practical significance.

116

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 (National Bureau of Statistics, 2021), 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 of transportation network and medical facilities in the urban area of Beijing are much higher than those in the suburbs (Figure 1b).

(a)   (b)
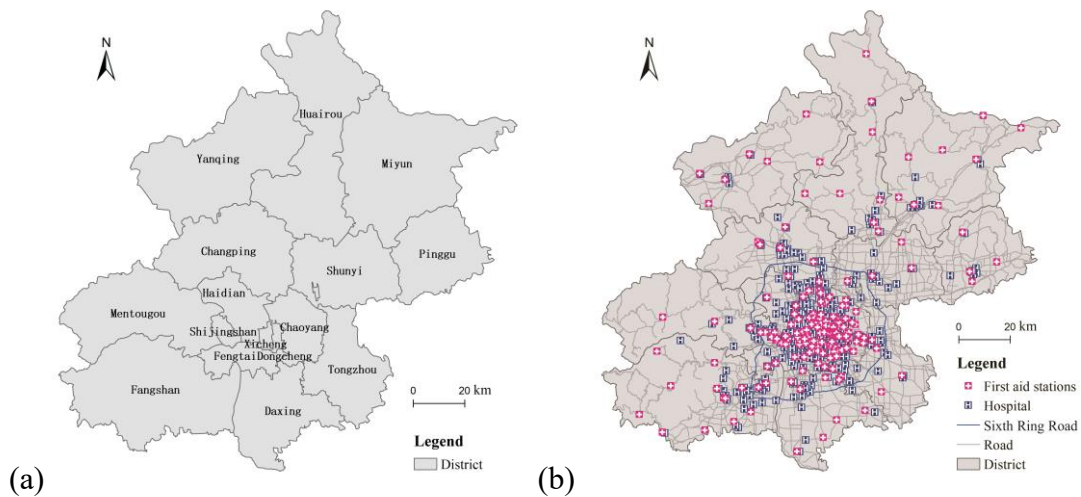
Figure 1. (a) Administrative division of Beijing and (b) EMS facility locations in Beijing, produced in ArcGIS 10.8.

6

2.2 Dataset

The data involved in this paper mainly include traffic data, meteorological data, EMSs data, and demographic data. Based on traffic data and meteorological data, we could build a topology road network (using node and edge primitives to describe interconnected linear features (roads) and points (roads junctions) on a map) with transfer time as impendence under inclement weather conditions and corresponding normal weather conditions. Combining the topology road network with medical facility locations and the distribution of the population by ArcGIS 10.8, we could further analyze the spatial accessibility of EMSs.

2.2.1 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.

2.2.2 Meteorological data

The meteorological data utilized in this paper are TRMM (Tropical Rainfall Measuring Mission) precipitation data obtained from NASA, with a spatial resolution of 0.1°×0.1° (approximately 10 km×10 km) and a temporal resolution of 30 minutes. The whole city of Beijing is covered by 175 grids.

According to the classification of precipitation, moderate rain is defined as the rainfall is 5.0~14.9 mm per 12 hours (China Meteorological Administration, 2012). We chose intermediate value of the interval and average it to each hour. In this study, we

set a rule that if the precipitation of more than 10 grids (over 5% area of the city) in Beijing is greater than 1.5 mm in 2 hours, it is considered a precipitation event. This amount of precipitation may not high enough to cause the rainfall-runoff exceed the drainage capacity of the sewer network in Beijing (DB11/ 685—2021, DB 11/T 1575—2018). But the precipitation would cause slippery roads and decrease in drivers' visibility, which would lead to a reduction of traffic efficiency and accessibility (Chu and Fwa, 2018; Katz et al., 2012). 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.

2.2.3 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 (Beijing Emergency Medical Center, 2021), 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 (Gaode Maps, 2021). After coordinate correction and deduplication, it contains a total of 630 general hospitals, 76 of which are third-level grade-A hospitals (the highest level in the evaluation system of hospitals in mainland China).

2.2.4 Demographic data

The demographic data of 2019 were obtained from WorldPop (2018) with a spatial resolution of 100 m×100 m. The data records present the population size.

3 Methodology

Figure 2 illustrates 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 transfer time to hospitals are calculated. Finally, the spatial accessibility to the population is calculated, and hotspots are identified. Both the service area analysis and the OD Cost Matrix analysis are GIS-based, and were done in ArcGIS 10.8. In this study, we made the following assumptions: (1) The ambulances move at the average speed all the time and would always take the shortest path in space; (2) In network analysis, the location of facilities is approximately considered to be on the nearest road point vertically; (3) In OD analysis, we use the centroid as the origin point to represent the whole grid, and the shortest path to hospital of all points within the grid is the same; (4) The prehospital EMSs is divided into two parts: the ambulances depart from the first-aid station to the scene and from the scene to the nearest hospital; (5) The proper limitation of EMS response time is 15 minutes. The case where patients transfer directly from the scene to an EMS facility via private transportation will not be considered in this study. (6) The hospitals' carrying capacity is not been considered in this study, and we assume that the demand of EMSs would not exceed the first aid stations' and hospitals' carrying capacity.
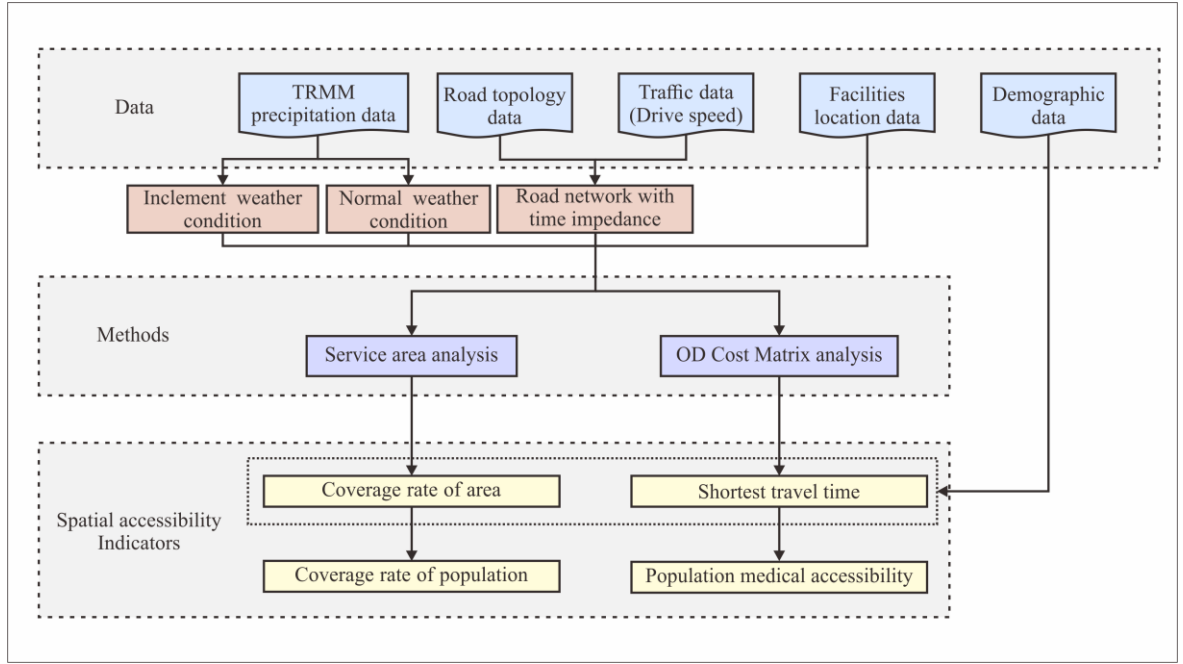
Figure 2. Methodology of this study, produced in CorelDraw 2019.

