

Article

Study on Spatio-Temporal Patterns of Commuting under Adverse Weather Events: Case Study of Typhoon In-Fa

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Abstract: This study focuses on the main urban area of Yangzhou City and conducts a quantitative comparative analysis of traffic accessibility during normal weather and extreme precipitation conditions (typhoon) based on GPS trajectories of buses. From both temporal and spatial dimensions, it comprehensively examines the impact of extreme precipitation on bus travel speed, travel time, and the commuting range of residents in the main urban area of Yangzhou City. (1) Through the mining and analysis of multi-source heterogeneous big data (bus GPS trajectory data, bus network data, rainfall remote sensing data, and road network data), it is found that the rainstorm weather greatly affects the average speed and travel time of buses. In addition, when the intensity of heavy rainfall increases (decreases), the average bus speed and travel time exhibit varying degrees of spatio-temporal change. During the morning and evening rush hour commuting period of rainstorm weather, there are obvious differences in the accessibility change in each typical traffic community in the main urban area of Yangzhou city. In total, 90% of the overall accessibility change value is concentrated around -5 min~ 5 min, and the change range is concentrated around -25 ~ 10 %. (2) To extract the four primary traffic districts (Lotus Pond, Slender West Lake, Jinghua City, and Wanda Plaza), we collected Points of Interest (POI) data from Amap and Baidu heat map, and a combination analysis of the employment–residence ratio model and proximity methods was employed. The result show that the rainstorm weather superimposed on the morning peak hour has different degrees of impact on the average speed of the above-mentioned traffic zones, with the most obvious impact on the Lotus Pond and the smallest impact on Wanda Plaza. Under the rainstorm weather, the traffic commute in the main urban area of Yangzhou in the morning and evening peak hour is basically normal. The results of this paper can help to quantify the impact of typhoon-rainstorm weather events on traffic commuting in order to provide a scientific basis for the traffic management department to effectively prevent traffic jams, ensure the reliability of the road network, and allow the traffic management department to more effectively manage urban traffic.

Keywords: accessibility; feature of spatio-temporal evolution; extreme weather events; typhoon “In-Fa”; main urban area of Yangzhou City



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1. Introduction

The Fifth Assessment Report of the United Nations Intergovernmental Panel on Climate Change (IPCC) pointed out that the global climate system has experienced substantial transformations over the past century, marked by a notable rise in global temperatures, and it is expected that the frequency of adverse weather events on a global scale will escalate rapidly and the range of their impacts will tend to widen in the 21st century [1,2]. Adverse weather events can lead to traffic congestion on urban roads, extended commuting time

for residents, increased travel costs, etc. Moreover, superimposition of typhoon-rainstorm weather events and urban morning and night commuting peak hours will further aggravate the impact on the commuting accessibility for residents. How to quantitatively assess the impact of extreme weather events on the accessibility of residents' transportation commuting, and implement effective spatial and temporal response measures to further improve the ability of disaster prevention and resilience, enhance the security of the transportation network system, and strengthen the resilience of the transportation network is a key issue that needs to be solved urgently [3–6]. Transit is an important part of the urban transportation system, and it is the main way for residents to commute and travel. According to the annual report of Yangzhou transportation, it is known that the proportion of commuting trips by public transportation in the main city of Yangzhou reached 30% in 2020. Therefore, mining the spatial and temporal characteristics of impacts of adverse weather events on urban public transportation commute travel, and quantitatively assessing the impact of adverse weather events on the accessibility of urban residents' commute travel can provide scientific decision support for the transportation management department to develop prompt contingency strategies and implement effective emergency management measures.

At present, domestic and foreign scholars have carried out extensive studies on the impact of adverse weather events on urban commuting, and found that the commuting impact of adverse weather events varies with different areas and road hierarchy. However, due to the limited data, researchers have only analyzed the limited area or a specific section, and there is a lack of research on large-scale urban transportation networks and the spatio-temporal heterogeneity of extreme weather events regarding urban transportation. In terms of research indicators, the majority of prior studies have analyzed the impacts of different typhoon-rainstorm events and their intensity on traffic flow [7–9], vehicle speed [10–13], travel time [14,15], and traffic accidents [16–18], etc., while fewer studies have been conducted on the indexes of commuting accessibility. In terms of research methodology, except for employing the questionnaire survey to study the impact of adverse weather events on residents' travel mode, travel time, and travel distance, with the popularization of the Internet and the continuous improvement of computer data processing capabilities, multi-source heterogeneous big data mining technology [19–22] provides an accurate and reliable data source and analysis method for studying the impact of adverse weather events on the accessibility of commute travel. However, most of the current research has only involved data mining technology to conduct quantitative studies on the impact of typhoon-rainstorm weather events on commuting on the daily scale [23–26]. Residents' commuting trips are affected by many features of typhoon-rainstorm weather events such as the start time, duration, impact range, and intensity. To summarize, the current relevant studies have not been able to deeply reveal and characterize the spatio-temporal heterogeneity of the impact of dynamic changes in the intensity of adverse weather events on the commuting travel of urban residents, and it is difficult to apply this to the decision making of emergency protection of transportation travel in critical time and spatial areas.

Given the shortcomings of the above studies in terms of temporal granularity [27,28], indicator selection and spatial analysis [29], this paper will study the impact of typhoon-rainstorm events on commuting in Yangzhou City. Based on the public transportation GPS (Global Positioning System) trajectory data, remote sensing of rainfall data, Points of Interest (POI) data, Baidu heat map, related road networks and other data, the paper has employed multi-source heterogeneous big data mining and analysis techniques to first build a public transportation commuting circle of typical residential districts. Then, in-depth excavation of the temporal and spatial variation laws of average bus speed, travel time and commuting distance under different rainstorm intensities has been conducted to quantitatively assess the impact of typhoon-rainstorm events on commuting. The study is conducive to provide a scientific basis for traffic management departments to effectively prevent traffic congestion, ensure the reliability of the road network, and promote traffic management departments to manage urban traffic in a more refined way.

2. Study Area, Data and Methods

2.1. Study Area

Yangzhou is located in the middle of Jiangsu Province, at the intersection of the Yangtze River and the Beijing-Hangzhou Grand Canal, and is an important part of Jiangsu's Yangtze River Economic Belt. In addition, it is a city in the close circle of the Nanjing Metropolitan Circle and a city in the Yangtze River Delta city cluster, and one of the twenty-seven cities in the central area of the Yangtze River Delta, with a relatively well-developed urban road network. According to the 2020 census data of Yangzhou city, the population distribution is mainly concentrated in Guangling and Hanjiang districts, which are selected as the study area in this paper. The main urban area of Yangzhou City covers an area of 906.36 km², with a total population of 1.2692 million people. Among them, the number of employees in primary industry is 95,500, the number of employees in secondary industry is 409,200, and the number of employees in tertiary industry is 474,800. It can be seen that the residential population in the main urban area of Yangzhou City is highly matched with the number of job positions available, indicating a relative balance between jobs and housing in the region, which further indicates that the main city of Yangzhou is mainly characterized by internal commuting. In addition, the public transportation system in the main city of Yangzhou is relatively complete, and transit is the main commuting mode of transportation. Therefore, this paper selects 51 bus routes within the main urban area of Yangzhou, including No. 1, No. 29, No. 37, No. 108, etc. (Figure 1).

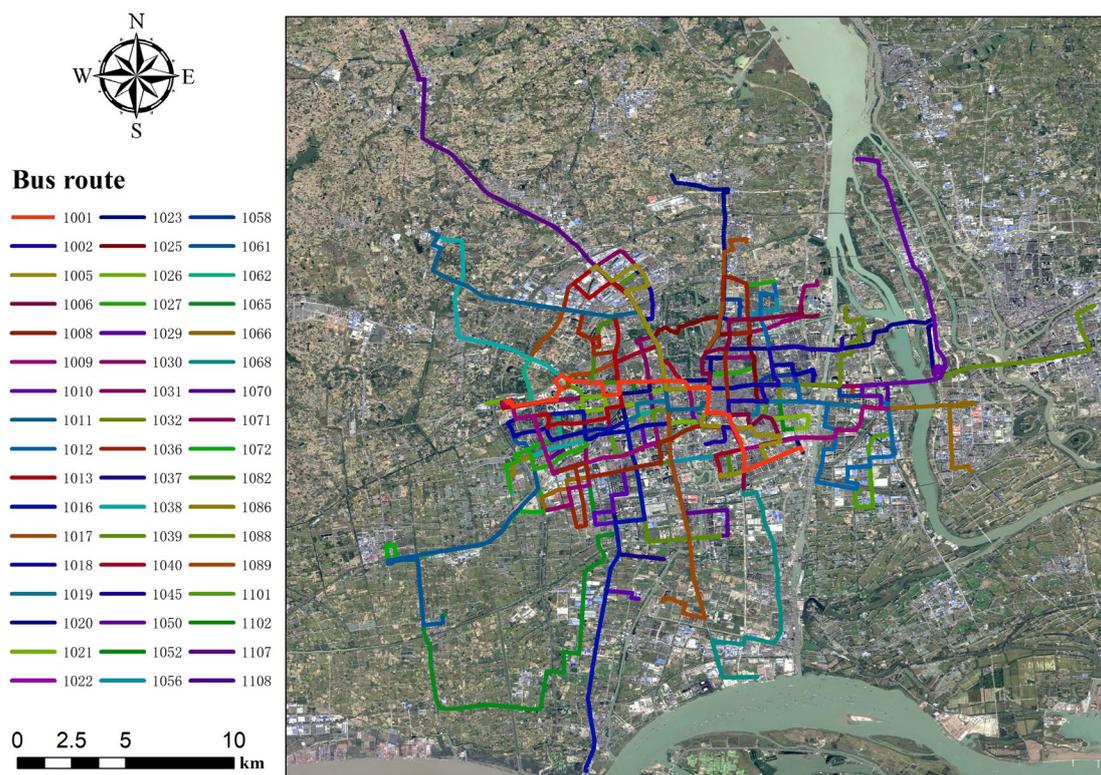


Figure 1. Bus route map in the central urban areas of Yangzhou.

