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

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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

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

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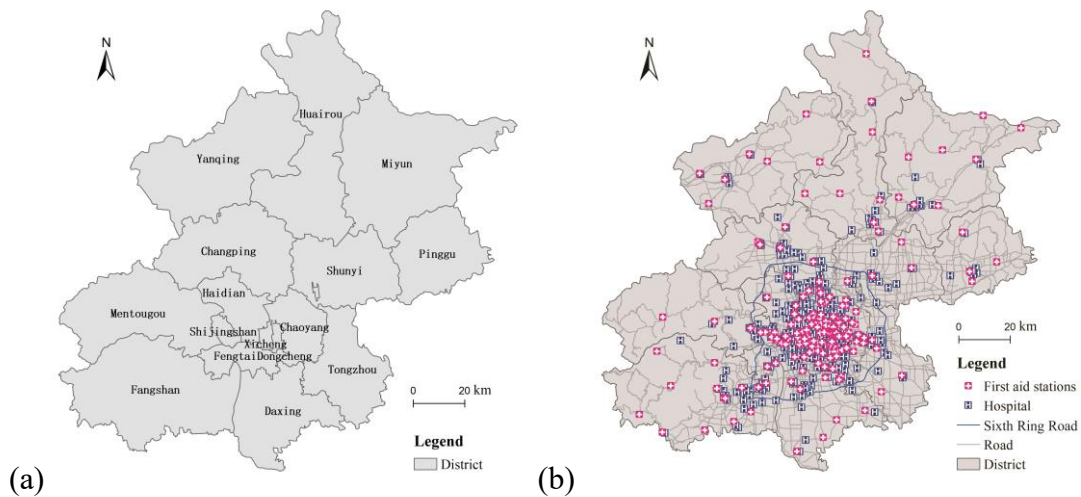
Figure 1. (a) Administrative division of Beijing and (b) EMS facility locations in Beijing, produced in ArcGIS 10.8.

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

160   set a rule that if the precipitation of more than 10 grids (over 5% area of the city) in

161   Beijing is greater than 1.5 mm in 2 hours, it is considered a precipitation event. This

162   amount of precipitation may not high enough to cause the rainfall-runoff exceed the

163   drainage capacity of the sewer network in Beijing (DB11/ 685—2021, DB 11/T 1575—

164   2018). But the precipitation would cause slippery roads and decrease in drivers'

165   visibility, which would lead to a reduction of traffic efficiency and accessibility (Chu

166   and Fwa, 2018; Katz et al., 2012). The average precipitation of the whole city on each

167   date is averaged by the precipitation of all grids. In 2019, 19 working days of rainfall

168   and 3 working days of snowfall were selected.

169

170   **2.2.3 Medical facilities data**

171   The medical facilities mentioned in this paper mainly refer to two categories. One is

172   the first-aid stations, and the other is hospitals, as shown in Figure 1b. The locations of

173   these first-aid stations were obtained from the distribution map of first-aid stations

174   (Beijing Emergency Medical Center, 2021), including 72 stations in the downtown area

175   and 98 stations in the suburbs. The hospital point data were extracted from the online

176   map point of interest (POI) data of Beijing in 2019 (Gaode Maps, 2021). After

177   coordinate correction and deduplication, it contains a total of 630 general hospitals, 76

178   of which are third-level grade-A hospitals (the highest level in the evaluation system of

179   hospitals in mainland China).

180

181   **2.2.4 Demographic data**

182   The demographic data of 2019 were obtained from WorldPop (2018) with a spatial

183   resolution of 100 m×100 m. The data records present the population size.