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 two 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 four 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) and eq.(2):

$$r_c = \frac{v_p - v_b}{v_b} \qquad (1)$$

10

where r_c is the traffic speed reduction rate in the selected period of the precipitation day to its corresponding baseline day; v_p is the traffic speed in the selected period of the given precipitation day, and it is the average of the real-time traffic speed in every 2 minutes during the selected time period in that day; v_b is the traffic speed in the selected period of the baseline precipitation days, which is calculated by eq.(2):

$$v_b = \frac{\sum_{j=0}^{m} v_{d_j}}{m} \qquad (2)$$

where v_{d_j} is the traffic speed in the selected period of a baseline day, and it is the average of the real-time traffic speed in every 2 minutes during the selected time period in that day; 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. In different scenarios, the time impedance varies, since the traffic speed of each road is set according to the real-time traffic speed record of the chosen date and chosen period. 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

246 corresponding baseline conditions, the service area analysis of the 15-minute (Yin et

247 al., 2021) arrival time was carried out. The total area of the obtained service area

248 polygon is calculated to obtain the EMS coverage. The coverage rate of area is

249 calculated by eq. (3):

250
$$r_a = \frac{\sum A_s}{A} \times 100\% \qquad (3)$$

251 In eq. (3), r_a is the coverage rate of the area; A is the total area of the city, and A_s is

252 the area of the service area.

253 3.2.2 The coverage rate of population

254 To analyze the matching degree between the EMS coverage and the population

255 distribution and identify the hotspots whose EMS coverage of the population is most

256 affected in inclement weather, we downscaled the calculation to the township scale.

257 Based on the grid population data of WorldPop and the coverage areas of EMSs under

258 different scenarios analyzed by service areas, we calculated the coverage rates of EMSs

259 of the population for each township. In each scenario, the polygon of service area

260 obtained from the result of service area analysis is used to mask the population grid,

261 and the covered population divided by the total population is the population coverage

262 of the township (eq. (4)).

263
$$r_p = \frac{\sum P_s}{P} \times 100\% \qquad (4)$$

264 In eq. (4), r_p is the coverage rate of the population; P is the total population of the

265 township, and P_s is the population that is covered by the service area.

266

267 3.3 The spatial accessibility to hospitals

268 The spatial accessibility to hospitals is quantified by two indicators: the shortest

269 transfer time and the total transfer time. The shortest transfer time is calculated by the

OD (Origin-destination) 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 transfer 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. This could be interpreted as a sampling method, because we use the centroid point of the grid to represent the other possible starting points in the grid, and we ignored the tolerance caused by the travel time inside the grids.

The total transfer time is introduced to quantify the cumulative transfer time for each population grid based on its population size, which is the number of potential users of EMSs. The total transfer time is defined in this study by the shortest transfer time of each population grid to the nearest hospital multiplied by its population. The numerical value has no practical significance, and is only used for comparing the spatial differences among regions. For each population grid centroid i, its total transfer time (T) is calculated by eq.(5):

$$T = od_i \times P_i \qquad (5)$$

In eq. (5), od_i is the minimum transfer 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 periods: 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

294 significant negative impact on the accessibility of EMSs. We divided the city into the

295 inner city and suburban areas along the Sixth Ring Road. Taking the average 15-minute

296 coverage of the area of all Mondays in November as an example: (1) in the whole city

297 (both inner city and suburban), the coverage rate of EMSs is 38.72% in morning rush

298 hours, compared with 40% (±0.3%) in the remaining periods; (2) in the inner city, the

299 coverage rate is 77.37% in morning rush hours, compared with 83% (±0.6%) in the

300 remaining periods. Therefore, the accessibility of EMSs during the morning rush period

301 deserves more attention. Hence, our subsequent analysis is mainly concentrated on the

302 morning rush period.

303

304 **4.1 Impact of inclement weather on the traffic and EMSs coverage**

305 **4.1.1 The correlation between precipitation and traffic speed**

306 Figure 3 shows the relationship between average precipitation during morning rush

307 hours in the city and the average traffic speed reduction rate of all roads that have speed

308 loss in the city on weekdays. The unit of precipitation data is mm/2h, which indicates

309 the total precipitation in the 2 hours of morning rush hours. The negative values indicate

310 that the traffic speed decreases in inclement weather conditions. We could see that the

311 average traffic speed would decrease 10%~15% on most precipitation days. The

312 average speed decreases most on July 1st, July 9th, September 10th and December 16th,

313 reached 18%~25%. July 1st (Party's Day) and September 10th (Teachers Day) are special

314 days in China and the traffic speed is affected by both the inclement weather and traffic

315 control. December 16th was a snowy day with a precipitation of 0.13 mm/2h, and

316 snowfall has a greater impact on traffic than a rainfall with the same precipitation

317 (Agarwal et al., 2005). Figure 4 illustrates the spatial difference of traffic speed

318 reduction and distribution of precipitation on precipitation days. A large number of red

319 roads (with traffic speed reduction over 10 km/h) can be observed in the 4 days

320 mentioned above. By comparing the distribution of precipitation and traffic speed

321 reduction on different dates in Figure 4, it can be found that the precipitation in the four

322 days with the most severe speed reduction was moderate, and the precipitation

323 distribution of the whole city was relatively uniform. Compared with other rain days,

324 although the precipitation on July 5, August 9 and September 19 was larger and

