Evaluation of Urban Transportation Resilience under Extreme Weather Events

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Abstract: The frequent occurrence of extreme weather events (EWEs) in recent years has posed major hazards to urban transportation as well as socioeconomic impacts. A quantitative evaluation of the urban transportation resilience to minimize the impact caused by EWEs becomes critical to the rapid recovery of urban transportation after disasters. However, there is, generally, a lack of reliable data sources to monitor urban transportation performance under EWEs. This empirical study proposes a performance indicator (displacement) and quantitative method for evaluating the urban transportation performance under EWEs based on bus GPS trajectory datasets. Furthermore, the transportation resilience of it is quantified, and the variation is compared across temporal and spatial dimensions. The method is applied in a case study of Fuzhou, China, under rainstorm events. The results show that the Gulou and Jinan subareas have the highest transportation resilience during the yellow and red rainstorm warnings. By formulating an emergency plan and taking mitigation measures, the transportation performance in the Jinan subarea during the red rainstorm warning was improved by 36% compared to the yellow rainstorm warning. The empirical study not only fills the knowledge gap for quantifying the transportation resilience across the geographical boundary under rainstorm events, but also estimates the operation status of the road network. The results will help policymakers prioritize the resource distribution and develop effective policies or measures to further improve transportation resilience in the city.

Keywords: extreme weather events; transportation resilience; bus trajectory data; evaluation

1. Introduction

In recent years, due to global warming, extreme weather events (EWEs), such as hurricanes and floods, have become more frequent, showing an upward trend [1,2]. In addition, due to the rise in sea level and the impact of human activities [3,4], this trend is expected to escalate further [5,6]. According to statistics from the Center for Research on the Epidemiology of Disasters (CRED), between the years 2012 and 2016, the world encountered 1818 cases of natural disasters mainly related to EWEs. Between 2017 and 2021, this number increased by 9%, taking the total to 1982 cases. In terms of the countries affected globally, China is one of the regions most affected by EWEs [7]. In 2021, 17 cases of EWEs affected approximately 32.8 million people and amounted to economic losses worth USD 73.29 million in China. The infrastructure systems have been identified as vulnerable sectors affected by EWEs [8]. EWEs impose significant threats to transportation infrastructure systems due to their high uncertainty, massive scale, and destructiveness. The high frequency of EWEs has led to various risks and disruptions in urban transportation...
systems [9–13]. For example, a rainstorm washes out roadbed bridges, falling water tables cause the structural settlement of highway facilities, and heavy water accumulation on both sides of roads could block the traffic.

As the most affected urban infrastructure systems in a disaster [14], the transportation system acts as the link between various social activities in the city, making them the lifeline of the city network [15]. During EWEs, they can provide access to impacted areas to support emergency response and long-term recovery operations after a disaster, which is essential for the stable function of the city. Thus, it becomes imperative to strengthen transportation resilience. The ability of a transportation system to resume normal functioning during the post-disruption period could describe its resilience [16–18]. A quantitative evaluation of transportation resilience thereby minimizes the impact caused by various natural disasters and becomes critical to the rapid recovery of urban transportation systems after disasters [19–21]. Thus, it is necessary to select the quantitative indicators and propose effective empirical methods to quantify the resilience [22].

The need to examine urban transportation resilience under EWEs has grabbed the academic limelight. Early studies indicated that qualitative approaches were usually used to evaluate transportation resilience. Murray-Tuite [23] defined resilience in transportation and proposed several indicators to assess transportation resilience under EWEs. Ta et al. [24] proposed a definition of freight transportation resilience based on the interactions among organizations, infrastructure, and users, and developed a structured framework in terms of the properties of freight transportation resilience to facilitate the overall ability of the freight transportation to recover from disruptions. Similarly, Tamvakis et al. [25] discussed the basic parameters of transportation resilience based on its components and proposed a framework for evaluating its resilience. Reggiani [26] discussed the relationship between resilience and transportation and presented a complete conceptual framework for transportation resilience. Although much work has been done on evaluating transportation resilience previously, most of these methods were qualitative and theoretical frameworks based on the definition and characteristics of transportation resilience.

Ip and Wang [27] proposed a quantitative method to evaluate the resilience of transportation networks. Transportation resilience was measured by calculating the weighted average number of reliable independent paths with all the other urban nodes in the networks. Omer et al. [28] proposed a road network infrastructure resilience framework to evaluate the resilience of the road connecting Manhattan to the rest of New York City. The resilience of the road network was measured by the ratio of travel time before and after a disruption. Stamos et al. [29] developed a data-driven approach for evaluating the resilience of the European passenger transportation networks during EWEs. Twumasi-Boakye et al. [30] developed a resilience index based on vehicle distance and travel time to quantitatively evaluate the resilience of the transportation network in the bridge-damaged areas of the Tampa Bay region in Florida. Ilbeigi [31] used the systematic quantitative approach of cumulative sum (CUSUM) statistical process control charts to statistically monitor the closeness centrality of a transportation network through time, in order to detect unusual patterns due to an extreme event. Chen et al. [32] proposed a method to quantitatively evaluate the urban public transportation resilience based on the system’s function curves. Bus service rates and online taxi rates were used to characterize system functions, and quantitatively evaluate the public transportation resilience during the Zhengzhou storm and flooding in 2021. Based on the quantitative literature review, it was found that a major challenge for quantifying transportation resilience is the lack of empirical observations in disasters [33]. Most quantitative studies only consider the temporal variance of the transportation network. Specifically, the developed evaluation methods could not capture the real-time performance and recovery process of the transportation network in different subareas of the city under EWEs. The spatial variation of transportation resilience under different EWEs may lead to different levels of impact in different subareas [34]. It is important to propose targeted improvement plans and emergency policies based on the
resilience level of different subareas and to allocate limited resources more effectively to the relatively low resilient subareas [35,36].