184

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.
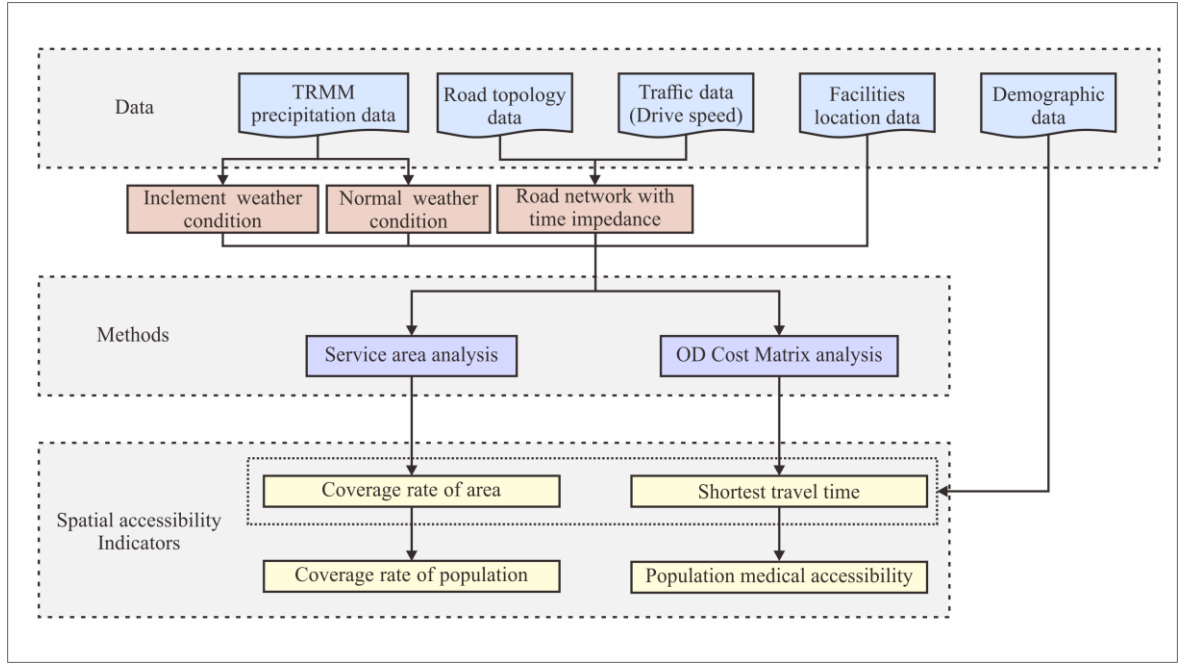
Figure 2. Methodology of this study, produced in CorelDraw 2019.

208 **3.1 Fluctuation of traffic speed under inclement weather**

209   For each weekday with precipitation, the traffic speed data of the selected period are

210 extracted and averaged. To avoid the inherent temporal variations of traffic speed

211 resulting from the day-of-week effects, holiday effects (Cools et al., 2007), season, and

212 other non-meteorological related factors, we introduce baseline days for inclement

213 weather days in this study to calculate the traffic speed fluctuation. For a given

214 precipitation day, we search for the same day of week in the two weeks forward and

215 backward to obtain the corresponding baseline days without precipitation. Only

216 nonholidays without precipitation events are selected as baseline days; otherwise, we

217 would continue to look forward or backward until four baseline days are found. The

218 average speed data of the four baseline days in the selected period were then averaged

219 as the baseline speed for the given precipitation day, and the traffic speed reduction rate

220 was calculated by eq. (1) and eq.(2):

221
$$r_c = \frac{v_p - v_b}{v_b} \qquad (1)$$

10

222   where r_c is the traffic speed reduction rate in the selected period of the

223   precipitation day to its corresponding baseline day; v_p is the traffic speed in the

224   selected period of the given precipitation day, and it is the average of the real-time

225   traffic speed in every 2 minutes during the selected time period in that day; v_b is the

226   traffic speed in the selected period of the baseline precipitation days, which is calculated

227   by eq.(2):

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

229   where v_{d_j} is the traffic speed in the selected period of a baseline day, and it is the

230   average of the real-time traffic speed in every 2 minutes during the selected time period

231   in that day; m is the number of baseline days. In this case, m equals 4. The average

232   traffic speed reduction rate is obtained by averaging the reduction rates of all roads with

233   reduced speed in the city.

234

235   **3.2 Analysis of coverage rate**

236   **3.2.1 The coverage rate of area**

237   A service area is a region that encompasses all roads that are accessible within a

238   specified impedance. Either distance or time can be used as impedance. In this study,

239   the time needed to pass through the road is calculated by the length of each road divided

240   by its corresponding traffic speed, and the service area analysis is carried out with time

241   as the impedance. In different scenarios, the time impedance varies, since the traffic

242   speed of each road is set according to the real-time traffic speed record of the chosen

243   date and chosen period. The core idea of the service area analysis function is to generate

244   service area polygons by setting each first-aid station as the starting point and the

