

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

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16

17 **Abstract**

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

25 timely EMSs. A case study was implemented in Beijing, which is a typical megacity in
26 China, based on the ground-truth traffic data of the whole city in 2019. The results show
27 that inclement weather has a general negative impact on EMSs accessibility. Under
28 inclement weather scenario, the area in the citywide that could get EMSs within 15
29 minutes would decrease by 13% compared to normal scenario, while in some suburban
30 townships, the population that could get 15-min EMSs would decrease by 40%. And
31 we found that snowfall has a greater impact on the accessibility of EMSs than rainfall.
32 Although on the whole, the urban area would have more traffic speed reduction.
33 Furthermore, towns with lower baseline EMSs accessibility is more vulnerable to
34 inclement weather. Under the worst scenario in 2019, 12.6% of population (about 3.5
35 million) could not get EMSs within 15 minutes, compared to 7.5% with the normal
36 condition. This study could provide a scientific reference for city planning departments
37 to optimize traffic under inclement weather and the site selection of emergency medical
38 facilities.

39

40 **Keywords**

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

43 **1 Introduction**

44 Emergency medical services (EMSs) are a pivotal part of the public health system,
45 and the response time of EMSs is a vital factor in decreasing morbidity and improving
46 survival(Blackwell and Kaufman, 2002). In China, the EMS system is mainly
47 composed of prehospital emergency services and in-hospital emergency services.
48 Prehospital emergency service refers to on-site emergency treatment, guardianship in
49 transit, and handover with in-hospital emergency institutions. The efficiency of
50 emergency services is highly vulnerable to inclement weather conditions such as rain,
51 snow, fog, etc. Because inclement weather conditions would reduce road capacity,
52 increase transfer time, and sometimes block roads completely(Agarwal et al., 2006;
53 Chang et al., 2013; Cools et al., 2010; Suarez et al., 2005; Zhang and Chen, 2019),
54 resulting in reduced spatial accessibility and delayed the response time of EMSs. In
55 addition, accidents such as traffic accidents and lightning accidents are more prone to
56 occur in inclement weather, which increases the demand for EMSs (Edwards, 1996;
57 Ramgopal et al., 2021). For example, on July 21, 2012, Beijing was hit by a rainstorm,
58 with the average cumulative rainfall reaching 170 mm, caused 63 roads to be seriously
59 flooded, and led to a one-third increase in the number of calls to the emergency center,
60 and the transfer time of ambulances was significantly prolonged, taking approximately
61 1.5~2 hours for each evacuation during the rainstorm, while the transfer time wouldn't
62 be more than 1 hour on usual (Wang et al., 2013; Beijing Evening,2012). On February
63 6, 2022, in Cleveland, US, an ambulance got stuck in the snow causing a long delay
64 getting the patient to the hospital (Fox 8 News, 2022). On August 3, 2021, in
65 Chattogram, Bangladesh, a daily rainfall of 190.6mm caused many ambulances with
66 patients stuck in different areas of the city (Business Standard, 2021). In the context of

67 global climate change and rapid urbanization, extreme inclement weather events strike
68 cities more frequently (Huber and Gullede, 2011; Stott, 2016; Stott et al., 2016), the
69 problem of urban rainstorms and waterlogging (the phenomenon of a stagnant water
70 disaster in an urban area due to heavy rainfall or continuous precipitation) has become
71 increasingly prominent. It is therefore of great importance to investigate the influence
72 of inclement weather on the spatial accessibility of EMSs.

73 The spatial accessibility of EMSs is defined by the travel impedance (distance or
74 time) between service locations and the scene (Guagliardo, 2004). A large body of
75 research on spatial accessibility is concerned with access to hospitals (Luo and Wang,
76 2003; Mao and Nekorchuk, 2013; Pan et al., 2018; Yang et al., 2020; Yin et al., 2021)
77 and first-aid stations (Hashtarkhani et al., 2020; Jones and Bentham, 1995; Shin and
78 Lee, 2018). To measure the EMSs accessibility, the two-step floating catchment area
79 (2SFCA) method is one of the common methods (Chen and Jia, 2019; Kanuganti et al.,
80 2016; Li et al., 2021; Luo and Qi, 2009). The 2SFCA method considers accessibility to
81 be mediated by not only the distance decay but also the interactions between supply
82 and demand (Chen and Jia, 2019), which is more suitable for normal scenarios. While
83 for studies focusing on the influence of inclement weather on EMSs, people concern
84 more about the transportation situation, instead of the interaction between supply and
85 demand. The coverage analysis method (Coles et al., 2017; Green et al., 2017; Yu et al.,
86 2020) or shortest path analysis method (Albano et al., 2014; Andersson and Stålhult,
87 2014) are more widely used. These methods could better characterize the reduction of
88 accessibility caused by the road service degradation. For example, Yu et al. (2020)
89 analyzed the accessibility of emergency service in England and identified vulnerability
90 hotspots by quantifying the EMSs coverage of area and population within different time
91 radii under different flood scenarios; Coles et al. (2017) measured the travel time and

92 service area coverage of EMSs in York, UK under flood scenarios by using FloodMap-
93 HydroInundation2D to model flood inundation; Yin et al. (2021) assessed the
94 vulnerability of EMSs to surface water flooding in Shanghai, China by quantifying
95 accessibility in terms of service area, response time, and population coverage,
96 considering four temporal scenarios (nighttime, evening, daytime, and morning-
97 evening peak) of average drive speeds based on a real-time traffic analysis from GPS
98 big data; Andersson and Stålhult (2014) used network analysis methods to generate the
99 shortest paths from hospitals to various administrative areas in Manila, Philippines, and
100 evaluated the impact of different flood events on these paths. Most of these studies
101 assumed that roads are impassable or traffic speed has a certain degree of reduction
102 when the flooded water depth reaches a specific depth, and further evaluated the impact
103 of rainstorm on EMSs accessibility. Due to insufficient recorded traffic data, relatively
104 few studies have been performed to analyze the impact of road access capacity on EMSs
105 accessibility according to actual traffic speed variation.

106 In this study, we explore the impact of inclement weather on traffic and EMS
107 accessibility based on ground-truth traffic data. Beijing which is the capital of China is
108 used as a case study. The reductions in EMSs accessibility of Beijing under inclement
109 weathers in 2019 are quantified, and the urban-rural disparities in the distribution of
110 emergency medical facilities are further analyzed. Our study provides an approach for
111 evaluating the effectiveness and fairness of EMSs based on ground-truth traffic data,
112 and the results can not only provide reference for the optimization of EMSs in Beijing,
113 but also provide reference cases for other cities, which has a great practical significance.