325 concentrated in the inner city, the traffic speed reduction of the whole city was not as

326 serious as the four days mentioned above, which may be caused by the decrease of

327 people's willingness to travel with the increase of rain.
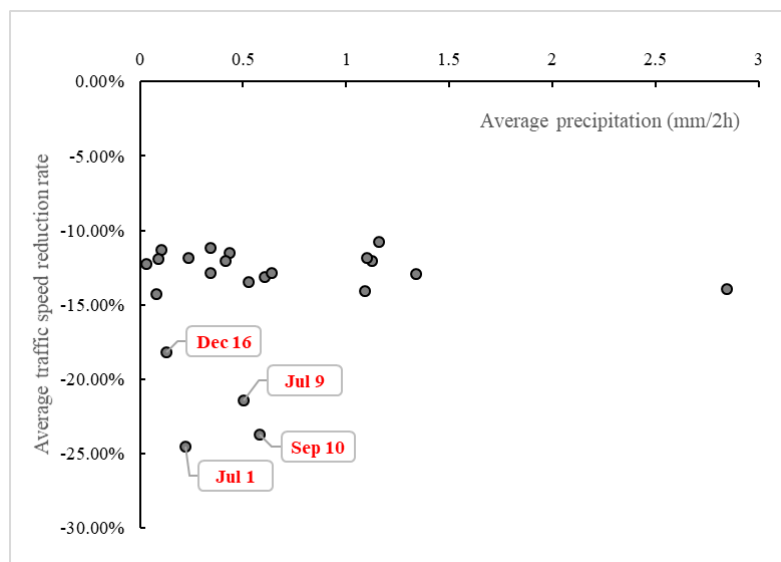
328

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

330 produced in Excel 2016.
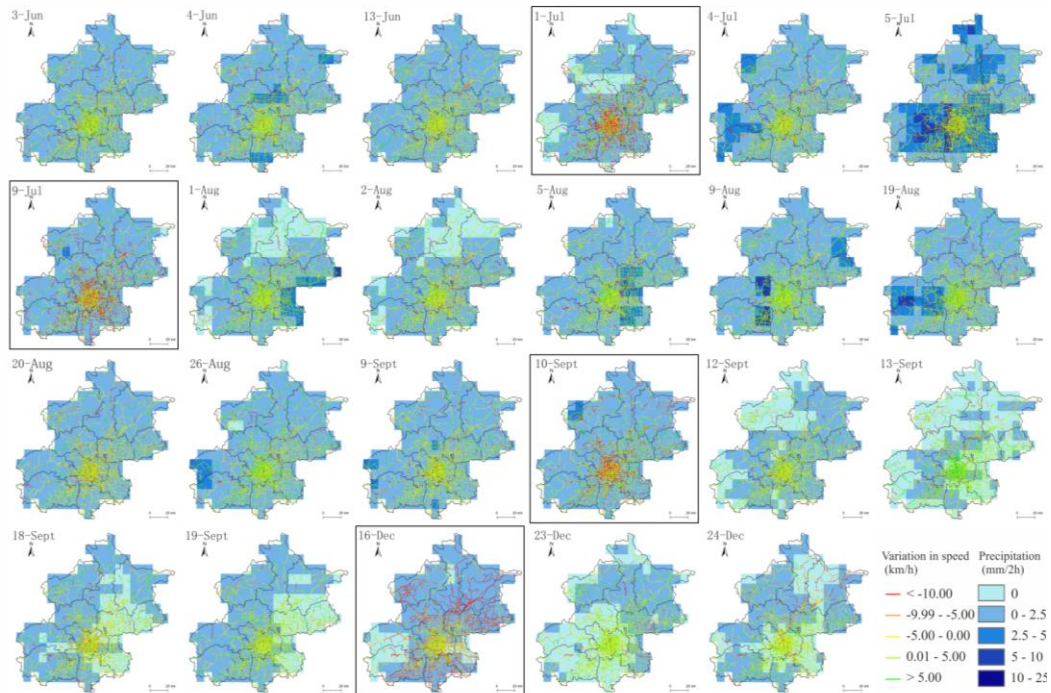
Figure 4. Variation in drive speed and distribution of precipitation on selected precipitation days (the 4 subfigures with black borders shows the 4 most affected scenarios), produced in ArcGIS 10.8 and CorelDraw 2019.

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: 1st July (Mon), 9th July (Tue), and 10th September (Tue), and one snowy day: 16th December (Mon), in which the 15-minute EMS coverage rate reduced by 4.6%, 5.6%, 4.2% and 13.3%. Combined with the spatial distribution of precipitation and traffic variation (Figure 4), the snowfall on December 16th caused a large traffic speed reduction of the suburban roads, which led to a

16

significant reduction in overall EMS coverage. Therefore, we chose these four days as

the worst weather scenario of the year and analyzed the spatial differences of medical

accessibility in the whole city.
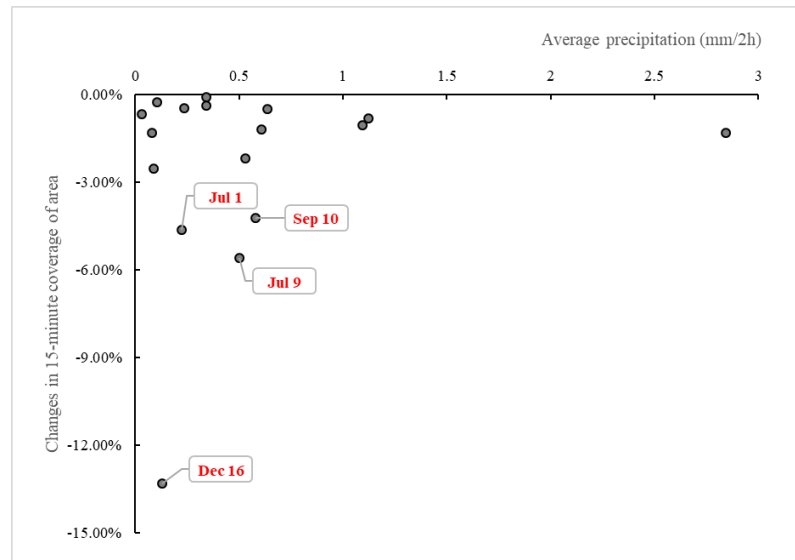
Figure 5. The correlation between the average precipitation and the relative change of the EMS
coverage rate of the area, produced in Excel 2016.