245   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.
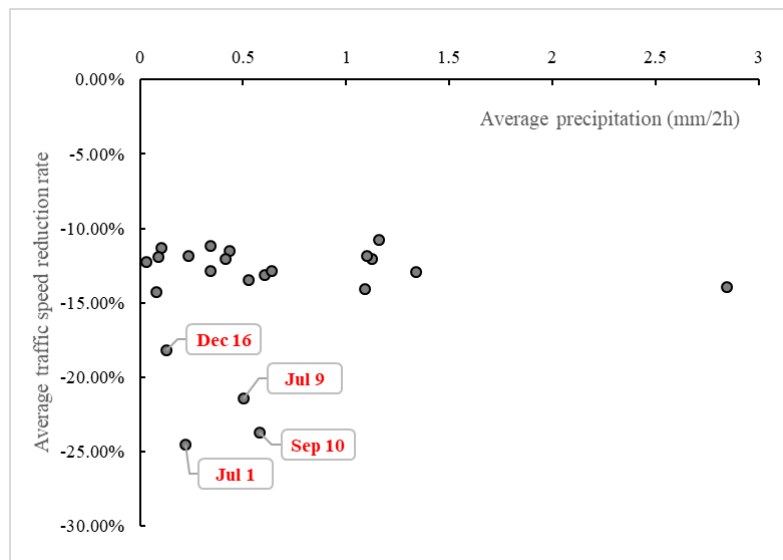
328

329 **Figure 3.** The correlation between average precipitation and average traffic speed reduction rate,
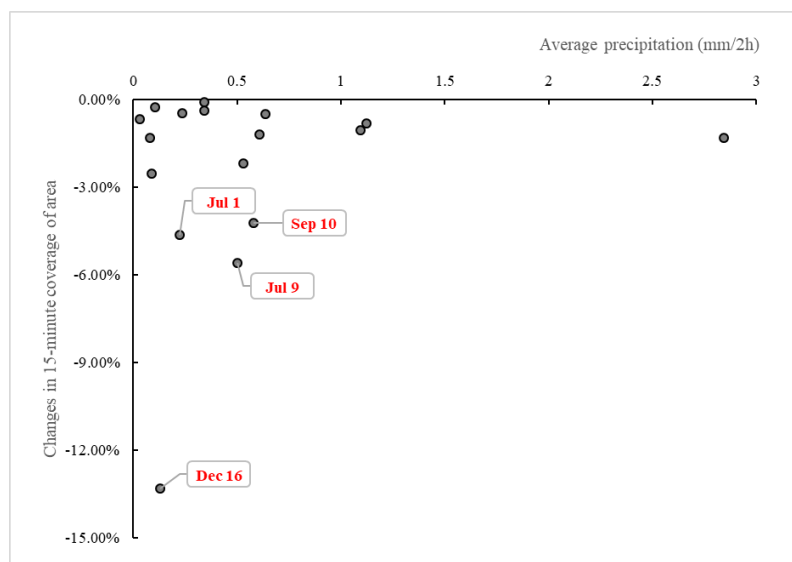
330 produced in Excel 2016.
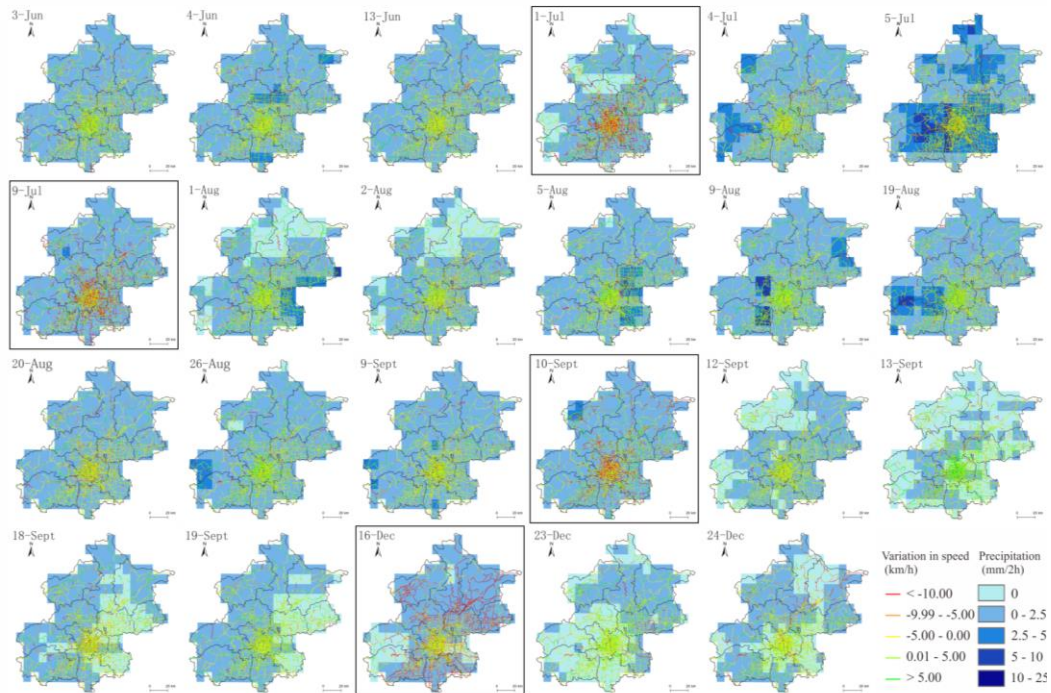
Figure 4. Variation in drive speed and distribution of precipitation on selected precipitation days (the 4 subfigures with black borders shows the 4 most affected scenarios), produced in ArcGIS 10.8 and CorelDraw 2019.