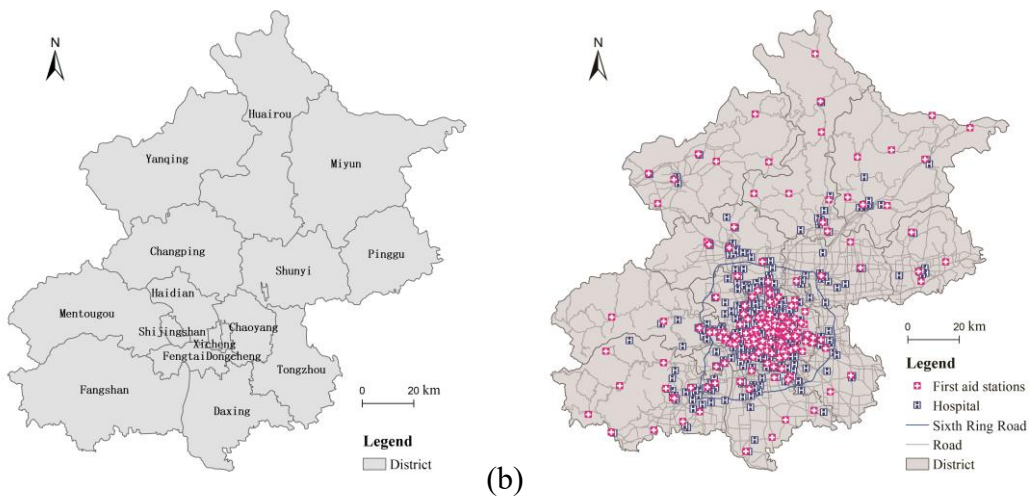
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115 **2 Study area and dataset**

116 **2.1 Study area**

117 Beijing, the capital of China, is located in the northern part of the North China Plain,
118 with a total area of 16,410.54 square kilometers (Figure 1a). According to the seventh
119 national census (<http://www.stats.gov.cn/tjsj/tjgb/rkpcgb/>), Beijing has a population of
120 21.89 million. As one of the largest metropolises in the world, Beijing has a monsoon-
121 driven humid continental climate, with an average annual precipitation of
122 approximately 600 mm, 80% of which is concentrated from June to September (Song
123 et al., 2014). The terrain of Beijing is high in the northwest and low in the southeast,
124 which is conducive to the formation of heavy rain and triggers strong convective
125 weather. Beijing has a typical monocentric urban structure, and the area within the Six
126 Ring Road is generally recognized as the urban core area. It is obvious that the density
127 of transportation network and medical facilities in the urban area of Beijing are much
128 higher than those in the suburbs (Figure 1b).

129



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

132

133 2.2 Dataset

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

142

143 2.2.1 Traffic and road network data

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

149

150 2.2.2 Meteorological data

151 The meteorological data utilized in this paper are TRMM precipitation data
152 obtained from NASA, with a spatial resolution of $0.1^{\circ} \times 0.1^{\circ}$ (approximately $10 \text{ km} \times 10$
153 km) and a temporal resolution of 30 minutes. The whole city of Beijing is covered by
154 175 grids.

155 According to the China Meteorological Administration, the moderate rain is defined
156 as the rainfall is 5.0~14.9 mm within 12 hours. We chose intermediate value of the
157 interval and average it to each hour. In this study, we set a rule that if the precipitation

158 of more than 10 grids (over 5% area of the city) in Beijing is greater than 1.5 mm in 2
159 hours, it is considered a precipitation event. The average precipitation of the whole city
160 on each date is averaged by the precipitation of all grids. In 2019, 19 working days of
161 rainfall and 3 working days of snowfall were selected.

162

163 **2.2.3 Medical facilities data**

164 The medical facilities mentioned in this paper mainly refer to two categories. One is
165 the first-aid stations, and the other is hospitals, as shown in Figure 1b. The locations of
166 these first-aid stations were obtained from the distribution map of first-aid stations
167 published on the official website of the Beijing Emergency Center, including 72 stations
168 in the downtown area and 98 stations in the suburbs. The hospital point data were
169 extracted from the online map point of interest (POI) data of Beijing in 2019. After
170 coordinate correction and deduplication, it contains a total of 630 general hospitals, 76
171 of which are third-level grade-A hospitals (the highest level in the evaluation system of
172 hospitals in mainland China).

173

174 **2.2.4 Demographic data**

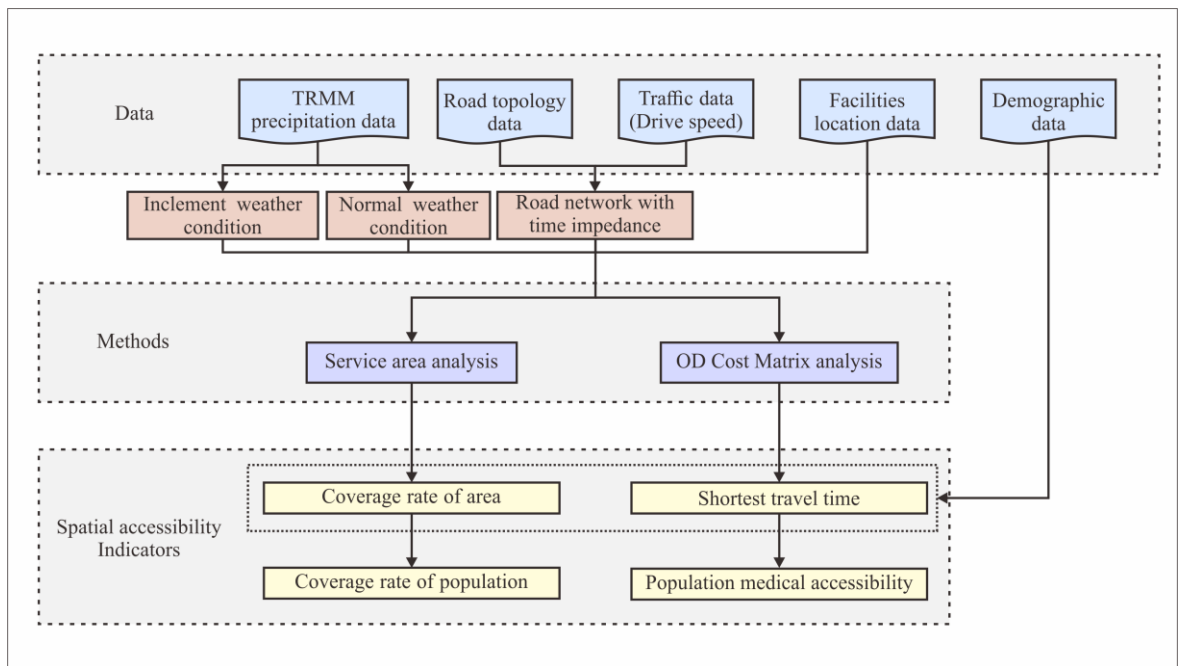
175 The demographic data of 2019 were obtained from WorldPop with a spatial
176 resolution of 100 m×100 m. The data records present the population size.