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. Figure 6 shows the 15-minute EMSs coverage rate of population under 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 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.
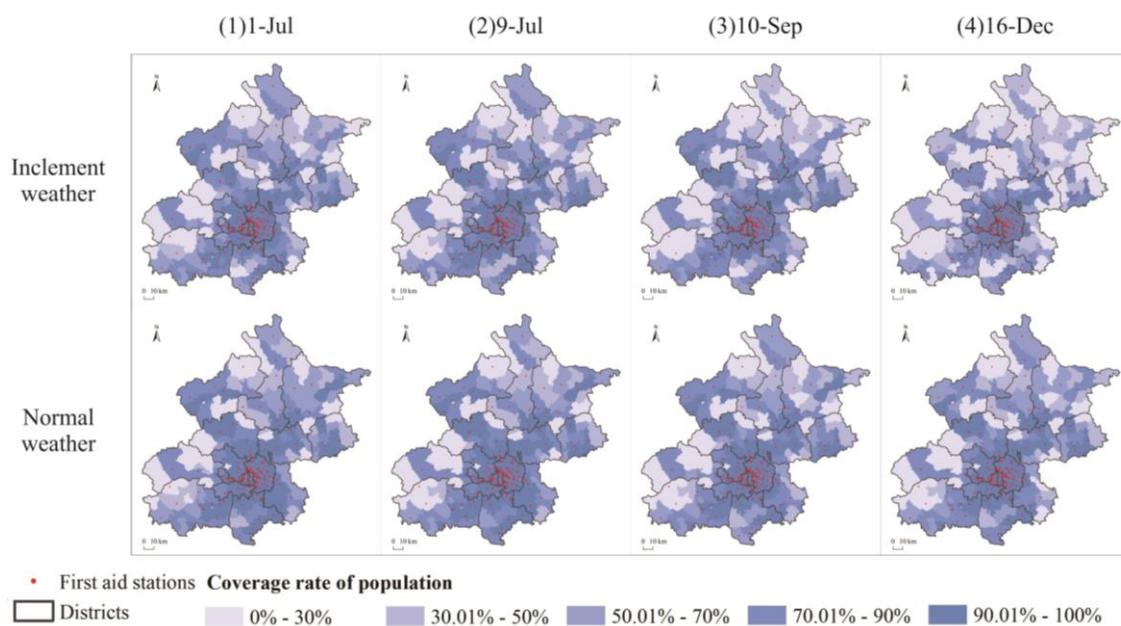
Figure 6. The EMSs coverage rate of population in townships under the inclement weather condition and normal weather condition on 1st July, 9th July, 10th September and 16th December, produced in ArcGIS 10.8 and CorelDraw 2019.

To illustrate the impact of inclement weather on the EMS coverage rate of the

population more clearly, Figure 7 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 hotspots that need to draw attention in EMS

383   construction planning. The suburb areas, such as Shunyi, Daxing, and Tongzhou, are

384   more vulnerable to inclement weather as they have less distribution of medical facilities

385   and sparser road networks, as well have a relatively higher proportion of the elderly

386   population over the age of 80. The average proportion of the elderly is 1.88% in the

387   whole city, 1.37% in the inner suburbs and 2.04% in the outer suburbs. On December

388   16th, 12.6% of population (3.5 million) could not get EMS within 15 minutes, compared

389   to 7.5% with the baseline condition.
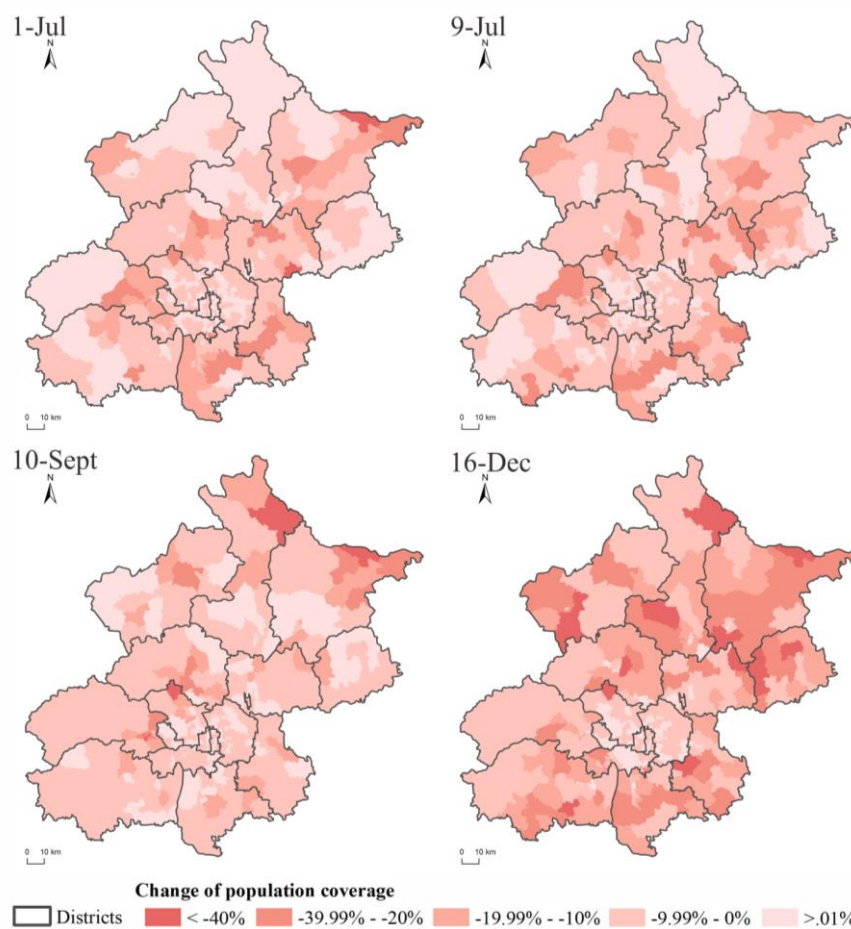
390

391   **Figure 7.** The change in EMS coverage rate of the population in townships in inclement weather

392   relative to normal weather on 1st July, 9th July, 10th September, and 16th December, produced in ArcGIS

393   10.8 and CorelDraw 2019.

394   Figure S1 shows the correlation between the baseline EMS coverage rate of the

395   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%. Based on the results, we analyzed the reasons why that

suburban area would become more vulnerable under inclement weather. Combined

with the traffic speed reduction and the EMS coverage reduction, on rainy days,

although the urban area has more traffic speed loss, the suburban area still experiences

more EMS coverage loss. 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.