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

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

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

349   accessibility in the whole city.

350

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

353

4.2 The spatial distribution of EMS accessibility under the worst scenario

4.2.1 EMSs coverage rate of population

356   We calculated the 15-minute EMS coverage rate of the population under the four

357   most severely affected inclement weather conditions of 1st July, 9th July, 10th September,

358   and 16th December and their corresponding baseline conditions at the township scale in

359   Beijing. Figure 6 shows the 15-minute EMSs coverage rate of population under four

360   most severely affected inclement weather conditions of 1st July, 9th July, 10th

361   September and 16th December and their corresponding baseline conditions at the

362   township scale in Beijing. The results demonstrate that most parts of downtown areas,

363   including Dongcheng District, Xicheng District, Haidian District, and Chaoyang

364   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.
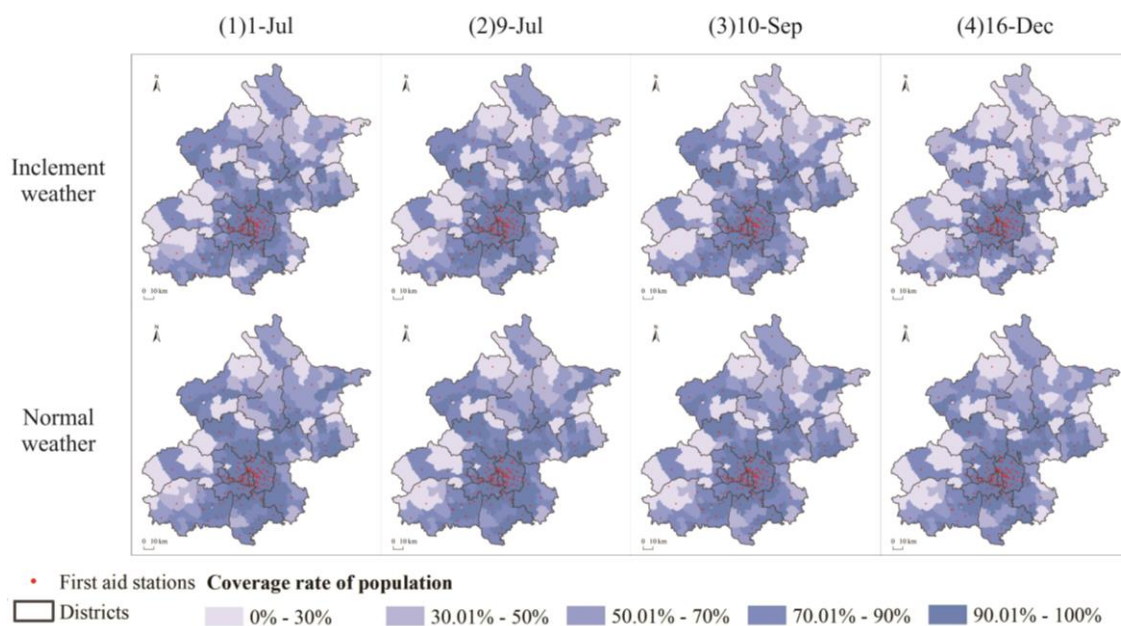
Figure 6. The EMSs coverage rate of population in townships under the inclement weather condition
and normal weather condition on 1st July, 9th July, 10th September and 16th December, produced in
ArcGIS 10.8 and CorelDraw 2019.