177

178 **3 Methodology**

179 Figure 2 illustrates the methodology of this study. We first divide the weather
180 conditions into two categories, inclement weather conditions and normal weather
181 conditions, according to precipitation data. Second, the time impedance of each road

182 section is analyzed based on the road network and traffic speed for both inclement and
 183 normal weather conditions, and the respective coverage rate of first-aid stations and the
 184 shortest transfer time to hospitals are calculated. Finally, the spatial accessibility to the
 185 population is calculated, and hotspots are identified. Both service area analysis and OD
 186 Cost Matrix analysis are GIS-based, and was done in ArcGIS 10.8. In this study, we
 187 assume that (1) The ambulances move at the average speed all the time and would
 188 always take the shortest path in space; (2) In network analysis, the location of facilities
 189 is approximately considered to be on the nearest road point vertically; (3) In OD
 190 analysis, we use the centroid as the origin point to represent the whole grid, and the
 191 shortest path to hospital of all points within the grid is the same; (4) The prehospital
 192 EMSs is divided into two parts: the ambulances depart from the first-aid station to the
 193 scene and from the scene to the nearest hospital. The case where patients transfer
 194 directly from the scene to an EMS facility via private transportation will not be
 195 considered in this study.



196

197

Figure 2. Methodology of this study

198 3.1 Fluctuation of traffic speed under inclement weather

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

$$211 \quad r_c = \frac{v_p \frac{\sum_{j=0}^m v_{d_j}}{m}}{\frac{\sum_{j=0}^m v_{d_j}}{m}} \quad (1)$$

212 where r_c is the traffic speed reduction rate in the selected period of the precipitation
213 day to its corresponding baseline days; v_p is the traffic speed in the selected period of
214 the given precipitation day; v_{d_j} is the traffic speed in the selected period of a baseline
215 day, and m is the number of baseline days. In this case, m equals 4. The average traffic
216 speed reduction rate is obtained by averaging the reduction rates of all roads with
217 reduced speed in the city.

218 3.2 Analysis of coverage rate

219 3.2.1 The coverage rate of area

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

221 specified impedance. Either distance or time can be used as impedance. In this study,
222 the time needed to pass through the road is calculated by the length of each road divided
223 by its corresponding traffic speed, and the service area analysis is carried out with time
224 as the impedance. The core idea of the service area analysis function is to generate
225 service area polygons by setting each first-aid station as the starting point and the
226 traveling time as the driving radius. Under the inclement weather conditions and their
227 corresponding baseline conditions, the service area analysis of the 15-minute(Yin et al.,
228 2021) arrival time was carried out. The total area of the obtained service area polygon
229 is calculated to obtain the EMS coverage. The coverage rate of area is calculated by eq.
230 (2):

$$231 \quad r_a = \frac{\sum A_s}{A} \times 100\% \quad (2)$$

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

234 **3.2.2 The coverage rate of population**

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

$$244 \quad r_p = \frac{\sum P_s}{P} \times 100\% \quad (3)$$

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

247

248 3.3 The spatial accessibility to hospitals

249 The spatial accessibility to hospitals is quantified by two indicators: the shortest
250 transfer time and the total transfer time. The shortest transfer time is calculated by the
251 OD (Origin-destination) cost matrix analysis method, which can find and measure the
252 minimum cost path from multiple starting points to single or multiple destinations in
253 the network. In this study, we calculate the minimum transfer time od_i required for
254 each population grid centroid to reach the nearest hospital. To reduce the calculation
255 cost, the population grid data with 100 m resolution are aggregated and converted into
256 1000 m resolution. This could be interpreted as a sampling method, because we use the
257 centroid point of the grid to represent the other possible starting points in the grid, and
258 we ignored the tolerance caused by the travel time inside the grids.

259 The total transfer time is introduced to quantify the cumulative transfer time for each
260 population grid based on its population size, which is the number of potential users of
261 EMSs. It is defined in this study by the shortest transfer time of each population grid to
262 the nearest hospital multiplied by its population. For each population grid centroid i , its
263 population medical accessibility index (PA) is calculated by eq.(4):

$$264 \quad PA = od_i \times P_i \quad (4)$$

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

266

267 4 Results

268 Based on the characteristics of morning and evening rush traffic flow on weekdays,

269 the diurnal variation in traffic can be divided into four periods: morning rush hours
270 (7:00-9:00), daily regular hours (9:00-17:00), evening rush hours (17:00-19:00), and
271 evening regular hours (19:00-22:00). We compared EMS coverage at different periods
272 of the day, and the results show that the period of morning rush hours has the most
273 significant negative impact on the accessibility of EMSs. We divided the city into the
274 inner city and suburban areas along the Sixth Ring Road. Taking the average 15-minute
275 coverage of the area of all Mondays in November as an example: (1) in the whole city
276 (both inner city and suburban), the coverage rate of EMSs is 38.72% in morning rush
277 hours, compared with 40% ($\pm 0.3\%$) in the remaining periods; (2) in the inner city, the
278 coverage rate is 77.37% in morning rush hours, compared with 83% ($\pm 0.6\%$) in the
279 remaining periods. Therefore, the accessibility of EMSs during the morning rush period
280 deserves more attention. Hence, our subsequent analysis is mainly concentrated on the
281 morning rush period.