2.2. Data and Preprocessing

2.2.1. Bus GPS Trajectory Data

In this paper, the GPS point data for 15–30 July and 12–18 December 2021 were extracted based on the GPS data of bus vehicles provided by Yangzhou City Bus Company, of which 24–30 July was typhoon-rainstorm weather (typhoon-rainstorm), and the 12–18 December was sunny weather. A total of 89,077,360 GPS data related to the selected 51 bus routes were extracted from the data, with a total size of 41.2 G. Through Python program-

ming, we screen the data of Yangzhou city's main urban area bus travel for 24–30 July (typhoon-rainstorm) and 12–18 December (normal weather conditions) during morning and evening peak hours (07:00–09:00, 17:00–19:00) and eliminate invalid or abnormal data simultaneously. The trip time of bus operation is extracted by the trip time extraction algorithm. The travel time can be calculated by Equation (1):

$$T_{(i,i+1)} = A_{i+1} - D_i \quad (1)$$

where A_{i+1} is the moment corresponding to the GPS record of the bus driving into the next stop; D_i is the moment corresponding to the GPS record of its driving out of the previous stop; and $T_{(i,i+1)}$ is the travel time between the two stops to be extracted.

After preprocessing, about 300,000 valid route data per day are obtained, and the track data represent the state of public transportation operation, which includes location information such as latitude and longitude, vehicle speed, and time information of the public transportation at each data point at the current time.

2.2.2. Job-Housing Space Identification

The internet open-source data selected in this paper are POI data and thermal diagram data (<https://map.baidu.com>, accessed on 15 April 2022). Based on the POI data, the working and residential space was identified in the main urban area of Yangzhou city [30,31], and the population thermal map data were used for spatio-temporal displacement analysis of residents' occupation and residential areas, improving the accuracy of job and residential space identification.

The Baidu thermal map is based on the geographical location information of smartphones and is updated every 15 min. Through location clustering, it can reflect the flow of urban populations and spatial aggregation, thus describing the spatio-temporal changes in residents between their place of residence and place of work. This paper selects the thermal maps on 1 May (rest days) and 9 May (working days) in 2022 and divides them into seven thermal grades, among which Grade 1 is non-thermal, 2–3 is medium-thermal, 4–5 is sub-thermal, and 6–7 is high (Figure 2). Then, it calculates the thermal values of different properties, and analyzes the changes in thermal values from 7 a.m. to 11 p.m., so as to obtain the population agglomeration in different periods, and study the spatial-temporal displacement of the residents in service.

In order to identify the jobs and residential spaces based on the Baidu thermal map data, analyze the public transportation attendance time, commuting distance and flow characteristics of urban residents in the main urban area of Yangzhou, we compare and analyze the urban planning data and POI data of the main urban area of Yangzhou City, combined with the classification standards of the National Economic Industry Classification and Code (GB/T4754-2017) [32]. This article divides the selected POI data into 11 categories [33]. We selected wholesale and retail trade services, accommodation and catering services, banking and financial services, education services, community life services, medical services and entertainment services to study.

In this paper, the regular grid division method is used to divide the study area into 500×500 grids based on ArcGIS, and the working space is identified by quantitatively counting the proportion of various POI frequencies to all POI frequencies in the grid. For each type of POI, functional properties are identified by constructing frequency density and category ratios with the following formula:

$$F_i = \frac{n_i}{N_i} \quad (i = 1, 2, 3 \dots, 11) \quad (2)$$

$$C_i = \frac{F_i}{\sum_{i=1}^{11} F_i} \times 100\% \quad (i = 1, 2, 3 \dots, 11) \quad (3)$$

where i represents the POI type; n represents the number of the i th-type POI in the cell; N_i represents the total number of the i th-type POI; F_i represents the frequency density of the

i th-type POI in the total number of POI of that type: C_i represents the proportion of the frequency density of the i th-type POI in the frequency density of all types of POI in the cell.

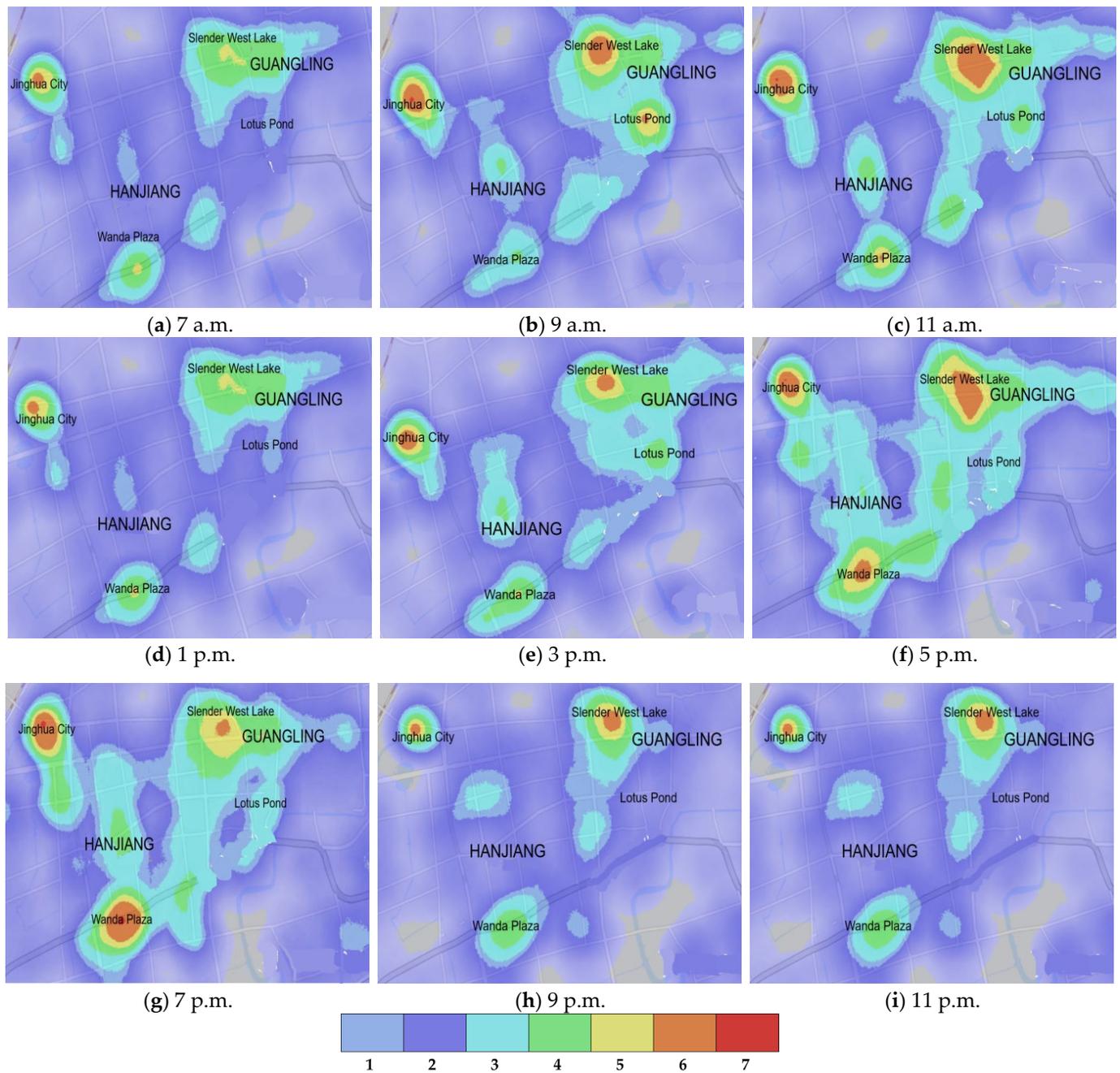


Figure 2. Heat maps of the central urban areas of Yangzhou on 9 May 2021. Record time is from 7 a.m. to 11 p.m.

We calculate the frequency density and type ratio of 11 POIs according to the formula and selected the type proportion value of 50% as the standard to judge the functional nature of the unit. When the proportion of POIs of a certain type in a grid cell is 50% or more, the grid unit is determined to be a single functional area of a POI nature. When the ratio of all types of poi within a grid cell does not reach 50%, then the cell is a mixed functional area. The mixture type depends on the two main POI types in the grid cell. When the POI is not included within the grid cell, this type of grid cell is called a valueless zone.

According to the calculation results of the above formulas and the change in heat value of the Baidu heat map, in this paper, Lotus Pond, Jinghua City, Slender West Lake and Wanda Plaza were selected as typical residential areas to carry out the research.