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

construction planning. The suburb areas, such as Shunyi, Daxing, and Tongzhou, are more vulnerable to inclement weather as they have less distribution of medical facilities and sparser road networks, as well have a relatively higher proportion of the elderly population over the age of 80. 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 16th, 12.6% of population (3.5 million) could not get EMS within 15 minutes, compared to 7.5% with the baseline condition.
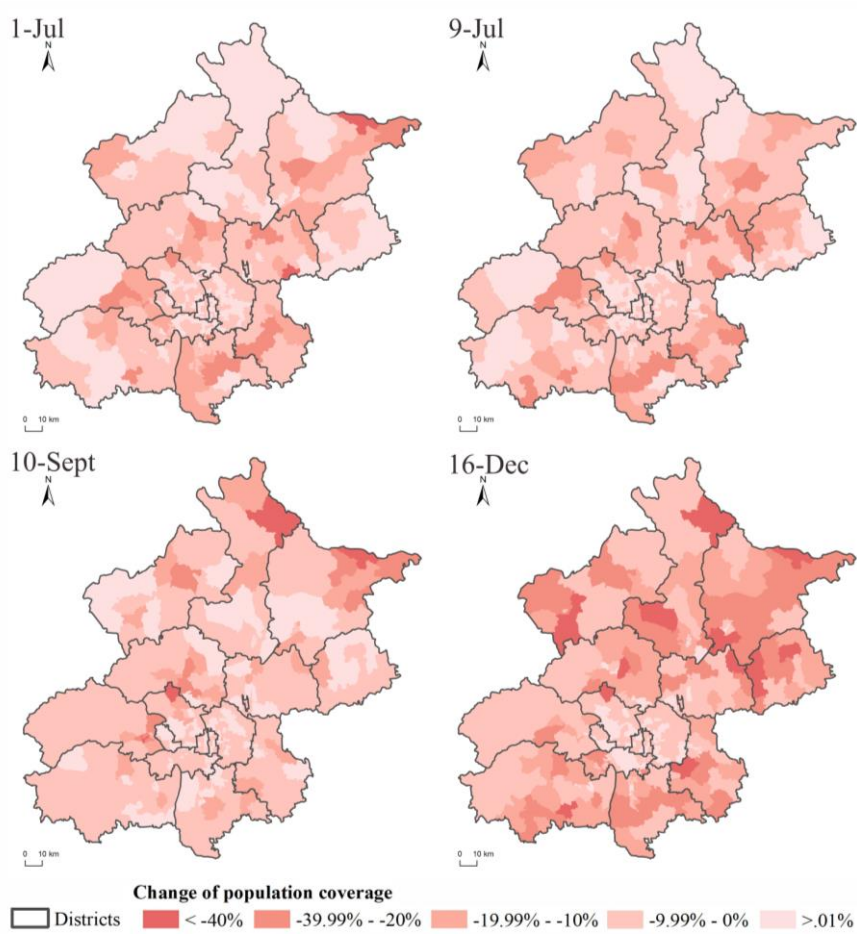
Figure 7. The change in EMS coverage rate of the population in townships in inclement weather relative to normal weather on 1st July, 9th July, 10th September, and 16th December, produced in ArcGIS 10.8 and CorelDraw 2019.

Figure A1 shows the correlation between the baseline EMS coverage rate of the population of each township and its reduction under inclement weather. The results

396   reveal that the population of the towns with low baseline EMS coverage rate would lose

397   more EMS coverage under inclement weather, especially on snowy day. The average

398   traffic speed reduction in the urban area (within the Sixth Ring road) was -26.64%, -

399   23.27%, -25.20% and -15.77% on 1st July, 9th July, 10th September, and 16th

400   December, while that in the suburban area (outside the Sixth Ring Road) was -19.59%,

401   -19.08%, -17.27% and -23.21%. Based on the results, we analyzed the reasons why that

402   suburban area would become more vulnerable under inclement weather. Combined

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

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

405   more EMS coverage loss. Once the inclement weather affects the traffic on some road,

406   the urban areas still have many other roads than can bypass, but not in suburbs. On

407   snowy days, the suburban area has more traffic speed reduction, and with the sparser

408   road network, the EMS coverage in the suburban area would shrink much more than

409   rainy days.

410

411   **4.2.2 The accessibility to hospitals**

412   Figure 8 shows the increased transfer time from each population grid to the nearest

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

414   and 16th December relative to the baseline condition. The value indicates the impact of

415   inclement weather on accessibility to hospitals. The situation is slightly different on

416   rainy days and snowy days. On rainy days, the shortest time to reach the nearest hospital

417   generally could increase by 0–10 minutes in most parts of Beijing due to slower traffic

418   speed on the roads caused by rain. Although in some small parts of suburban areas, the

419   shortest time to the nearest hospital would be slightly shortened on indicating that the

420   traffic will be smoother in some areas when it rains, which may be due to the reduction

421 of traffic demand (Maze et al., 2006). While on 16th December, affected by snow, the