4.2.2 The accessibility to hospitals

Figure 9 shows the increased transfer time from each population grid to the nearest

hospital under the four inclement weather conditions of 1st July, 9th July, 10th September,

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 transfer 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 transfer time was also prolonged by 11–30 minutes.

Increased travel time (min): ■ < 0   ■ 0 - 10   ☐ 11 - 20   ■ 21 - 30   ■ > 30
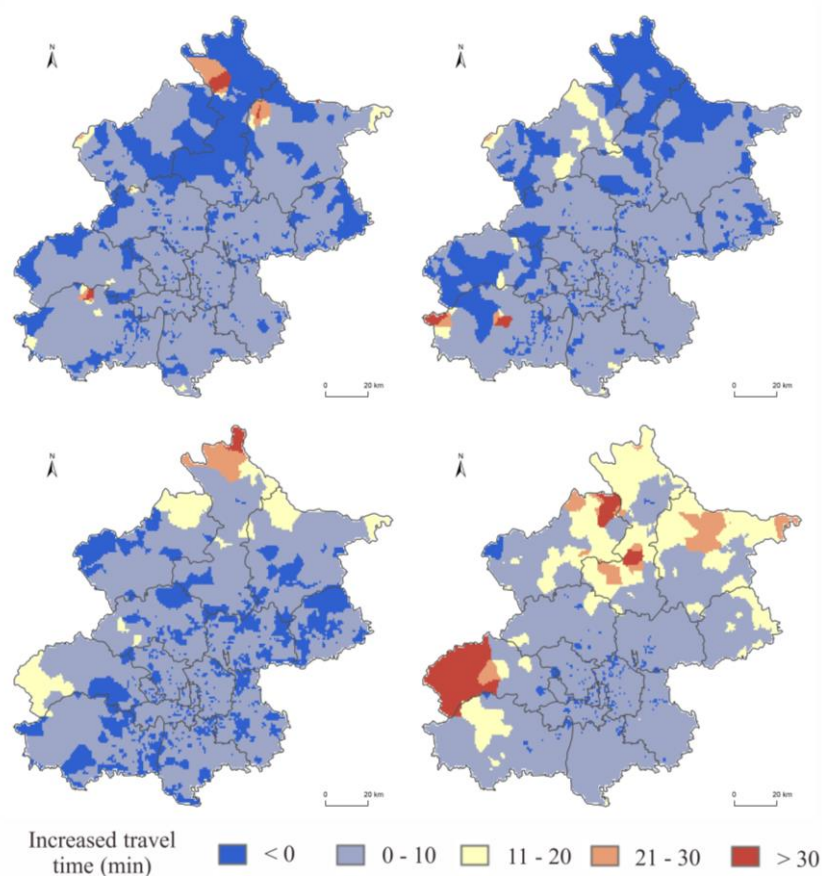
Figure 9. Increased transfer time to hospitals on 1st July, 9th July, 10th September, and 16th December, produced in ArcGIS 10.8 and CorelDraw 2019.

We did a zonal statistic of the average baseline transfer time to hospital and the

average increased transfer time to hospitals to each town, and the correlation between

the two indicators shown in Figure S2 indicate the similar pattern with the EMS

434 coverage, which is the towns with low baseline accessibility to hospitals would also

435 more affected by inclement weather.

436 Overlaying the demographic grid data, the size of the population affected by a

437 delay of over 10 minutes would be 0.02 million on 1st July, 0.03 million on 9th July,

438 0.05 million on 10th September, and 0.3 million on 16th December.

439 Figure 11 shows the change in the total transfer time under inclement weather

440 conditions on 1st July, 9th July, 10th September, and 16th December, relative to the

441 baseline conditions. The results show that on three rainy days, 1st July, 9th July, and 10th

442 September, within the Sixth Ring Road extent, the total transfer time increased

443 significantly under inclement weather, which means that, although the transfer time

444 would not increase much in urban areas, due to the high population density, the

445 cumulative delay time for total potential demand would be significant. In the suburbs,

446 the total transfer time would increase slightly or even decrease, especially in some areas

447 of Huairou, Yanqing, and Miyun districts, which means that, although the transfer time

448 would increase greatly, due to its low population density, the cumulative delay time for

449 total potential demand would not be serious. However, due to the influence of snowfall

450 on 16th December, the total transfer time in the whole city was slightly or moderately

451 increased, and there were almost no regions where the total transfer time decreased,

452 which means snowfall would cause an even cumulation of delay time for total potential

453 demand across the whole city, both urban and suburban.
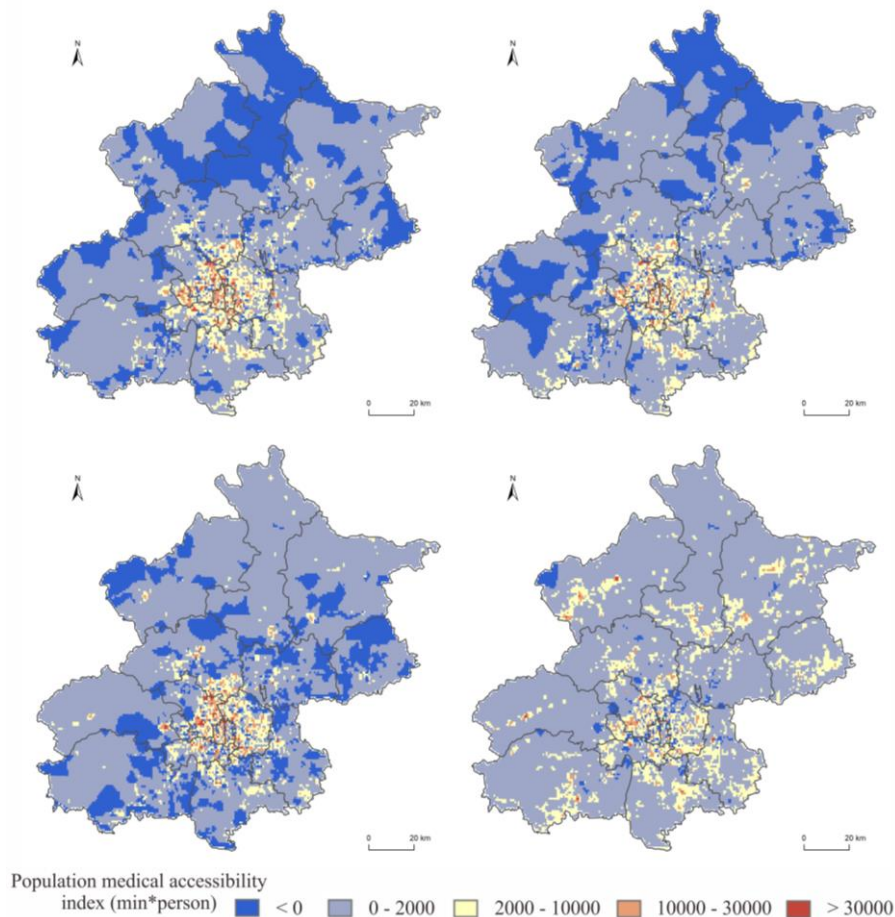
Figure 11. The change in the total transfer time on 1st July, 9th July, 10th September, and 16th December, produced in ArcGIS 10.8 and CorelDraw 2019.