2.2.3. Multi-Satellite Combined Inversion of Precipitation Data

The IMERG precipitation product class used in this study is Final-Run, which includes monthly scale rainfall information observed from ground stations, and Final-Run offers the best quality of IMERG precipitation products and is the most suitable for research fields such as climate and hydrological simulation. The time resolution of the original IMERG product is 0.5 h, while the time resolution of precipitation observation information at ground stations is 1 h, so the IMERG precipitation product within the same hour is integrated to one-hour resolution for subsequent rainfall intensity analysis. In this paper, we used the hourly precipitation product of the IMERG Final-Run from 25 to 28 July 2021, with a spatial resolution of 0.1, and trimmed it to the scope of the study area (IMERG precipitation data can be accessed on the PMM site, <https://pmm.nasa.gov/data-access/Downloads/gpm>, accessed on 2 April 2022). Figure 3 shows the route diagram of typhoon “In-fa” in transit, and the rainfall data of Yangzhou city in July 2021 were obtained through the Yangzhou Meteorological Observation Station (Figure 4).

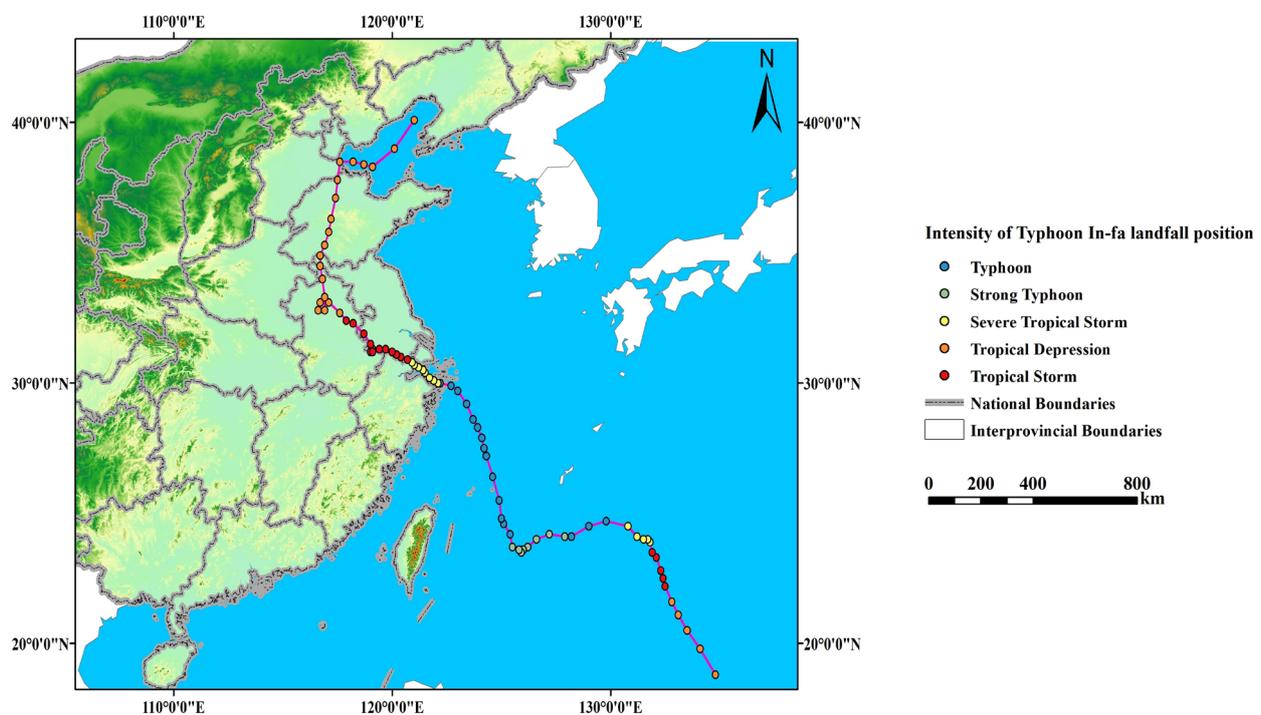


Figure 3. Typhoon In-fa transit route map.

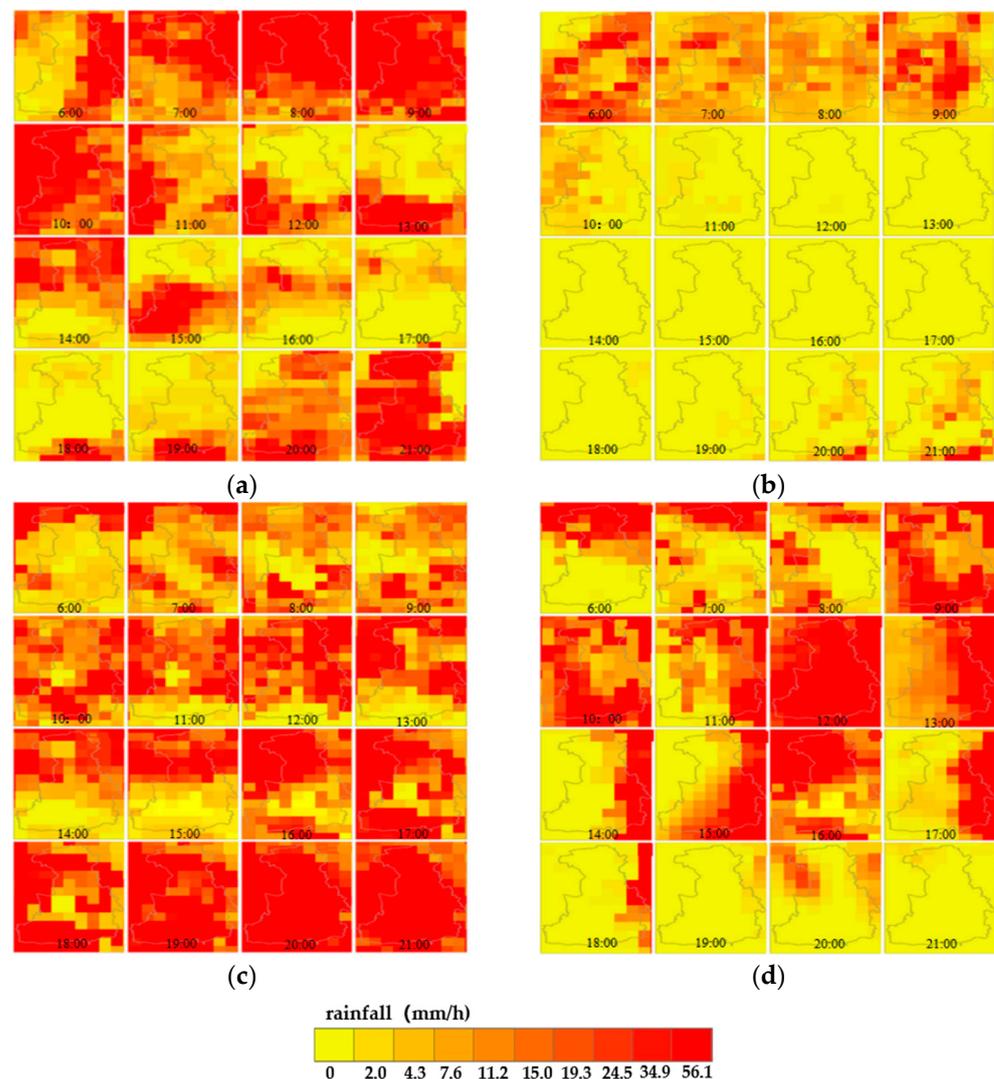


Figure 4. The spatio-temporal evolution of rainfall data in Yangzhou on 25–28 July 2021: (a) rainfall data on 25 July 2021; (b) rainfall data on 26 July 2021; (c) rainfall data on 27 July 2021; (d) rainfall data on 28 July 2021.

2.3. Methods

2.3.1. Technology Roadmap

This paper focuses on the impact of typhoon-rainstorm weather events on the commuting accessibility of urban residents from two aspects: vehicle speed and travel time, based on GPS trajectories of buses in the main urban area of Yangzhou City and partial weather data in July and December 2021. Using the population thermal data provided by the Baidu map, analysis of jobs and residential space is conducted to determine typical residential areas. Then, the paper constructs public transportation commuting circles under different weather conditions and the method of spatial statistical analysis is applied to calculate the area of the commuting circle under different weather conditions. Finally, with comparison of the travel circle areas in different weather conditions, the results of commuting characteristics of typical communities in typhoon-rainstorm weather are obtained. The research process of this paper is shown in Figure 5.