422 whole city's road traffic generally slowed down, and the transfer time to the nearest

423 hospital increased by 10–40 minutes. The western part of Mentougou District and a

424 small part of the northern Yanqing District were the most affected, with the time needed

425 to reach the nearest hospital prolonged by more than 30 minutes, up to 45 minutes. In

426 Huairou district, the eastern part of Yanqing district, and the northern part of Miyun

427 district, the transfer time was also prolonged by 11–30 minutes.
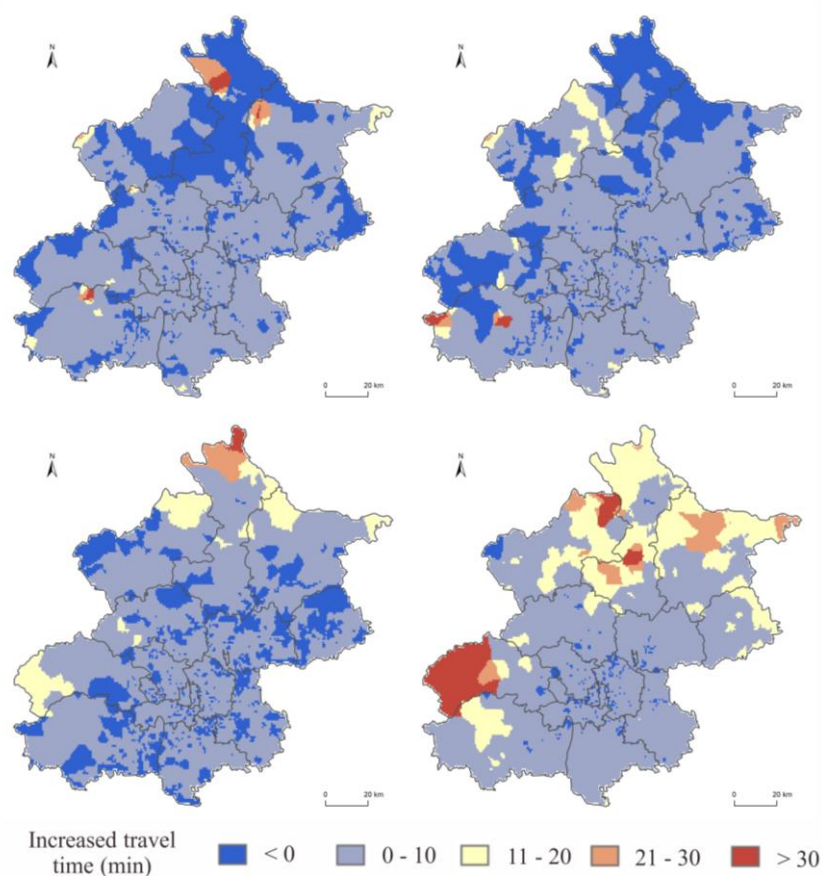
428

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

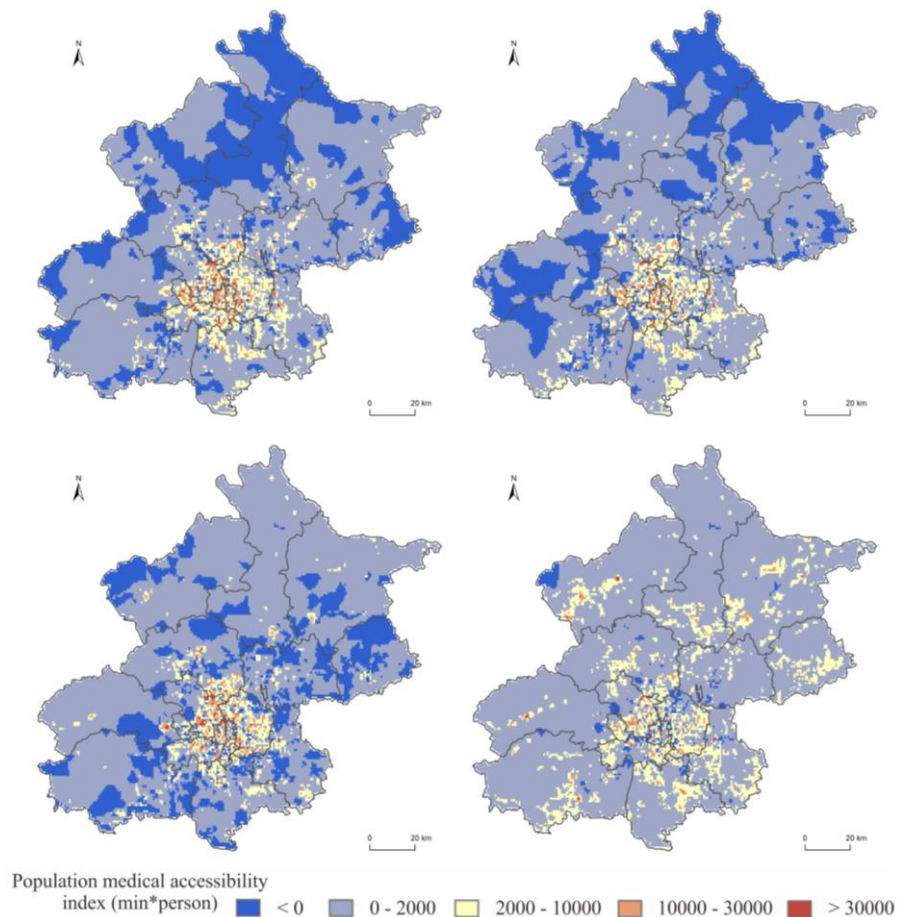430 December, produced in ArcGIS 10.8 and CorelDraw 2019.