5 Conclusions and discussion

Our 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, and the shortest transfer time to the nearest hospital. Our study reveals the influence of precipitation on the accessibility and equity of EMSs, which could help guide EMS construction planning in cities, get prepared for extreme weather conditions, and finally assist the decision-making of the corresponding government departments. The main

467   conclusions are as follows:

468   First, the results show that inclement weather, such as rainfall and snowfall, could

469   have a negative impact on the accessibility of EMSs overall. Precipitation reduces the

470   driving speed of vehicles on the road, thus reducing EMS coverage. In severe cases, the

471   EMS coverage rate of the area can be reduced by more than 10%. Besides, snowfall has

472   a greater impact on EMSs accessibility than rainfall.

473   Second, the EMSs accessibility is more affected by inclement weather in places with

474   low baseline accessibility to EMSs. And the results reveal a serious rural-urban

475   disparity in emergency medical facilities distribution in Beijing: The EMSs

476   accessibility of population in some townships of the outer suburbs is very low and

477   would also greatly reduce under inclement weather.

478   Third, some specific days may affect the traffic flow, which has an amplification

479   effect on the traffic congestion caused by inclement weather. When they encounter the

480   inclement weather, there are potential risks of decrease of traffic efficiency and EMSs

481   accessibility, which should be given sufficient attention.

482   To the best of our knowledge, there was no studies have been performed to analyze

483   the impact of road access capacity on EMSs accessibility under inclement weather

484   according to actual traffic speed variation. Our study provides an attempt to analyze the

485   spatial accessibility of EMSs under inclement weather based on city-scale ground truth

486   traffic data and meteorological data, where the former is usually difficult to obtain. In

487   previous literatures (Yin et al., 2021; Coles et al., 2017; Albano et al., 2014), simulation

488   methods were widely used on the research on EMSs accessibility or traffic capacity

489   under inclement weather; however, the ground-truth traffic data that covers every road

490   in the whole city under precipitation scenarios, was hardly used in the previous studies

491   of the impact of weather on traffic and accessibility. Our study could be a good

empirical verification in this field of study. We also found that snowfall may have a greater impact, which is hard to find out using flood simulation methods. 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 are also suitable for both holidays and workdays and can be easily applied to other cities once traffic data or empirical formulas regarding the impact of inclement weather on road traffic can be obtained.

There are also some parts in our research that can be improved in future research. First, we averaged the traffic speed reduction rate of all the roads in the city, as well as the precipitation data, which could conceal congestion hotspots. Besides, all the calculation was done by the 2-hour selected period, which may neglect the delayed responses of rainfall runoff and temporal variation of rainfall. In further studies, with higher resolution precipitation, along with corresponding traffic data, we could narrow the scale to blocks, pay more attention to local congestions, and analyze the correlation of precipitation and traffic speed on a finer scale. Second, due to the data limitation, we could only analyze the EMSs accessibility in 2019, and the precipitation intensity in this year was not quite high. If had longer time series precipitation and traffic data, we could analyze the impact of precipitation magnitude to the traffic and accessibility, instead of simply dividing the days in a binary manner into inclement and non-inclement weather days. Under such precipitation conditions, the EMSs accessibility has been affected to a certain extent, and it would be much more difficult to get timely EMSs under even more extreme inclement weather condition. In previous studies, Yin et al. (2021) found that surface water flooding could result in nonlinear impacts on EMS spatial coverage in Shanghai: 5- and 20-year pluvial flooding both exerted very minor

517   and the effect of 100-year surface water flooding appears to be more pronounced.

518   Future studies should take extreme precipitation events into account. Third, due to the

519   lack of high-resolution DSM (Digital Surface Model) data, we did not run a

520   hydrological flood simulation in Beijing, which could reveal the relationship of

521   precipitation and the actual amount of water on the streets. This could be improved in

522   the future studies with more high-resolution topographic data. Fourth, we used the "15-

523   minutes arrival time" as a main boundary in this study, however, the proper response

524   time would vary in different countries or cities. So, the setting of response time

525   boundary should be adjusted considering the actual situation of the city when the

526   method in this paper is applied to other cities. Fifth, we aggregated the population grid

527   evenly in the city. If a varying resolution could have been applied with a finer grid in

528   the heavily populated center, and a coarser grid towards the outskirts, it may capture

529   more of the dynamics in a metropolis with varying population and infrastructure

530   densities.

531   **Appendices**

532   **Supplementary figures**
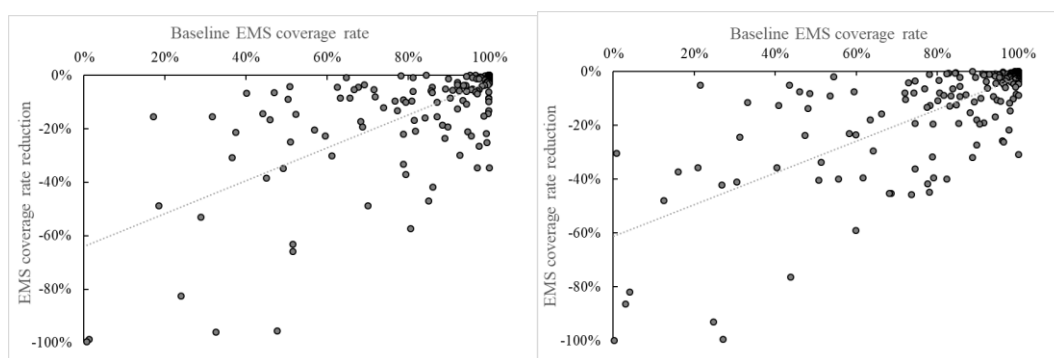
533
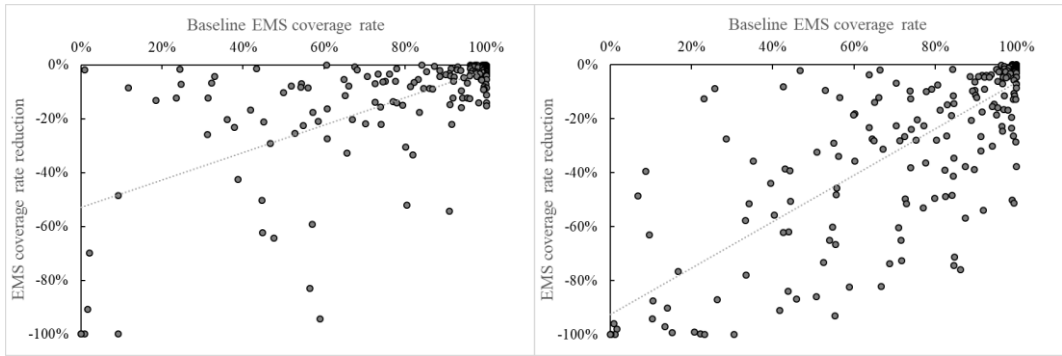
534   (a)   (b)