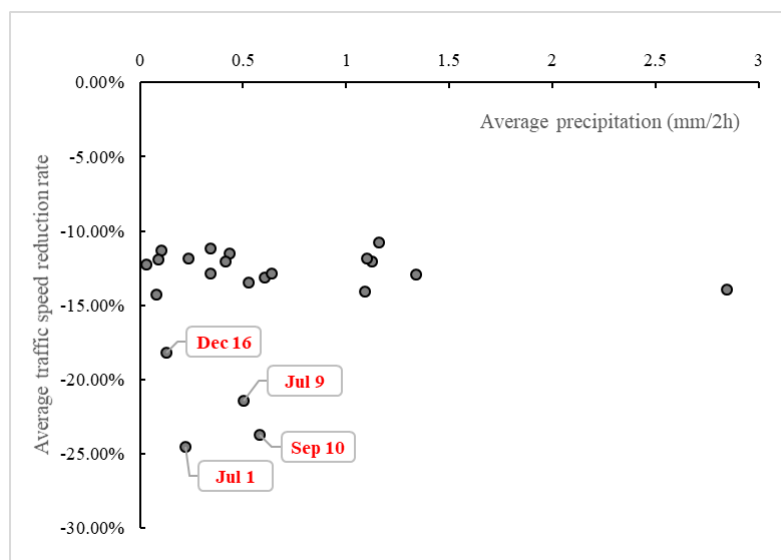
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283 **4.1 Impact of inclement weather on the traffic and EMSs coverage**

284 **4.1.1 The correlation between precipitation and traffic speed**

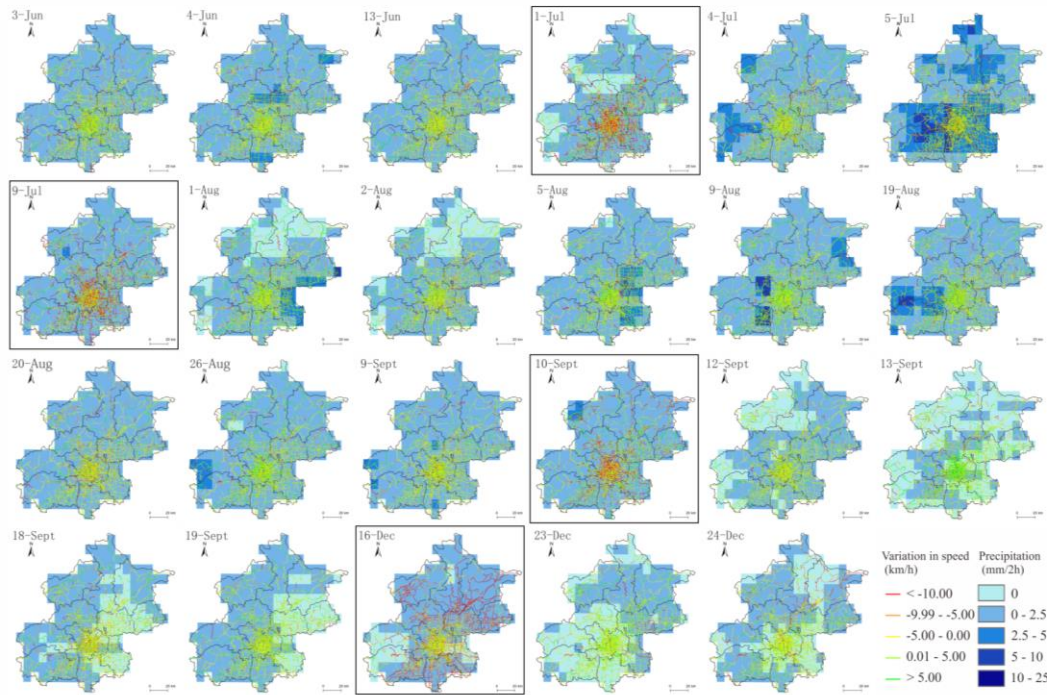
285 Figure 3 shows the relationship between average precipitation during morning rush
286 hours in the city and the average traffic speed reduction rate of all roads that have speed
287 loss in the city on weekdays. The unit of precipitation data is mm/2h, which indicates
288 the total precipitation in the 2 hours of morning rush hours. The negative values indicate
289 that the traffic speed decreases in inclement weather conditions. We could see that the
290 average traffic speed would decrease 10%~15% on most precipitation days. The
291 average speed decreases most on July 1st, July 9th, September 10th and December 16th,
292 reached 18%~25%. July 1st (Party's Day) and September 10th (Teachers Day) are special
293 days in China and the traffic speed is affected by both the inclement weather and traffic

294 control. December 16th was a snowy day with a precipitation of 0.13 mm/2h, and
 295 snowfall has a greater impact on traffic than a rainfall with the same precipitation
 296 (Agarwal et al., 2005). Figure 4 illustrates the spatial difference of traffic speed
 297 reduction and distribution of precipitation on precipitation days. A large number of red
 298 roads (with traffic speed reduction over 10 km/h) can be observed in the 4 days
 299 mentioned above. By comparing the distribution of precipitation and traffic speed
 300 reduction on different dates in Figure 4, it can be found that the precipitation in the four
 301 days with the most severe speed reduction was moderate, and the precipitation
 302 distribution of the whole city was relatively uniform. Compared with other rain days,
 303 although the precipitation on July 5, August 9 and September 19 was larger and
 304 concentrated in the inner city, the traffic speed reduction of the whole city was not as
 305 serious as the four days mentioned above, which may be caused by the decrease of
 306 people's willingness to travel with the increase of rain.



307

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



309

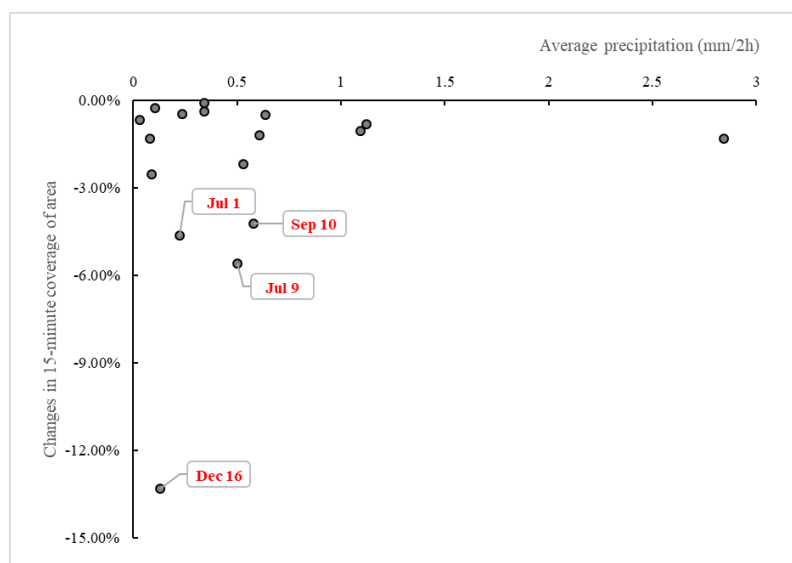
310 **Figure 4.** Variation in drive speed and distribution of precipitation on selected precipitation days