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

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

433 the two indicators shown in Figure A2 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 9 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 9. 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

492 empirical verification in this field of study. We also found that snowfall may have a

493 greater impact, which is hard to find out using flood simulation methods. The results

494 from this study provide a scientific reference for city planning departments in Beijing

495 to optimize the site selection of emergency service facilities and get prepared for traffic

496 dispersion on inclement weather. The relevant methods mentioned in this paper are also

497 suitable for both holidays and workdays and can be easily applied to other cities once

498 traffic data or empirical formulas regarding the impact of inclement weather on road

499 traffic can be obtained.

500 There are also some parts in our research that can be improved in future research.

501 First, we averaged the traffic speed reduction rate of all the roads in the city, as well as

502 the precipitation data, which could conceal congestion hotspots. Besides, all the

503 calculation was done by the 2-hour selected period, which may neglect the delayed

504 responses of rainfall runoff and temporal variation of rainfall. In further studies, with

505 higher resolution precipitation, along with corresponding traffic data, we could narrow

506 the scale to blocks, pay more attention to local congestions, and analyze the correlation

507 of precipitation and traffic speed on a finer scale. Second, due to the data limitation, we

508 could only analyze the EMSs accessibility in 2019, and the precipitation intensity in

509 this year was not quite high. If had longer time series precipitation and traffic data, we

510 could analyze the impact of precipitation magnitude to the traffic and accessibility,

511 instead of simply dividing the days in a binary manner into inclement and non-

512 inclement weather days. Under such precipitation conditions, the EMSs accessibility

513 has been affected to a certain extent, and it would be much more difficult to get timely

514 EMSs under even more extreme inclement weather condition. In previous studies, Yin

515 et al. (2021) found that surface water flooding could result in nonlinear impacts on EMS

516 spatial coverage in Shanghai: 5- and 20-year pluvial flooding both exerted very minor

and the effect of 100-year surface water flooding appears to be more pronounced. Future studies should take extreme precipitation events into account. Third, due to the lack of high-resolution DSM (Digital Surface Model) data, we did not run a hydrological flood simulation in Beijing, which could reveal the relationship of precipitation and the actual amount of water on the streets. This could be improved in the future studies with more high-resolution topographic data. Fourth, we used the "15-minutes arrival time" as a main boundary in this study, however, the proper response time would vary in different countries or cities. So, the setting of response time boundary should be adjusted considering the actual situation of the city when the method in this paper is applied to other cities. Fifth, we aggregated the population grid evenly in the city. If a varying resolution could have been applied with a finer grid in the heavily populated center, and a coarser grid towards the outskirts, it may capture more of the dynamics in a metropolis with varying population and infrastructure densities.