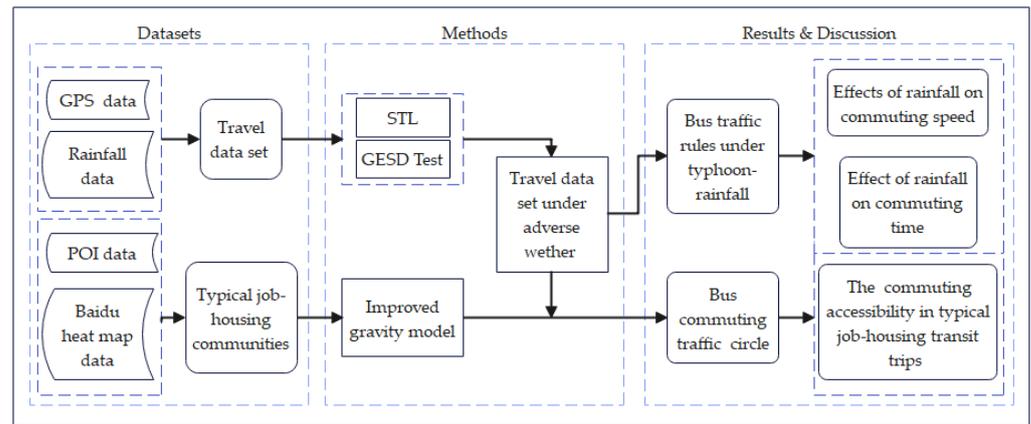


Figure 5. Flowchart of processing commuting accessibility under the typhoon-rainstorm.

2.3.2. Calculation of the Average Bus Line Speed Based on the GPS Trajectory Data

Under the typhoon-rainstorm weather events, the reduction in bus travel speed directly leads to the delay in commuting. According to the collected bus GPS trajectory data, the average travel speed of the whole bus line is calculated after excluding the invalid or abnormal data. The paper calculates the average travel speed V_i between adjacent GPS points with Equation (4):

$$V_i = \frac{\sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2}}{T_{(i,i+1)}} \quad (4)$$

where x_i and y_i are the position coordinates of the i th GPS point; x_{i+1} and y_{i+1} are the position coordinates of the $i + 1$ GPS point; the distance between two points can be found according to the position coordinates of the two points; $T_{(i,i+1)}$ is the time from the i th point to the $i + 1$ point.

We can calculate the average speed of bus line V_j by using Formula (5):

$$V_j = \frac{\sum_{i=1}^n V_i}{n}, \quad i = 1, 2, 3, \dots, \quad j = 1, 2, 3, \dots \quad (5)$$

2.3.3. Construction of Bus Commuting Circle Based on Improved Gravity Model

We define commuting accessibility as the ease with which a traveler can move from their original location to a specific destination using a particular transportation system. The commuting range of urban residents forms a commuting cycle. The size of the commuting circle is related to the commuting time and the mode of travel. This paper selects public transport as the way of travel of residents. On the basis of the improved gravity model of Joseph and others [34], this paper improves the bus travel mode, travel time threshold [35] and the attraction index of the work space, so as to make the accessibility calculation more practical, as shown in Equations (6) and (7).

$$A_i = \sum_{j \in T_{ij} \leq t_0(c)} \frac{S_j \times N_j \times T_{ij}^{-1}}{C_j} \quad (6)$$

$$C_j = \sum_{k=1}^m P_k t_{ij}^{-1}, \quad k = 1, 2, 3, 4 \quad (7)$$

where A_i is the end point space accessibility of the residential area i ; a higher A_i value means better accessibility of the workspace at the starting point i ; S_j is the road capacity of commuter point j (determine the road capacity according to the road grade); N_j is the attraction index of the workspace j , using the thermal level shown in the thermal map of Figure 2 above (the higher the level, the greater the attraction of the area); T_{ij} is the

travel time required for the bus from the start i to the end j ; C_j indicates the competition of residential residents in the working area after meeting the time threshold t_{ij} under the influence of typhoon-rainstorm weather; P_k is the population of a residential area at k (Lotus pond is represented by 1, Slender West Lake by 2, Jinghua City by 3, and Wanda Plaza by 4); m is the number of vocational and residential areas that meet the conditions.

We import the calculated accessibility index (A_i) into ArcGIS based on the results of the job-housing spatial analysis in Section 2.2.2 to obtain the radii of the bus commuting circle in different residential areas for a given time threshold.

2.3.4. Detection of Outliers

For the time series of the speed and travel time, the speed and travel time are the random fluctuations caused by other factors, and these fluctuations are mainly the comprehensive results caused by traffic accidents or typhoon-rainstorm events. The selected bus GPS trajectory data contain the driving data under normal weather conditions. In order to better distinguish the driving data under different weather conditions, we need to detect outliers among these data. Since the local weighted regression seasonal trend decomposition can reflect the periodicity of changes in vehicle speed and travel time, the local weighted regression seasonal trend decomposition method was chosen to decompose vehicle speed and travel time, decomposing long-term trends, seasonal changes, and residual parts [36,37]. At the same time, in order to determine the observations of vehicle speed and travel time in the travel time data set under typhoon-rainstorm weather, the article conducts a generalized extremum dispersion test on the residual portion of the road network dataset obtained by the local weighted regression seasonal trend decomposition method mentioned above, which is conducive to identify vehicle speed and travel time observations that deviate significantly from normal traffic conditions. The extreme weather data set was collected, and the start and ending time of the speed and travel time that were significantly different from the above observation values were analyzed to form a new data set.

Local weighted regression seasonal trend decomposition involves the segmentation of time series into long-term trends, seasonal changes, and residual parts. This can be expressed by Equation (5).

$$y_S = S_T + S_S + S_R \quad (8)$$

Specifically, y_S , S_T , S_S , S_R are the observed time series, long-term trends, seasonal variation, and residual parts, respectively.

The generalized extremal dispersion test [38] was employed to detect outliers in univariate normal data sets. The test formula applied to each observation within a sample of size N is shown in Equation (6), where n_i is the i th observation in the sample; \bar{n} is the representative of the mean, and s represents the standard deviation of the sample.

$$Z_i = \frac{\max_i |n_i - \bar{n}|}{s} \quad (9)$$

Subsequently, the observations n_i corresponding to the maximized test statistic Z_i were removed from the sample, and the test statistic for the remaining observations was recalculated. This procedure was iterated until the μ observations (potential outliers) were eliminated. Next, corresponding to the calculated μ -test statistic, the μ -test critical value was calculated using Equation (7).

$$\tau_i = \frac{(m-i)t_{p,m-i-1}}{\sqrt{(m-i-1 + t_{p,m-i-1}^2)(m-i-1)}} \quad (10)$$

where $t_{p,m-i-1}$ correspond to the 100p percentage value and $(m - i - 1)$ degrees of freedom. The formula for calculating the value of ρ is shown in Equation (8):

$$\rho = 1 - \frac{\theta}{2(m - i - 1)} \quad (11)$$

where θ is the confidence level. The count of outliers within the sample is determined by the maximum i , such as $Z_i > \tau_i$. In this study, we set μ to 20% of the total observations of travel times in a bus line, and θ was set to 0.05. Choosing a relatively high value for μ prevents the absence of identifying any outliers in the selected confidence level.

According to the above rainfall data, combined with the detection results of speed and travel time, space–time superposition analysis, and the actual disaster report text information mining verified that the rainstorm weather will lead to an increase in typhoon-rainstorm speed frequency and prolong the travel time.

3. Analysis of the Impact of Typhoon-Rainstorm Events on Commuting Accessibility

3.1. Temporal Patterns of Different Weather Conditions regarding Vehicle Speed

As shown in Figure 6, without rainfall (e.g., 14:00–19:00 on 24 July), the average bus speed is affected by the evening peak hours, and the speed decreased slightly, but the average speed of the bus was maintained above 20 km/h. When the rainfall is within 0~40 mm, the bus speed shows a fluctuation change, and the speed fluctuates more under the influence of the morning and evening rush hours. When the rainfall reaches more than 40 mm, and is superimposed on the morning and evening rush hours, the superposition effect is obvious (like 17:00–19:00 on 26 July), but it is not true that the greater the precipitation, the lower the average bus speed. The average bus speed is the lowest (18 km/h) when the precipitation is 80mm, while the speed rises to 24 km/h with a precipitation value of 103 mm. This is because the evening peak hour is over, and it is not obvious that the bus commuter speed is only affected by the intensity of rainfall. And when the rainfall decreases or stops, the average bus speed slowly recovers. The purple part in Figure 6 shows the change in the rainfall and average bus speed of Yangzhou over time when typhoon “In-fa” affected Yangzhou (for example, 6:00–17:00 on 27 July). Under the influence of the typhoon, the precipitation reached its maximum (118 mm), and when the morning peak effect was superimposed, its impact on the average speed of the bus was obvious. At this moment, the average speed of the bus was only 17 km/h, but with the decrease in precipitation, the average speed of the bus slowly recovered after the morning peak hour. To sum up, rainfall has a certain impact on the average speed of public buses, and the impact of superimposed morning and evening peak precipitation is more obvious. Moreover, with the decrease in precipitation, the average speed of public buses will continue to rise.

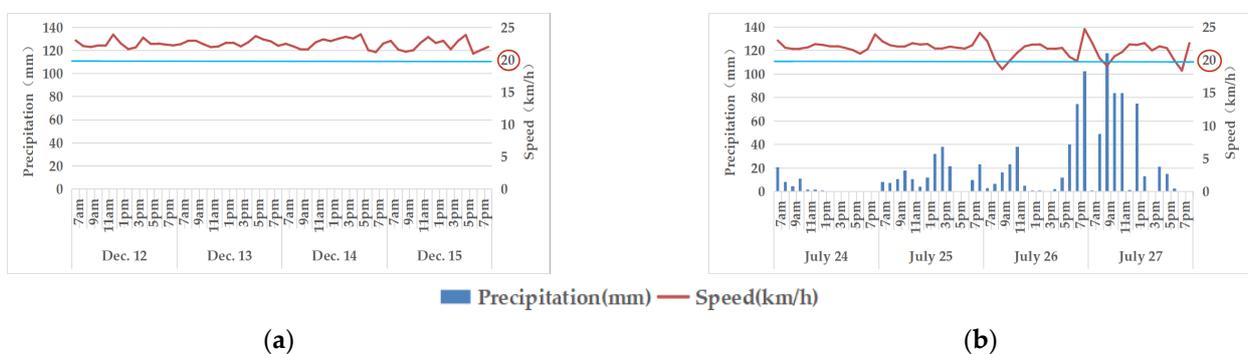


Figure 6. The temporal feature of average speed under different weather conditions: (a) normal weather; (b) typhoon-rainstorm.