311 (the 4 subfigures with black borders shows the 4 most affected scenarios)

312 4.1.2 The correlation between precipitation and EMSs coverage rate

313 The change in the coverage rate of EMSs was calculated by subtracting the coverage
 314 rate under the inclement weather condition from that under the corresponding baseline
 315 condition. Figure 5 shows the correlation between the average precipitation during
 316 morning rush hours and the relative change values of the EMS coverage rate of the area.
 317 The negative values indicate that the coverage of EMSs decreases in inclement weather
 318 conditions. Consistent with the pattern of the traffic speed reduction, the worst loss of
 319 coverage rate also occurred on three rainy days: 1st July (Mon), 9th July (Tue), and 10th
 320 September (Tue), and one snowy day: 16th December (Mon), in which the 15-minute
 321 EMS coverage rate reduced by 4.6%, 5.6%, 4.2% and 13.3%. Combined with the spatial
 322 distribution of precipitation and traffic variation (Figure 4) to analyze, the snowfall on
 323 December 16th caused a large traffic speed reduction of the suburban roads, which led
 324 to a significant reduction in overall EMS coverage. Therefore, we chose these four days

325 as the worst weather scenario of the year and analysis the spatial differences of medical
326 accessibility in the whole city.



327

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

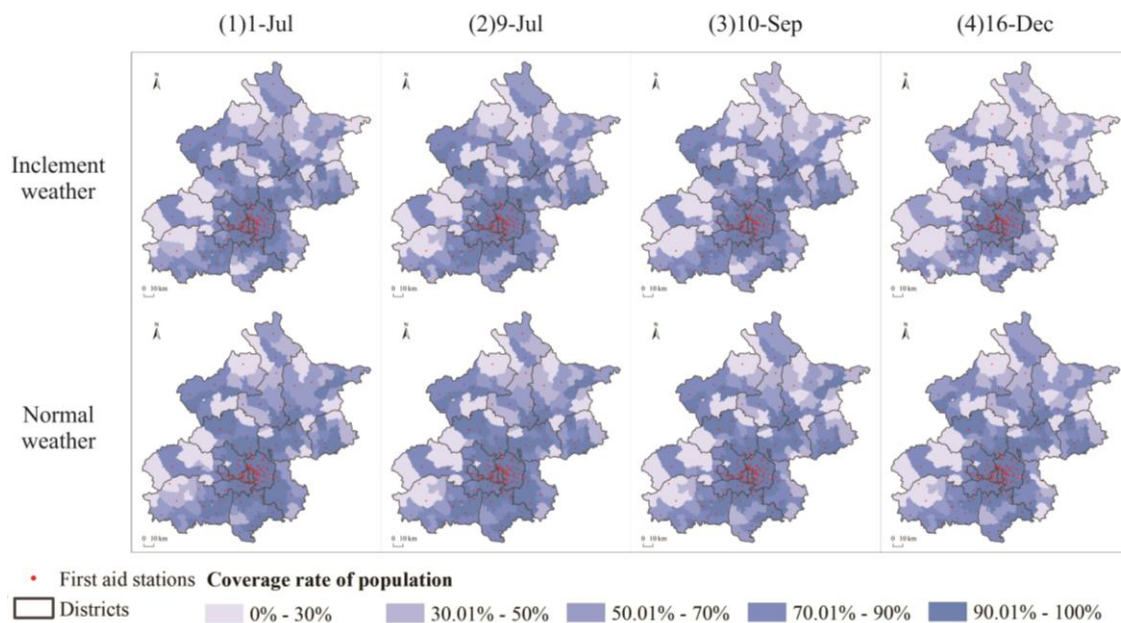
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331 4.2 The spatial distribution of EMS accessibility under the worst scenario

332 4.2.1 EMSs coverage rate of population

333 We calculated the 15-minute EMS coverage rate of the population under the four
334 most severely affected inclement weather conditions of 1st July, 9th July, 10th September,
335 and 16th December and their corresponding baseline conditions at the township scale in
336 Beijing. Figure 6 shows the 15-minute EMSs coverage rate of population under four
337 most severely affected inclement weather conditions of 1st July, 9th July, 10th
338 September and 16th December and their corresponding baseline conditions at the
339 township scale in Beijing. The results demonstrate that most parts of downtown areas,
340 including Dongcheng District, Xicheng District, Haidian District, and Chaoyang
341 District, could have 90%–100% population coverage of EMSs, regardless of the
342 weather conditions. In the large area of suburbs, the coverage rate of the population

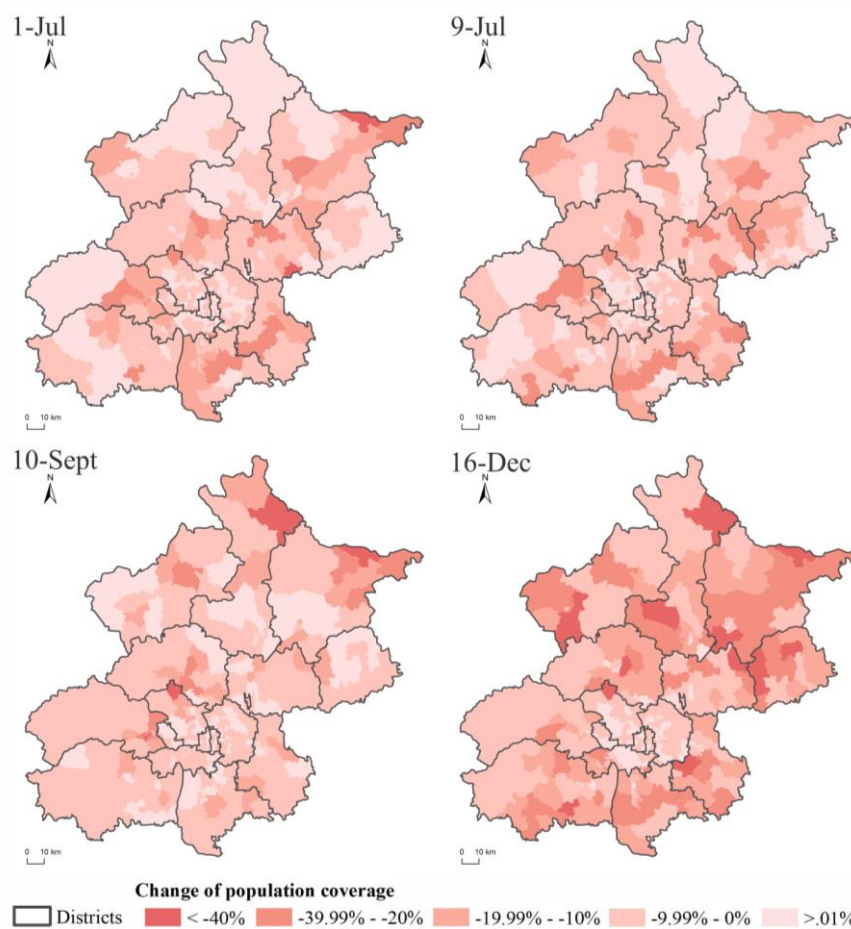
343 varied from lower than 30% to 90%. Under inclement weather conditions, the coverage
 344 rate in some towns in the suburbs would drop sharply, with the worst townships having
 345 a 40% reduction. The reason behind this difference is that the distribution of first-aid
 346 stations in Beijing is similar to the distribution of the road network, which is dense in
 347 the central urban area and sparse in the suburbs.