535

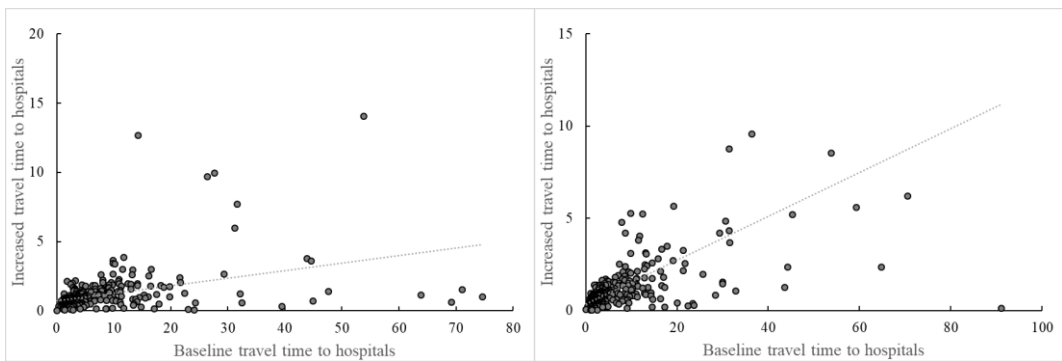536   (c)   (d)

537   **Figure S1.** The correlation between the baseline EMS coverage rate of population and its reduction

538   percentage in inclement weather. (a) 1st July, (b) 9th July, (c) 10th September, and (d) 16th December,

539   produced in Excel 2016.

540

541

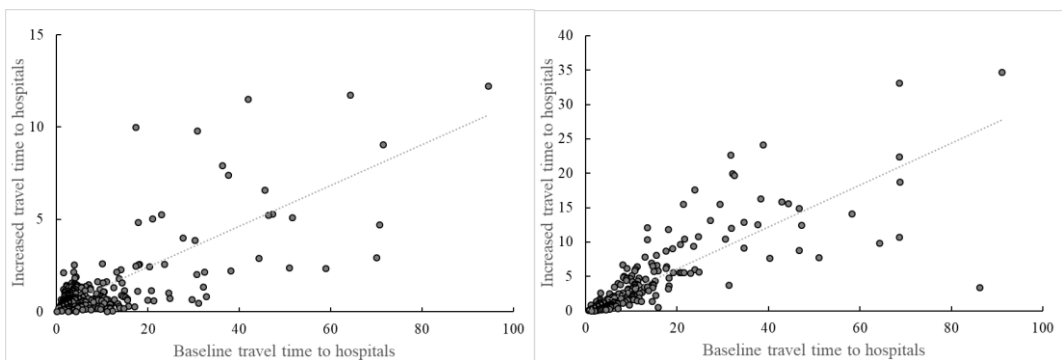542   (a)   (b)

543

544   (c)   (d)

545   **Figure S2.** The correlation between the baseline transfer time to hospitals and the increased transfer

546   time in inclement weather. (a) 1st July, (b) 9th July, (c) 10th September, and (d) 16th December, produced

547   in Excel 2016.

548

Data availability

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

Author contributions

552   KL planned the research; JZ, ML provided the traffic data; YZ and KL analyzed the

553   data, YZ wrote the manuscript draft; KL, XN, MW, and DY reviewed and edited the

554   manuscript.

Competing interests

556   The authors declare that they have no conflict of interest.

Acknowledgments

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, 2847-2865,2014.

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.

Beijing Emergency Medical Center. Available at: https://beijing120.com/channel/184 (last access: 30 August 2021).

Beijing Evening. Beijing rainstorm, 120 calls increased by 1/3, trauma and car accident injury increased significantly. Available at: http://news.sohu.com/20120722/n348746024.shtml (last accessed 30 August 2021), 2012.

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, 288-295,2002.

Business Standard. Ambulances stuck in torrential rain drowning Ctg roads. Available at: https://www.tbsnews.net/bangladesh/ambulances-stuck-torrential-rain-drowning-ctg-roads-283114 (last accessed 1 December 2022), 2019.

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. Geography of Climate Change, Routledge, 2013.

Chen, X., and Jia, P.: A comparative analysis of accessibility measures by the two-step floating catchment area (2sfca) method, Int J Geogr Inf Sci, 33, 1739-1758,2019.

China Meteorological Administration. Classification of precipitation. Available at: https://www.cma.gov.cn/2011xzt/2012zhuant/20120928_1_1_1_1/2010052703/201212/t20121212_19 5616.html (last access: 11 February 2023), 2012.

Chu, L. J., Fwa, T. F.: Pavement skid resistance consideration in rain-related wet-weather speed limits determination[J]. Road materials and pavement design, 19(2), 334-352, 2018.

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, 419-436,2017.

Cools, M., Moons, E., and Wets, G.: Assessing the impact of weather on traffic intensity, Weather, Climate, and Society, 2, 60-68,2010.

Cools, M., Moons, E., and Wets, G.: Investigating effect of holidays on daily traffic counts: time series approach, Transport Res Rec, 2019, 22-31,2007.

Edwards, J. B.: Weather-related road accidents in england and wales: a spatial analysis, J Transp Geogr, 4, 201-212,1996.

Fox8 News. Cleveland ambulance stuck in snow leads to long delay in emergency: I-Team. Available at: https://fox8.com/news/i-team/cleveland-ambulance-stuck-in-snow-leads-to-long-delay-in-emergency-i-team/ (last accessed 1 December 2022), 2021.