3.2. Spatial Pattern Analysis of the Influence of Different Weather Conditions on Vehicle Speed

In order to analyze the spatial influence of morning and evening peak hours on bus speed under different weather conditions, this paper analyzed the road network speed in the main urban area of Yangzhou, and obtained the average speed distribution map of the bus network under different weather conditions, as shown in Figure 7 (in the picture, the Lotus Pond is represented by 1, 2 for Slender West Lake, 3 for Jinghua City, and 4 for Wanda Plaza).

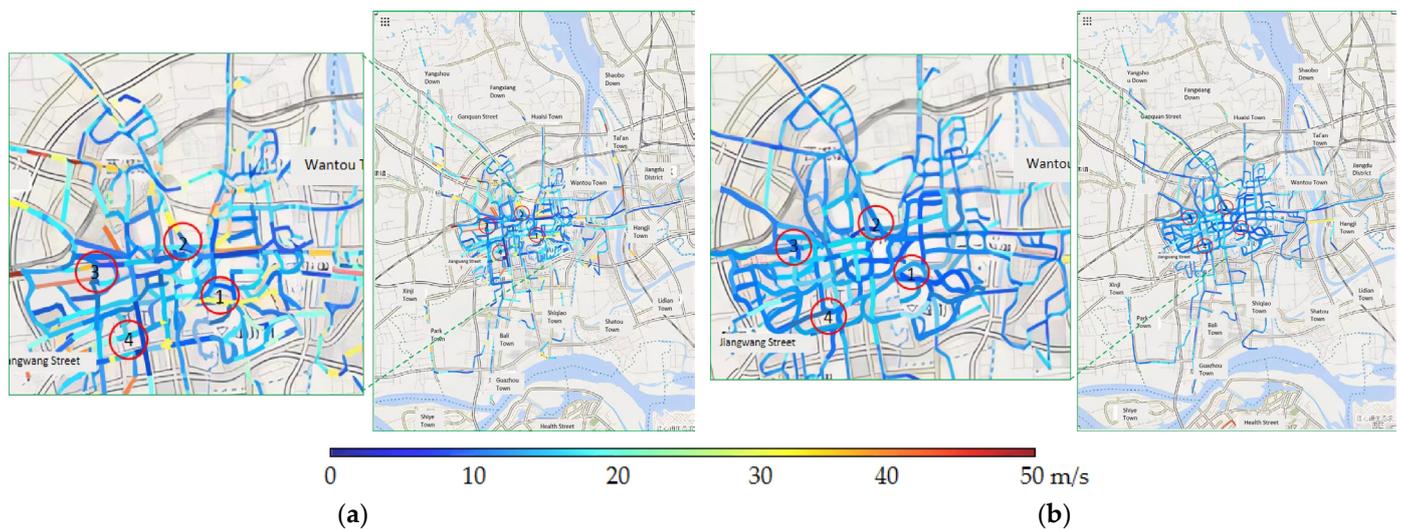


Figure 7. Spatial distribution of average speed under different weather conditions: (a) normal weather conditions; (b) typhoon-rainstorm weather conditions.

During the morning and evening peak hours under normal weather conditions, the average speed of approximately 36 out of 51 bus routes has been affected. Among them, the average speed of the corresponding bus lines in Core Pacific City, Wanda Plaza, Slender West Lake and Lotus Pond decreased, with an average speed of 20.6 km/h, down by 10%. During the morning and evening peak hours under typhoon-rainstorm conditions, the average speed of about 42 out of 51 bus routes was significantly affected, among which the average speed of the corresponding bus lines in Core Pacific City, Wanda Plaza, Slender West Lake and Lotus Pond decreased significantly under the above normal conditions, with an average speed of 18.9 km/h and amplitude reduction of 25%.

Through the above comparative analysis of the average speed distribution map of the road network under normal weather conditions and rainstorm weather conditions, it can be shown that different weather conditions have a certain impact on the average spatial speed of the public transportation network during morning and evening peak hours. Moreover, under the conditions of a typhoon-rainstorm, the superposition effect of the morning and evening peak is obvious. Among them, Jinghua City, Wanda Plaza, Slender West Lake and Lotus Pond, as areas with large traffic flow in the morning and evening peak hours, report a more significant delay, with a 25% increase. The average results of the four residential areas in the morning and evening peak hours during normal weather and heavy weather conditions are shown in Table 1.

Table 1. Bus commuting speed in four residential areas during morning and evening peak hours under different weather conditions.

Area	Normal Weather Speed (km/h) (12–18 December)			Typhoon-Rainstorm Weather Speed (km/h) (24–30 July)		
	Morning Peak	Evening Peak	Average Speed	Morning Peak	Evening Peak	Average Speed
Lotus Pond	21.8	20.8	21.3	18.0	18.7	18.4
Slender West Lake	20.2	19.4	19.8	18.7	19.1	18.9
Jinghua City	19.9	19.9	19.9	18.2	17.0	17.6
Wanda Plaza	22.3	20.5	21.4	21.1	20.5	20.8
	Total		20.6	Total		18.9

3.3. Influence of Different Weather Conditions on Travel Time

In order to analyze the influence of different weather conditions on the bus travel time during the morning and evening peak hours, we also selected 07:00–09:00 and 17:00–19:00 on 24–30 July 2021 (typhoon-rainstorm weather) and 12–18 December 2021 (normal weather conditions). Using the average speed sample data calculated based on bus GPS trajectory data as the research object, this study investigates the impact of different weather conditions on bus travel time. Under normal weather conditions, the statistics of bus commuting hours in the main urban areas during the morning and evening rush hours and off-peak hours are shown in Table 2. Figure 8 shows the comparison of morning and evening peak commuting hours under different weather conditions. This paper analyzes the bus travel time of 51 bus lines in the morning and evening peak hours, and the results show the following:

- (1) Under normal weather conditions, the average time consumption of 38% bus routes of 51 bus lines during the morning peak hour (07:00–09:00) is comparable to the average time consumption during the non-morning peak hours under normal weather conditions. In terms of changes in travel time, 56% increased, 6% decreased, and the change value of 50.6% was concentrated around $-7.5\sim 12$ min. During the evening peak hour (17:00–19:00), 30% of the 51 bus lines were equivalent to the average time consumption of non-evening peak hours under normal weather conditions. In total, 65% of the average commuting time of public transportation increased, 5% of the average commuting time decreased, and the changes in the average commuting time of 55.8% of public transportation were concentrated in the range of $-10\sim 10$ min. The above analysis results show that morning and evening peak hours have a significant impact on bus travel time under normal weather conditions, but the impact of morning and evening peak hours on bus travel time is basically the same. The average time of public traffic service during morning and evening peak hours is 56 min, with an overall increase of $-15\sim 24\%$.
- (2) Under typhoon-rainstorm weather conditions, the average time consumption of 20% of the 51 bus lines during the morning peak hour (07:00–09:00) was comparable to the average time consumption of the morning peak hours under normal weather conditions, while 74% of the average hours increased, 6% of the average hours decreased, and 86.8% of the average time consumption change in public traffic was concentrated around -10 min ~ 5 min. During the evening peak hour (17:00–19:00), the average time consumption of 16% of the 51 bus lines was equivalent to that during normal weather conditions. The average time consumption of 80% of the public traffic increased, 4% decreased, and the average commuting time variation of 80% of public transportation was concentrated around $-9\sim 9$ min. The analysis results show that the superposition effect of rainstorm weather conditions and morning and evening peaks is obvious, and compared to the average commuting time during morning and evening rush hours under normal conditions, the average time consumption has an obvious rising trend. In addition, the average commuting time during the morning

peak hours is 60.47 min, and the average commuting time during the evening peak hours is 58.7 min, which indicates that the influence during the morning and evening peak hours on the average bus speed has an obvious difference.

Table 2. Average travel time of buses under normal weather.