348
 349 **Figure 6. The EMSs coverage rate of population in townships under the inclement weather condition**
 350 **and normal weather condition on 1st July, 9th July, 10th September and 16th December**
 351

352 To illustrate the impact of inclement weather on the EMS coverage rate of the
 353 population more clearly, Figure 7 shows the change in the EMS coverage rate of the
 354 population in townships in inclement weather relative to normal weather on the four
 355 days. The results identify several townships in the outer suburbs (Miyun, Huairou,
 356 Pinggu and Yanqing districts) that would experience the most severe decrease in
 357 population coverage under inclement weather conditions, with a maximum reduction
 358 of more than 40%. These areas are hot spots that need to draw attention in EMS
 359 construction planning. Compared with other districts in inner suburbs, such as Shunyi,

360 Daxing, and Tongzhou, these areas are farther away from the city center and have less
 361 distribution of medical facilities and sparser road networks and more vulnerable to
 362 inclement weather, and these areas are also regions with a relatively higher proportion
 363 of the elderly population over the age of 80 in the total population. The average
 364 proportion of the elderly is 1.88% in the whole city, 1.37% in the inner suburbs and
 365 2.04% in the outer suburbs. On December 16th, 12.6% of population (3.5 million) could
 366 not get EMS within 15 minutes, compared to 7.5% with the baseline condition.

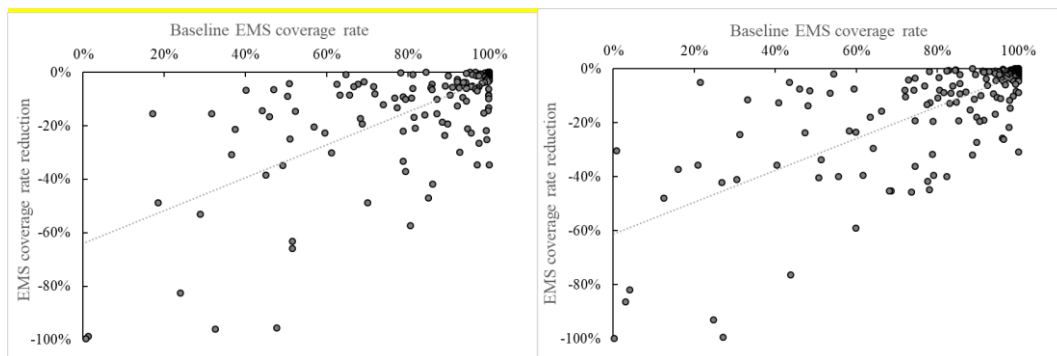


368 **Figure 7.** The change in EMS coverage rate of the population in townships in inclement weather
 369 relative to normal weather on 1st July, 9th July, 10th September, and 16th December

370
 371 Figure 8 shows the correlation between the baseline EMS coverage rate of the
 372 population of each township and its reduction under inclement weather. The results

373 reveal that the population of the towns with low baseline EMS coverage rate would lose
 374 more EMS coverage under inclement weather, especially on snowy day. The average
 375 traffic speed reduction in the urban area (within the Sixth Ring road) was -26.64%, -
 376 23.27%, -25.20% and -15.77% on 1st July, 9th July, 10th September, and 16th
 377 December, while that in the suburban area (outside the Sixth Ring Road) was -19.59%,
 378 -19.08%, -17.27% and -23.21%. Based on the results, we analyzed the reasons why that
 379 suburban area would become more vulnerable under inclement weather. Combined
 380 with the traffic speed reduction and the EMS coverage reduction, on rainy days,
 381 although the urban area has more traffic speed loss, the suburban area still experiences
 382 more EMS coverage loss. Once the inclement weather affects the traffic on some road,
 383 the urban areas still have many other roads than can bypass, but not in suburbs. And on
 384 snowy days, the suburban area has more traffic speed reduction, and with the sparser
 385 road network, the EMS coverage in the suburban area would shrink much more than
 386 rainy days.

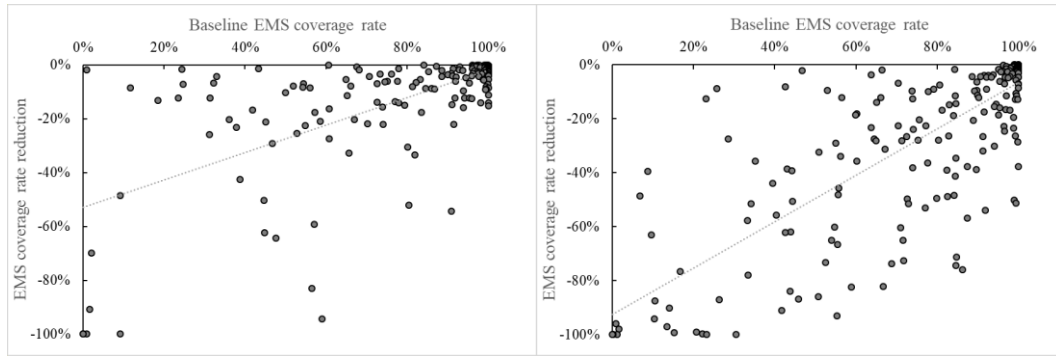
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(a) (b)