Appendices

Appendix A
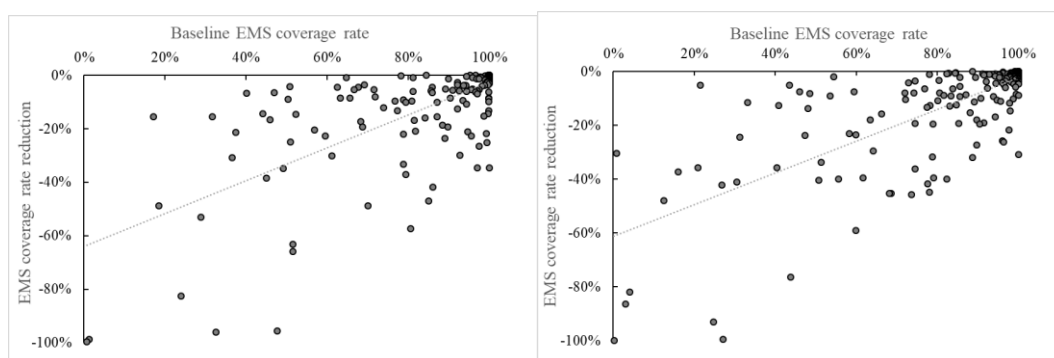
(a)   (b)
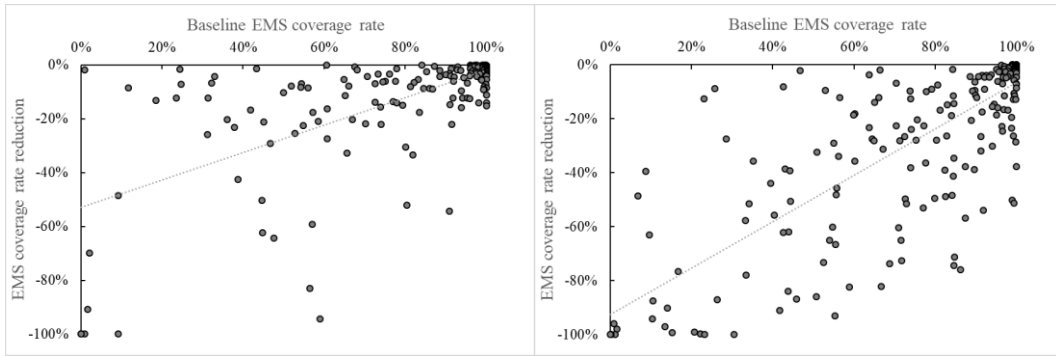
535

536   (c)   (d)
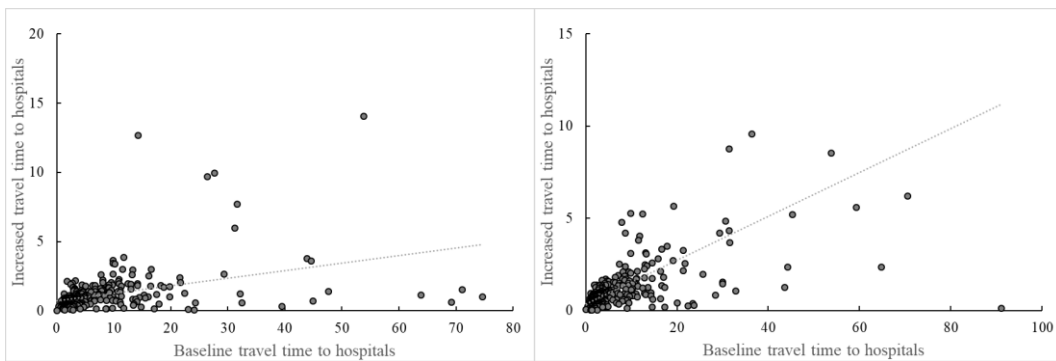
537   **Figure A1.** The correlation between the baseline EMS coverage rate of population and its reduction

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)

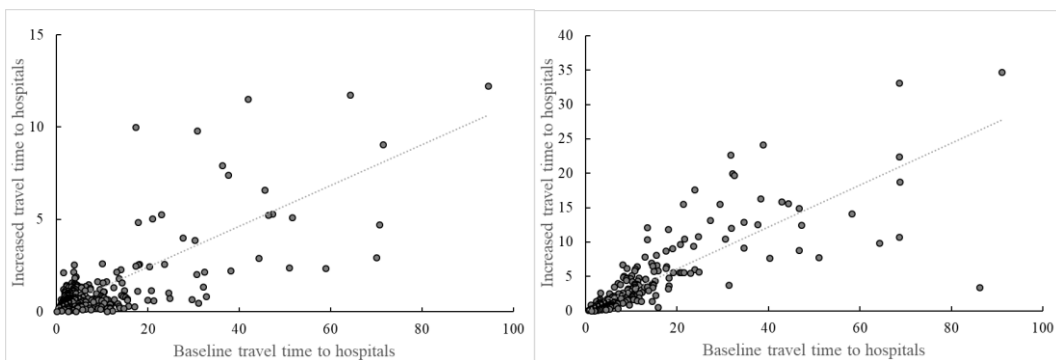543

544   (c)   (d)

545   **Figure A2.** 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

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