Time (min)	Bus Lines		
	Off-Peak Hours	Morning Peak Hour	Evening Peak Hour
40–42.5	2, 3, 10, 34, 58, 61, 82	-	-
42.5–45	36	2, 10	2
45–47.5	1, 38, 68, 70, 71, 89	11, 56	10
47.5–50	6, 13, 23, 27, 31, 35, 45, 56, 62, 102	45	11, 34, 56, 58, 61, 82
50–52.5	20	1, 3, 6, 8, 13, 23, 27, 31, 34, 35, 38, 68, 70, 71, 102	3, 6, 8, 13, 20, 23, 27, 31, 35, 36, 38, 45, 68, 70, 71, 89
52.5–55	8, 32, 37	32, 36, 37, 61, 62	1, 32, 102
55–57.5	5, 9, 108	5, 34, 58, 89	50, 37
57.5–60	11, 17, 19, 21, 29, 39	9, 17, 108	5, 9, 62, 108
60–62.5	40, 50, 65, 86	19, 20, 21, 29, 39, 40, 50, 65, 86	17, 19, 21, 29, 39, 40, 65, 86
62.5–65	12, 18, 25, 26, 30, 66, 72, 88, 101, 107	12, 18, 25, 26, 30, 66, 72, 88, 101, 107	12, 18, 25, 26, 30, 66, 72, 88, 101, 107

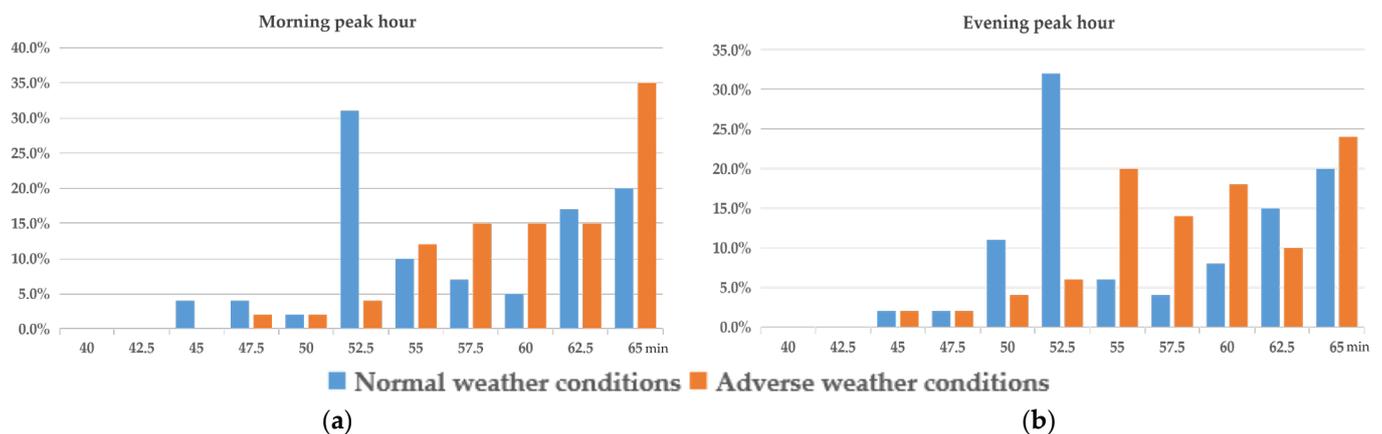


Figure 8. Public commuting time under different weather conditions: (a) different weather conditions superimposed on morning peak hour commuting time; (b) different weather conditions superimposed on evening peak hour commuting.

Through the above comparative analysis of the average time consumption under normal weather conditions and rainstorm weather conditions, it can be shown that different weather conditions have a certain impact on the average time of transit commuting during morning and evening peak hours. Moreover, in the condition of a typhoon-rainstorm, the superposition effect of morning and evening peak is obvious, with a 15% increase in average time consumption.

4. Analysis of the Impact of Different Adverse Weather Events on Commuting Travel in Typical Residential Areas

4.1. Analysis of the Effects of Typhoon-Rainstorm Weather on Commuting Speed in Typical Residential Areas

As is shown in Figure 9, under the conditions without rainfall (such as 12:00–18:00 on 24 July), the average bus speed of Lotus Pond, Jinghua City, Slender West Lake and Wanda Plaza was affected by the evening peak hours, and the speed in four areas showed fluctuations, among which Jinghua City and Slender West Lake were greatly affected, while Wanda Plaza was less affected.

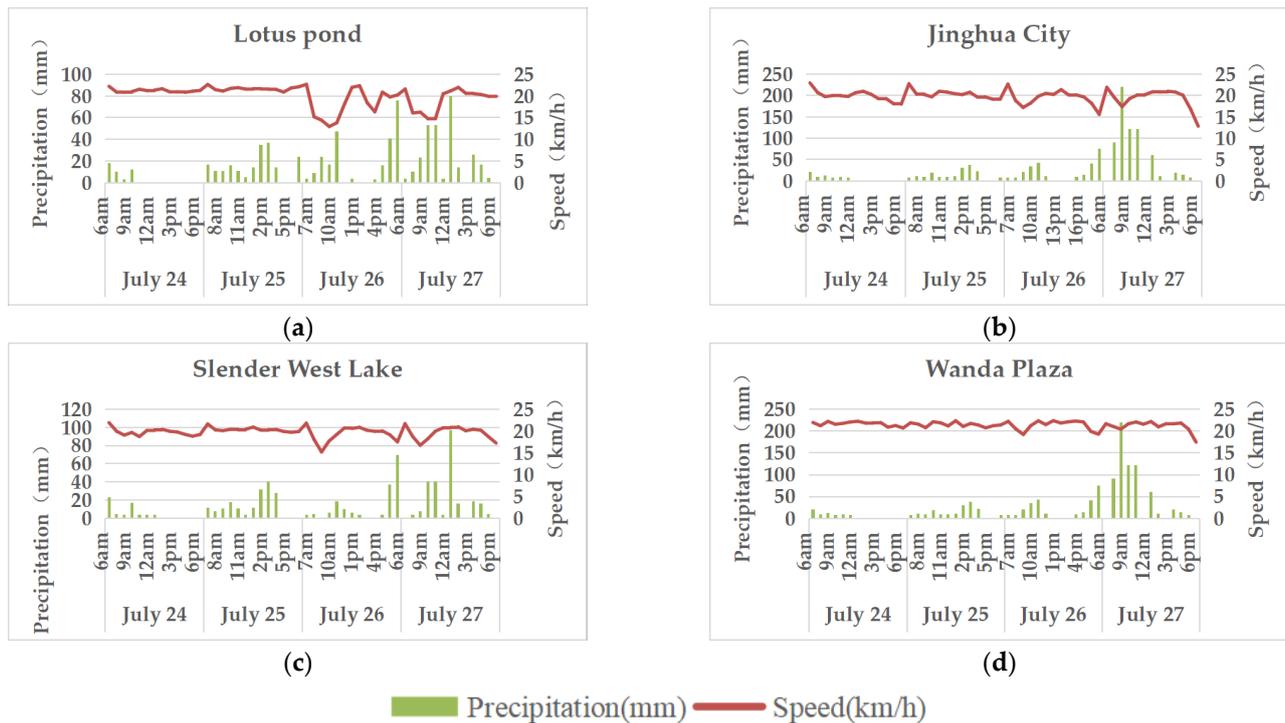


Figure 9. The temporal patterns of average speed under the typhoon-rainstorm in four typical residential communities: (a) Lotus Pond; (b) Jinghua City; (c) Slender West Lake; (d) Wanda Plaza.

When the rainfall lasts for a long time and the rainfall intensity gradually increases in the morning peak hour (such as 6:00–9:00 on 26–27 July), the average speed of bus decreases with the increase in the intensity of precipitation. As the precipitation intensity further increases, the average speed shows an upward trend, which is because the morning peak hour has passed, and the bus commuting speed is not obviously affected only by the rainfall intensity. As the precipitation intensity gradually decreases, the average bus commuting speed in Lotus Pond, Jinghua City, Slender West Lake and Wanda Plaza increases. When rainfall decreases or stops, the average speed of public transportation slowly recovers.

In order to further analyze the influence of different levels of rainfall conditions on the typical residential area commuting speed, we calculate the commuting speed of the above four typical residential areas under different levels of rainfall intensity (16 July moderate rain, 17 July light rain, 28 July rainstorm); found that the commuting of Lotus Pond and Slender West Lake residents is significantly affected by different levels of rainfall and morning peak hours, and the greater the rainfall intensity, the greater the impact on commuting speed (as shown in Figure 10). In Slender West Lake, Jinghua City and Wanda Plaza, the effect of different levels of rainfall and evening peak on bus commuting is more significant. Additionally, the superimposed effects of evening peak hours and precipitation of moderate rain and rainstorm are more obvious, and the impact of moderate rain on commuting speed is greater than that of rainstorms, while the impact of different rainfall levels in Wanda Plaza on its morning peak travel is not obvious.

To sum up, the influence of precipitation on the average commuting speed of each typical residential area shows a spatial difference, and the phenomenon is mainly caused by the spatial heterogeneity of precipitation intensity and the difference in the traffic flow of each typical residential area.