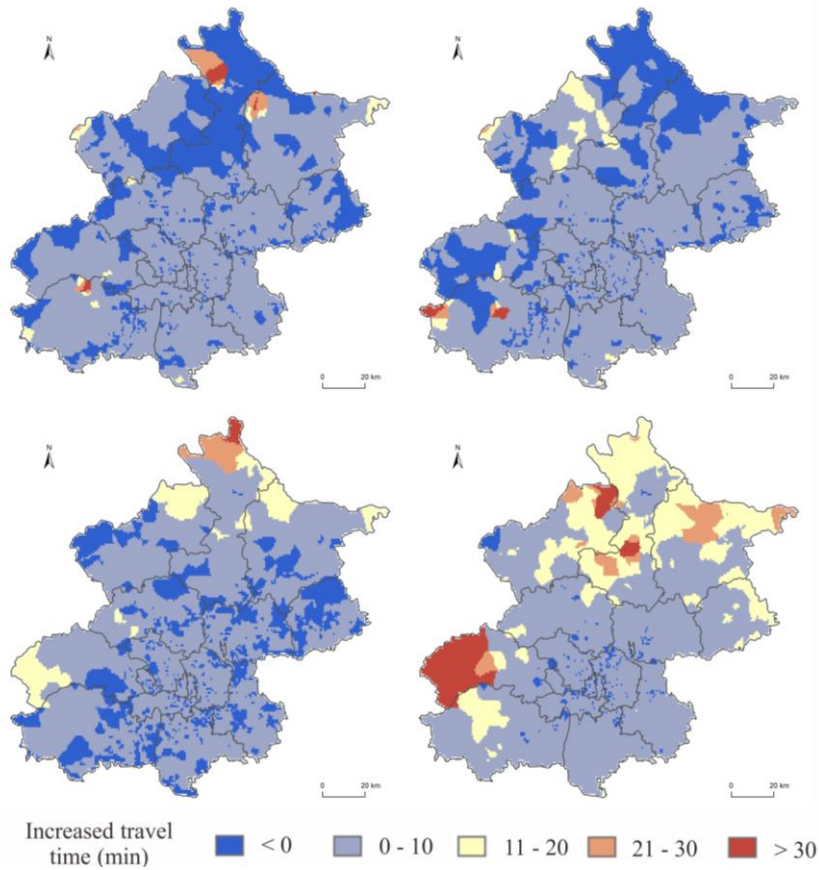
(c) (d)

Figure 8. The correlation between the baseline EMS coverage rate of population and its reduction

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

4.2.2 The accessibility to hospitals

Figure 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.



411

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

413

December

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

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

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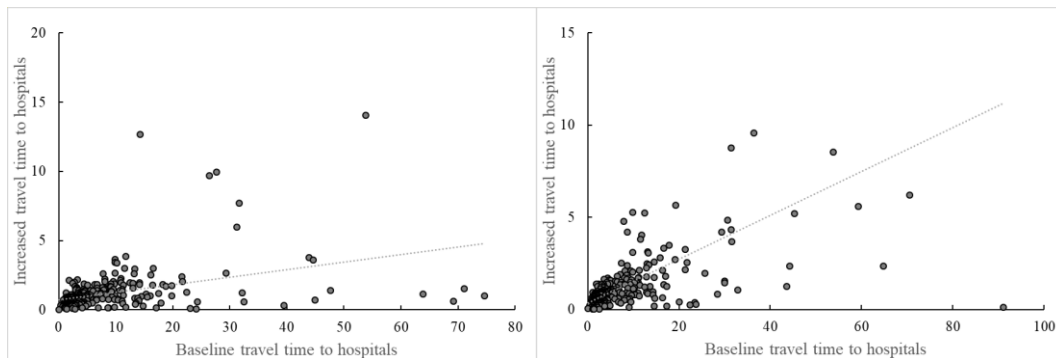
the two indicators shown in Figure 10 indicate the similar pattern with the EMS

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

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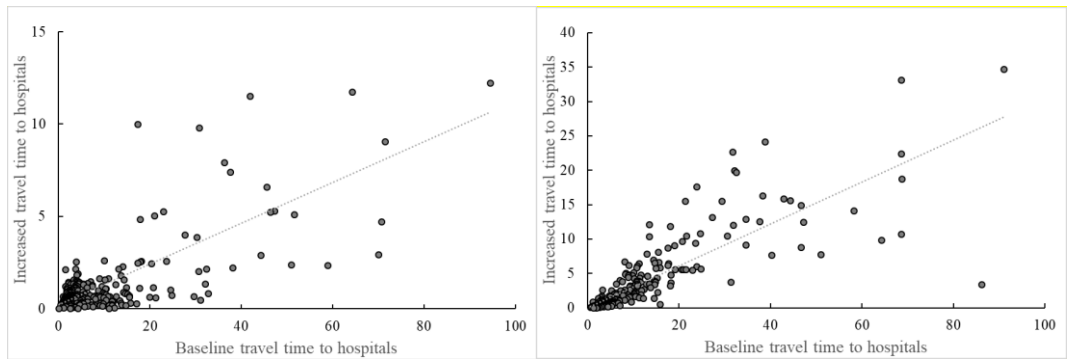
more affected by inclement weather.



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420

(a) (b)