Gaode Maps. Available at: https://lbs.amap.com/api/webservice/guide/api/search (lase access: 30 August 2021).

Green, D., Yu, D., Pattison, I., Wilby, R., Bosher, L., Patel, R., Thompson, P., Trowell, K., Draycon, J., and Halse, M.: City-scale accessibility of emergency responders operating during flood events, Nat Hazard Earth Sys, 17, 1-16,2017.

Guagliardo, M. F.: Spatial accessibility of primary care: concepts, methods and challenges, Int J Health Geogr, 3, 1-13,2004.

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, The International journal of health planning and management, 35, 788-798,2020.

Huber, D. G., and Gulledge, J.: Extreme weather and climate change: understanding the link, managing the risk, Pew Center on Global Climate Change Arlington, 2011.

Jin, Daeho, Oreopoulos, Lazaros, Lee, Dongmin, Tan, Jackson, Cho, Nayeong. 2021. Cloud-Precipitation Hybrid Regimes and their Projection onto IMERG Precipitation Data. Vol. -1, No. aop, DOI: 10.1175/JAMC-D-20-0253.1   ISSN: 1558-8424, 1558-8432

Jones, A. P., and Bentham, G.: Emergency medical service accessibility and outcomefrom road traffic accidents, Public Health, 109, 169-177,1995.

Kanuganti, S., Sarkar, A. K., and Singh, A. P.: Quantifying accessibility to health care using two-step floating catchment area method (2sfca): a case study in rajasthan, Transportation Research Procedia, 17, 391-399,2016.

Katz, B., O'Donnell, C., Donoughe, K., Atkinson, J. E., Finley, M. D., Balke, K. N., Kuhn, B. T., and Warren, D.: Guidelines for the use of variable speed limit systems in wet weather. No. FHWA-SA-12-022. United States. Federal Highway Administration. Office of Safety, 2012.

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, 103314,2021.

Luo, W., and Qi, Y.: An enhanced two-step floating catchment area (e2sfca) method for measuring spatial accessibility to primary care physicians, Health Place, 15, 1100-1107,2009.

Luo, W., and Wang, F.: 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 and design, 30, 865-884,2003.

Mao, L., and Nekorchuk, D.: Measuring spatial accessibility to healthcare for populations with multiple transportation modes, Health Place, 24, 115-122,2013.

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,

642   100052,2021.

643   Mohsenizadeh, M., Tural, M. K., and Kentel, E.: Municipal solid waste management with cost

644   minimization and emission control objectives: a case study of ankara, Sustain Cities Soc, 52,

645   101807,2020.

646   National Bureau of Statistics. Bulletin of the National Population Census.   Available at:

647   http://www.stats.gov.cn/tjsj/tjgb/rkpcgb/ (last access: 11 February 2023), 2021.

648   Pan, X., Kwan, M., Yang, L., Zhou, S., Zuo, Z., and Wan, B.: Evaluating the accessibility of healthcare

649   facilities using an integrated catchment area approach, Int J Env Res Pub He, 15, 2051,2018.

650   Ramgopal, S., Siripong, N., Salcido, D. D., and Martin-Gill, C.: Weather and temporal models for

651   emergency medical services: an assessment of generalizability, The American Journal of Emergency

652   Medicine, 45, 221-226,2021.

653   Shin, K., and Lee, T.: Improving the measurement of the korean emergency medical system's spatial

654   accessibility, Appl Geogr, 100, 30-38,2018.

655   Song, X., Zhang, J., AghaKouchak, A., Sen Roy, S., Xuan, Y., Wang, G., He, R., Wang, X., and Liu, C.:

656   Rapid urbanization and changes in spatiotemporal characteristics of precipitation in beijing metropolitan

657   area, J Geophys Res-Atomos, 119, 11250-11271, 2014.

658   Stott, P. A., Christidis, N., Otto, F. E., Sun, Y., Vanderlinden, J. P., van Oldenborgh, G. J., Vautard, R.,

659   von Storch, H., Walton, P., and Yiou, P.: Attribution of extreme weather and climate-related events,

660   Wiley Interdisciplinary Reviews: Climate Change, 7, 23-41,2016.

661   Stott, P.: How climate change affects extreme weather events, SCIENCE, 352, 1517-1518,2016.

662   Suarez, P., Anderson, W., Mahal, V., and Lakshmanan, T. R.: Impacts of flooding and climate change

663   on urban transportation: a systemwide performance assessment of the boston metro area, Transportation

664   Research Part D: transport and environment, 10, 231-244,2005.

665   Wang, J., Du, F., Huang, J., and Liu, Y.: Access to hospitals: potential vs. Observed, CITIES, 100,

666   http://doi.org/10.1016/j.cities.2020.102671, 2020.

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

668   NAT HAZARDS, 67, 969-974,2013.

669   Wang, Y., Zhai, J., and Song, L.: Waterlogging risk assessment of the beijing-tianjin-hebei urban

670   agglomeration in the past 60 years, THEOR APPL CLIMATOL, 145, 1039-1051,2021.

671   WorldPop (www.worldpop.org - School of Geography and Environmental Science, University of

672   Southampton; Department of Geography and Geosciences, University of Louisville; Departement de

673   Geographie, Universite de Namur) and Center for International Earth Science Information Network

674   (CIESIN), Columbia University (2018). Global High Resolution Population Denominators Project -

675   Funded   by   The   Bill   and   Melinda   Gates   Foundation   (OPP1134076).

676   https://dx.doi.org/10.5258/SOTON/WP00645

677   Yang, Y., Yin, J., Ye, M., She, D., and Yu, J.: Multi-coverage optimal location model for emergency

678   medical service (ems) facilities under various disaster scenarios: a case study of urban fluvial floods in

679   the minhang district of shanghai, china, Nat Hazard Earth Sys, 20, 181-195,2020.

680   Yin, J., Yu, D., and Liao, B.: A city-scale assessment of emergency response accessibility to vulnerable

681   populations and facilities under normal and pluvial flood conditions for shanghai, china, Environ PlanB-

682   Urban, 48, 2239-2253, 2021.

683 Yu, D., Yin, J., Wilby, R. L., Lane, S. N., Aerts, J. C., Lin, N., Liu, M., Yuan, H., Chen, J., and

684 Prudhomme, C.: Disruption of emergency response to vulnerable populations during floods, Nature

685 Sustainability, 3, 728-736,2020.

686 Zhang, X., and Chen, M.: Quantifying the impact of weather events on travel time and reliability, J Adv

687 Transport, 2019,2019.

688