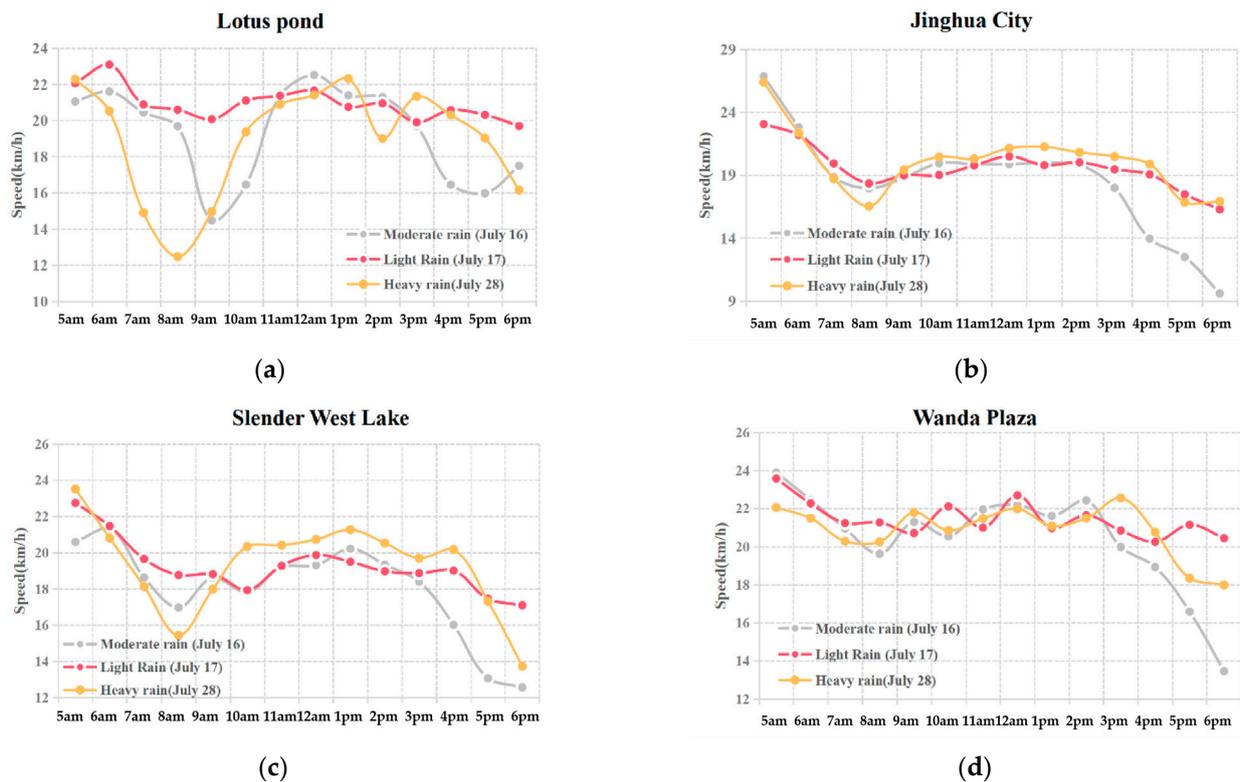


Figure 10. The temporal patterns of average speed under different levels of rainfall intensity in four typical residential communities: (a) Lotus Pond; (b) Jinghua city; (c) Slender West Lake; (d) Wanda Plaza.

4.2. Analysis of the Impact of Different Levels of Intensity Rainfall on Commuting Accessibility in Typical Residential Areas

In order to analyze the influence of typhoon-rainstorm weather conditions on commuting accessibility in typical residential areas, the spatial statistical analysis method was applied to calculate the radii of the bus commuting circle under different weather conditions and the study compared the changes in commuting accessibility under different weather conditions. The radii of the bus commuting circle under different weather conditions composed of four residential areas (Lotus Pond, Slender West Lake, Jinghua City and Wanda Plaza) were analyzed.

The analysis found that, in these four typical residential areas, the radii of the bus commuting circle were reduced. The radii of 20 min of the bus commuting circle of Lotus Pond were the most significant. The overall radii were reduced by 9–10.31%. The overall radii of the bus commuting circle of Slender Lake were reduced by no more than 6.63%. The overall radii of the bus commuting circle in Jinghua City decreased significantly, with an average reduction of 7.08%. The overall radii of Wanda Plaza's bus commuting circle decreased by no more than 5.5%. Among them, the radii of the 10-min bus commuting circle only reduced by 0.46%. Radii statistics for the different weather conditions, including the bus commuting circle drawn around the four residential areas, are shown in Table 3.

Table 3. Radii statistics and change in bus commuting circle under different weather conditions.

Area	BCC	Weather		Change	
		Normal Weather	Rainstorm Weather		
Wanda Plaza	10 min	3.57	3.55	−0.02	−0.46%
	20 min	7.13	6.77	−0.36	−5.08%
	30 min	10.70	10.11	−0.59	−5.49%
	40 min	14.27	13.50	−0.77	−5.38%
	50 min	17.83	16.71	−1.13	−6.32%
	60 min	21.40	20.50	−0.90	−4.20%
Jinghua City	10 min	2.94	2.69	−0.24	−8.31%
	20 min	5.88	5.34	−0.54	−9.14%
	30 min	8.82	8.15	−0.67	−7.59%
	40 min	11.75	11.39	−0.36	−3.05%
	50 min	14.69	13.44	−1.25	−8.52%
	60 min	17.63	16.59	−1.04	−5.91%
Slender Lake	10 min	3.30	3.16	−0.14	−4.36%
	20 min	6.61	6.48	−0.12	−1.89%
	30 min	9.91	9.40	−0.51	−5.10%
	40 min	13.21	12.34	−0.88	−6.63%
	50 min	16.52	15.45	−1.07	−6.46%
	60 min	19.82	18.71	−1.11	−5.60%
Lotus Pond	10 min	3.07	2.75	−0.32	−10.31%
	20 min	6.13	5.58	−0.55	−9.01%
	30 min	9.20	8.57	−0.63	−6.81%
	40 min	12.26	11.69	−0.57	−4.61%
	50 min	15.33	14.53	−0.80	−5.21%
	60 min	18.39	17.86	−0.53	−2.88%

Note: The size of the commuting circle is indicated by radii in km.

Under the rainstorm conditions, the circle area in the Jinghua City radii changed the most significantly, while the circle radii in Wanda Plaza changed the least. This is because Jinghua City is the commercial center in the west of Yangzhou, with many residents commuting and a high entertainment travel flow. Under rainstorm weather conditions, the bus travel here is not only affected by rainfall, but also affected by traffic flow and road capacity. The intersection of Wanda Plaza is equipped with special bus turn signal lights, which is near the Chengnan Expressway, and bus travel is only affected by rainfall compared to other typical communities. According to the analysis results of the commuting accessibility of typical communities in typhoon-rainstorm weather conditions, it can be seen that rainstorms can reduce the radii of the bus commuting circle within the same time by affecting the travel speed of public transportation, which influences the accessibility of residents' commuting travel, thus reducing the comfort of residents' travel, increasing the travel time of residents, and causing a reduction in the demand for flexible travel (such as leisure, culture, sports, etc.).

5. Conclusions

The wide application of big data provides a new means to study the impact of adverse weather events on urban traffic. Based on the bus GPS trajectory data, rainfall remote sensing data, POIs, Baidu thermal map and related road network data, this paper analyzes the change in commuter travel accessibility of residents in the main urban area of Yangzhou City under superimposed effects of typhoon-rainstorm weather conditions and the morning and evening peak hours from two dimensions of time and space. We deeply analyze the temporal and spatial changes in the average bus speed, travel time and commuting distance under different rainstorm intensities, and construct a bus commuting travel circle in a typical residential area. The main conclusions are summarized as follows:

- (1) By analyzing and mining multi-source heterogeneous big data (bus GPS trajectory data, bus network data, rainfall remote sensing data, and road network data), we

found that with the increase (decrease) in rainstorm intensity, the average bus speed decreases (increases) and the travel time increases (decreases). Compared with non-morning and evening peak commuting hours, during morning and evening peak hours under normal weather conditions, the average speed of approximately 34 out of 51 bus routes was affected. The average bus speed was 20.6 km/h, with an overall reduction of 10%. The average time was 56 min, with an overall increase of $-15\sim 24\%$. During morning and evening peak hours under typhoon-rainstorm weather conditions, the average speed of approximately 42 out of 51 bus routes was significantly affected by rainfall. Among them, the average speed of the corresponding bus lines in Jinghua City, Wanda Plaza, Slender West Lake and Lotus Pond decreased significantly compared with the above normal conditions. The average bus speed was only 18.9 km/h, and the reduction amplitude was 25%. The average commute during the morning peak hour was 60.47 min. The average commute during the evening peak hour was 58.7 min, with an overall increase of 15%.

- (2) Based on Amap POI data and Baidu thermal map data, the study extracts the four main residential areas (Lotus Pond, Slender West Lake, Jinghua City and Wanda Plaza), and uses the improved gravity model to quantitatively calculate the commuting accessibility of the several residential areas. It is found that the superposition of rainstorm weather and morning peak hours has different degrees of impact on the average speed of the above residential areas, with the most obvious impact on Jinghua City and the smallest impact on Wanda Plaza. Under the rainstorm weather conditions, the traffic commute in the main urban area of Yangzhou is basically normal, mainly due to the improvement of the prediction accuracy of typhoon-rainstorm weather and the timely traffic prevention measures, which reduces the travel of public transportation to a certain extent.

Although some meaningful conclusions have been obtained by research and analysis, this paper still has some limitations. Due to the limited scope of data acquisition and the immature technical means for data processing, this paper only studies the typhoon-rainstorm days in adverse weather, and the lack of precipitation data leads to the limited application scope of this study. In addition, due to the lack of traffic flow data and more transportation data (such as bicycles, electric bicycles, private cars, etc.) [39], the study failed to further analyze the changes in travel modes caused by typhoon-rainstorm weather events, which led to changes in bus commuting speeds and travel times. It failed to analyze in depth the changes in traffic flow to explain the impact mechanism of typhoon-rainstorm weather on urban road traffic.