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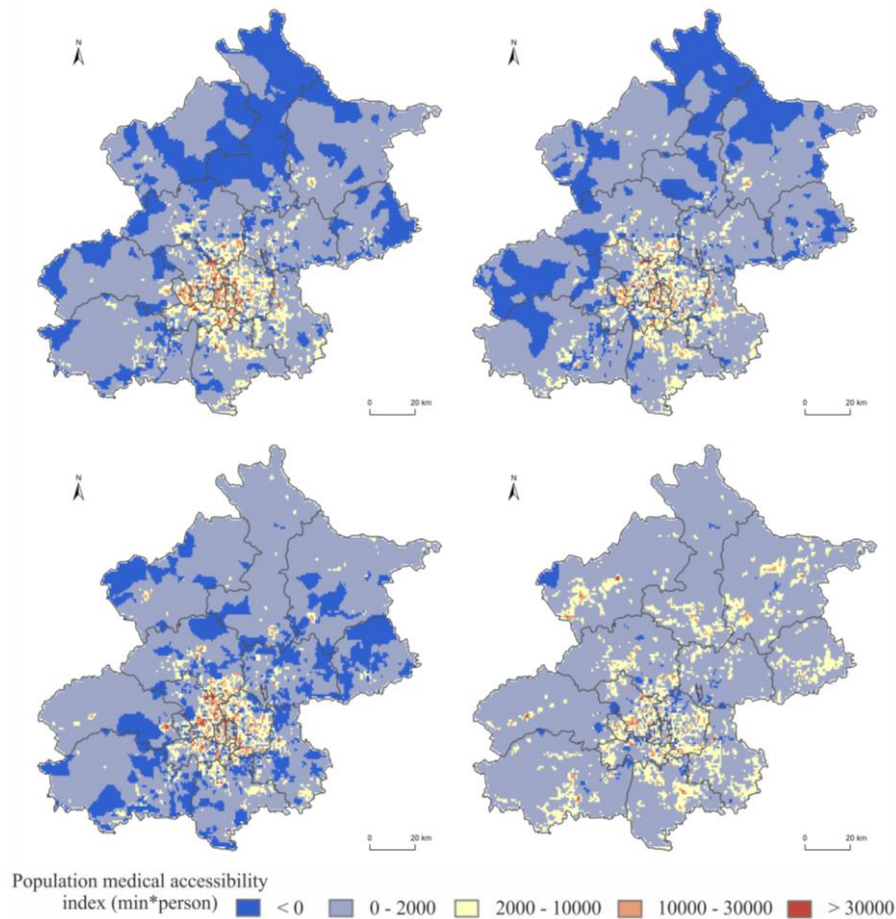
(c) (d)

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

425 Overlaying the demographic grid data, the size of the population affected by a
426 delay of over 10 minutes would be 0.02 million on 1st July, 0.03 million on 9th July,
427 0.05 million on 10th September, and 0.3 million on 16th December.

428 Figure 11 shows the change in the total transfer time under inclement weather
429 conditions on 1st July, 9th July, 10th September, and 16th December, relative to the
430 baseline conditions. The results show that on three rainy days, 1st July, 9th July, and 10th
431 September, within the Sixth Ring Road extent, the total transfer time increased
432 significantly under inclement weather, which means that, although the transfer time
433 would not increase much in urban areas, due to the high population density, the
434 cumulative delay time for total potential demand would be significant. In the suburbs,
435 the total transfer time would increase slightly or even decrease, especially in some areas
436 of Huairou, Yanqing, and Miyun districts, which means that, although the transfer time
437 would increase greatly, due to its low population density, the cumulative delay time for
438 total potential demand would not be serious. However, due to the influence of snowfall
439 on 16th December, the total transfer time in the whole city was slightly or moderately

440 increased, and there were almost no regions where the total transfer time decreased,
441 which means snowfall would cause an even cumulation of delay time for total potential
442 demand across the whole city, both urban and suburban.



443

444 **Figure 11.** The change in the total transfer time on 1st July, 9th July, 10th September, and 16th

445

December

446

447 **5 Conclusions and discussion**

448 Our study evaluates the spatial accessibility of EMSs in Beijing under different
449 weather conditions in 2019 based on city-scale ground-truth traffic data updated every
450 2 minutes. The spatial accessibility of EMSs was quantified by the coverage rate of the
451 first-aid stations' service area, the coverage rate of first-aid stations' service population,
452 and the shortest transfer time to the nearest hospital. **Our study reveals the influence of**

453 precipitation on the accessibility and equity of EMSs, which could help guide EMS
454 construction planning in cities, get prepared for extreme weather conditions, and finally
455 assist the decision-making of the corresponding government departments. The main

456 conclusions are as follows:

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

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

467 Third, some specific days may affect the traffic flow, which has an amplification
468 effect on the traffic congestion caused by inclement weather. When they encounter the
469 inclement weather, there are potential risks of decrease of traffic efficiency and EMSs
470 accessibility, which should be given sufficient attention.

471 To the best of the authors' knowledge, this study provides a first attempt to analyze
472 the spatial accessibility of EMSs under inclement weather based on city-scale ground-
473 truth traffic data and meteorological data, where the former is usually difficult to obtain.
474 In previous literature, simulation methods were widely used on the research on EMSs
475 accessibility or traffic capacity under inclement weather. The ground-truth traffic data
476 that covers every road in the whole city, was hardly used in the previous studies of the
477 impact of weather on traffic and accessibility. Our study could be a good empirical

478 verification in this field of study. The reduction extent of EMSs accessibility was close
479 to previous studies. We also found that snowfall may have a greater impact, which is
480 hard to find out using flood simulation methods. The results from this study provide a
481 scientific reference for city planning departments in Beijing to optimize the site
482 selection of emergency service facilities and get prepared for traffic dispersion on
483 inclement weather. The relevant methods mentioned in this paper is also suitable for
484 both holidays and workdays and can be easily applied to other cities once traffic data
485 or empirical formulas regarding the impact of inclement weather on road traffic can be
486 obtained.

487 However, there are also some limitations in this study. First, we averaged the traffic
488 speed reduction rate of all the roads in the city, as well as the precipitation data, which
489 could conceal congestion hotspots. In further studies, with higher resolution
490 precipitation, along with corresponding traffic data, we could narrow the scale to blocks,
491 pay more attention to local congestions, and analyze the correlation of precipitation and
492 traffic speed on a finer scale. Second, due to the data limitation, we could only analyze
493 the EMSs accessibility in 2019, and the precipitation intensity in this year was not quite
494 high. If with longer time series precipitation and traffic data, we could analyze the
495 impact of precipitation magnitude to the traffic and accessibility, instead of simply
496 dividing the days in a binary manner into inclement and non-inclement weather days.
497 Under such precipitation conditions, the EMSs accessibility has been affected to a
498 certain extent, and it would be much more difficult to get timely EMSs under even more
499 extreme inclement weather condition. So, the future studies should take the risk of
500 extreme precipitation event into account. Third, due to the lack of high-resolution DSM
501 data, we didn't run a hydrological flood simulation in Beijing, which could reveal the
502 relationship of precipitation and the actual amount of water on the streets. And this

503 could be improved in the future studies with more high-resolution topographic data.

504

505 **Data availability**

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

507 **Author contributions**

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

511 **Competing interests**

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

513 **Acknowledgments**

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

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