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References

- Ridder, N.N.; Pitman, A.J.; Westra, S.; Ukkola, A.; Do, H.X.; Bador, M.; Hirsch, A.L.; Evans, J.P.; Di Luca, A.; Zscheischler, J. Global hotspots for the occurrence of compound events. *Nat. Commun.* **2020**, *11*, 5956. [\[CrossRef\]](#)
- Markolf, S.A.; Hoehne, C.; Fraser, A.; Chester, M.V.; Underwood, B.S. Transportation resilience to climate change and extreme weather events—Beyond risk and robustness. *Transp. Policy* **2019**, *74*, 174–186. [\[CrossRef\]](#)
- Yin, J.; Ren, X.; Liu, R.; Tang, T.; Su, S. Quantitative analysis for resilience-based urban rail systems: A hybrid knowledge-based and data-driven approach. *Reliab. Eng. Syst. Saf.* **2022**, *219*, 108183. [\[CrossRef\]](#)
- Böcker, L.; Dijst, M.; Prillwitz, J. Impact of everyday weather on individual daily travel behaviours in perspective: A literature review. *Transp. Rev.* **2013**, *33*, 71–91. [\[CrossRef\]](#)
- Kashfi, S.A.; Bunker, J.M.; Yigitcanlar, T. Modelling and analysing effects of complex seasonality and weather on an area's daily transit ridership rate. *J. Transp. Geogr.* **2016**, *54*, 310–324. [\[CrossRef\]](#)
- Tang, J.; Xu, L.; Luo, C.; Ng, T.S.A. Multi-disruption resilience assessment of rail transit systems with optimized commuter flows. *Reliab. Eng. Syst. Saf.* **2021**, *214*, 107715. [\[CrossRef\]](#)
- Button, K. *Transport Economics*; Edward Elgar Publishing: Herndon, USA, 2010.
- Litman, T. *Understanding Transport Demands and Elasticities: How Prices and Other Factors Affect Travel Behavior*; Victoria Transport Policy Institute: Victoria, BC, Canada, 2017.
- Tsapakis, I.; Cheng, T.; Bolbol, A. Impact of weather conditions on macroscopic urban travel times. *J. Transp. Geogr.* **2013**, *28*, 204–211. [\[CrossRef\]](#)
- Agarwal, M.; Maze, T.H.; Souleyrette, R.R. Impacts of Weather on Urban Freeway Traffic Flow Characteristics and Facility Capacity. *Mid-Cont. Transp. Res. Symp.* **2005**, *20*, 1121–1134.
- Angel, M.L.; Sando, T.; Chimba, D.; Kwigizile, V. Effects of rain on traffic operations on Florida freeways. *Transp. Res. Rec.* **2014**, *2440*, 51–59. [\[CrossRef\]](#)
- Rahman, A.; Lownes, N.E. Analysis of rainfall impacts on platooned vehicle spacing and speed. *Transp. Res. Part F Traffic Psychol. Behav.* **2012**, *15*, 395–403. [\[CrossRef\]](#)
- Xu, F.; He, Z.; Sha, Z.; Zhuang, L.; Sun, W. Assessing the impact of rainfall on traffic operation of urban road network. *Procedia Soc. Behav. Sci.* **2013**, *96*, 82–89. [\[CrossRef\]](#)
- Kwon, J.; Barkley, T.; Hranac, R.; Petty, K.; Compin, N. Decomposition of travel time reliability into various sources: Incidents, weather, work zones, special events, and base capacity. *Transp. Res. Rec.* **2011**, *2229*, 28–33. [\[CrossRef\]](#)
- Brazil, W.; White, A.; Nogal, M.; Caulfield, B.; O'Connor, A.; Morton, C. Weather and rail delays: Analysis of metropolitan rail in Dublin. *J. Transp. Geogr.* **2017**, *59*, 69–76. [\[CrossRef\]](#)
- Black, A.W.; Mote, T.L. Effects of winter precipitation on automobile collisions, injuries, and fatalities in the United States. *J. Transp. Geogr.* **2015**, *48*, 165–175. [\[CrossRef\]](#)
- Edwards, J.B. Weather-related road accidents in England and Wales: A spatial analysis. *J. Transp. Geogr.* **1996**, *4*, 201–212. [\[CrossRef\]](#)
- Theofilatos, A.; Yannis, G. A review of the effect of traffic and weather characteristics on road safety. *Accid. Anal. Prev.* **2014**, *72*, 244–256. [\[CrossRef\]](#)
- Weng, M.; Ding, N.; Li, J.; Jin, X.; Xiao, H.; He, Z.; Su, S. The 15-min walkable neighborhoods: Measurement, social inequalities and implications for building healthy communities in urban China. *J. Transp. Health* **2019**, *13*, 259–273. [\[CrossRef\]](#)
- García-Albertos, P.; Picornell, M.; Salas-Olmedo, M.H.; Gutiérrez, J. Exploring the potential of mobile phone records and online route planners for dynamic accessibility analysis. *Transp. Res. Part A Policy Pract.* **2019**, *125*, 294–307. [\[CrossRef\]](#)
- Wang, F.; Xu, Y. Estimating O-D travel time matrix by Google Maps API: Implementation, advantages, and implications. *Ann. GIS* **2011**, *17*, 199–209. [\[CrossRef\]](#)
- Huang, J.; Levinson, D.; Wang, J.; Zhou, J.; Wang, Z.-J. Tracking job and housing dynamics with smartcard data. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 12710–12715. [\[CrossRef\]](#)
- Li, J.; Li, X.; Chen, D.; Godding, L. Assessment of metro ridership fluctuation caused by weather conditions in Asian context: Using archived weather and ridership data in Nanjing. *J. Transp. Geogr.* **2018**, *66*, 356–368. [\[CrossRef\]](#)
- SUNGA, A.; DIAZ, C.E.; NAPALANG, M.S. The Influence of rainfall on mode choice and departure time of commuters: The case of Ortigas CBD workers. *J. East. Asia Soc. Transp. Stud.* **2017**, *12*, 771–783.
- Kalkstein, A.J.; Kuby, M.; Gerrity, D.; Clancy, J.J. An analysis of air mass effects on rail ridership in three US cities. *J. Transp. Geogr.* **2009**, *17*, 198–207. [\[CrossRef\]](#)
- Tao, S.; Corcoran, J.; Rowe, F.; Hickman, M. To travel or not to travel: 'Weather' is the question. Modelling the effect of local weather conditions on bus ridership. *Transp. Res. Part C Emerg. Technol.* **2018**, *86*, 147–167. [\[CrossRef\]](#)
- Zhou, Y.; Li, Z.; Meng, Y.; Li, Z.; Zhong, M. Analyzing spatio-temporal impacts of extreme rainfall events on metro ridership characteristics. *Phys. A Stat. Mech. Its Appl.* **2021**, *577*, 126053. [\[CrossRef\]](#)
- Zhou, M.; Wang, D.; Li, Q.; Yue, Y.; Tu, W.; Cao, R. Impacts of weather on public transport ridership: Results from mining data from different sources. *Transp. Res. Part C Emerg. Technol.* **2017**, *75*, 17–29. [\[CrossRef\]](#)
- She, S.; Zhong, H.; Fang, Z.; Zheng, M.; Zhou, Y. Extracting flooded roads by fusing GPS trajectories and road network. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 407. [\[CrossRef\]](#)

30. Lai, X.; Gao, C. Spatiotemporal Patterns Evolution of Residential Areas and Transportation Facilities Based on Multi-Source Data: A Case Study of Xi'an, China. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 233. [[CrossRef](#)]
31. Ma, D.; Liu, B.; Huang, Q.; Zhang, Q. Evolution Characteristics and Causes—An Analysis of Urban Catering Cluster Spatial Structure. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 302. [[CrossRef](#)]
32. GB/T4754-2017; Industrial Classification for National Economic Activities. Standards Press of China: Beijing, China, 2017.
33. Chen, Y.; Zhang, Z.; Lang, L.; Long, Z.; Wang, N.; Chen, X.; Wang, B.; Li, Y. Measuring the Spatial Match between Service Facilities and Population Distribution: Case of Lanzhou. *Land* **2023**, *12*, 1549. [[CrossRef](#)]
34. Joseph, A.E.; Phillips, D.R. *Accessibility and Utilization: Geographical Perspectives on Health Care Delivery*; Harper and Row: London, UK, 1984; p. 214.
35. Luo, W.; Wang, F. Measures of spatial accessibility to health care in a GIS environment: Synthesis and a case study in the Chicago region. *Environ. Plan. B Plan. Des.* **2003**, *30*, 865–884. [[CrossRef](#)]
36. Cleveland, R.B.; Cleveland, W.S.; McRae, J.E.; Terpenning, I. STL: A seasonal-trend decomposition. *J. Off. Stat.* **1990**, *6*, 3–73.
37. Rao, T.V.R. *Metal Casting: Principles and Practice*; New Age International: New Delhi, India, 1996; p. 294.
38. Rosner, B. Percentage points for a generalized ESD many-outlier procedure. *Technometrics* **1983**, *25*, 165–172. [[CrossRef](#)]
39. Zheng, Z.; Shen, W.; Li, Y.; Qin, Y.; Wang, L. Spatial equity of park green space using KD2SFCA and web map API: A case study of Zhengzhou, China. *Appl. Geogr.* **2020**, *123*, 102310. [[CrossRef](#)]

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