Recently, the use of technologies such as GPS tracking systems has provided researchers with real-time trajectory information in urban areas [37]. Donovan and Work [38] analyzed a dataset of nearly 700 million taxi trips in New York City and introduced paces (normalized travel times) between regions of the city as the key performance indicator to detect and measure the impact of unusual events on transportation, such as Hurricane Sandy in 2012. The effect of unusual events on transportation was only detected and measured in this study, and urban transportation resilience was not quantified. Zhang et al. [39] used taxi and bus trajectory data in Nanjing to quantify human mobility perturbation in urban areas during EWEs. However, this study only focused on evaluating the human mobility perturbation, and the perturbation varied over the time span of EWEs, with no consideration given to the spatial variation of the perturbation. It did not provide improvement measures from an emergency management perspective based on the magnitude of the perturbation.

In this study, a performance indicator and quantitative method are proposed for evaluating the urban transportation performance under EWEs based on bus GPS trajectory datasets from Fuzhou, China. It measures transportation performance by calculating the deviation of the total displacement of all buses under a rainstorm. Based on the transportation performance curve, this study quantifies transportation resilience and analyzes it in different subareas of the city across temporal and spatial dimensions.

The main contribution of this study is as follows: (1) displacement as a key performance indicator is selected for evaluating urban transportation performance and quantifying transportation resilience, and it can also improve the understanding of transportation resilience in cities. (2) Bus GPS trajectory data are used to evaluate and monitor urban transportation performance under EWEs. Bus GPS trajectory data can record transportation operations throughout the city. The empirical study may fill the knowledge gap for quantifying transportation resilience across a geographical boundary under rainstorm events, and the results provide valuable information for the development of an urban emergency policy from a transportation resilience perspective.

Following the introduction section, the paper is further divided into five sections. In Section 2, the bus GPS trajectory dataset from Fuzhou and data pre-process method are briefly described. In Section 3, the indicator and method for evaluating transportation resilience in different subareas are proposed. In Section 4, the proposed evaluation indicator and method are applied to calculate transportation resilience in three subareas of Fuzhou, Cangshan, Gulou, and Jinan, under rainstorm events based on the bus trajectory dataset in Fuzhou. In Section 5, the evaluation results of the transportation resilience from the three subareas under rainstorm events are discussed. The conclusion and future work are present in the last section.

2. Dataset

In this section, the bus GPS trajectory dataset in Fuzhou is introduced, and the data pre-process method to improve the accuracy of data is described.

2.1. Dataset Description

According to the statistical information, the total number of buses in Fuzhou by 2018 was 5370. Each bus was equipped with on-board GPS devices, which were interconnected with the data center of the Fuzhou Municipal Transportation Bureau. GPS trajectory information was transmitted to the central server approximately every thirty seconds during the operation. The total amount of data recorded every day was more than 4 million, and the size of the data was more than 1 GB. The Fuzhou bus GPS trajectory data selected in this study detailed every bus trip that occurred in the city between April 2018 and June 2018 (inclusive of the months). This dataset obtained from the Beidou Big Data Center in the Fujian University of Technology contained approximately 400 million bus GPS
trajectory data. Of these, about 80 million trajectory data were used in this study. Figure 1 shows an example of the raw bus trajectory data entries for 1 April 2018, where the BUSRDID, ROUTEID, PRODUCTID, TIMESTAMP, LONGITUDE and LATITUDE, and other information not relevant to this study were recorded for each bus trip.

![Figure 1. An example of raw bus trajectory data entries for 1 April 2018.](image)

In this study, only the BUSRDID, ROUTEID, PRODUCTID, TIMESTAMP, LONGITUDE, and LATITUDE of each trajectory were used. Table 1 shows an example of the parameters of the bus trajectories used in this study. The bus route from Fuzhou in 2018 is shown in Figure 2.

![Table 1. An example of the parameters of bus trajectories used in this study.](image)

<table>
<thead>
<tr>
<th>BUSRDID</th>
<th>DATATYPE</th>
<th>ROUTEID</th>
<th>PRODUCTID</th>
<th>ACTDATETIME</th>
<th>RECDATETIME</th>
<th>LONGITUDE</th>
<th>LATITUDE</th>
</tr>
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</table>
2.2. Data Pre-Processing

The bus trajectory dataset in Fuzhou presented the following problems: (1) redundancy and noise in trajectory data; (2) the drift of trajectory data points; (3) trajectory data outliers; (4) small amounts of trajectory data were missing. In order to improve the accuracy of data, the data were pre-processed before analysis. Firstly, according to the data usage instructions provided by Fujian Beidou Big Data Center, it was known that the DATATYPE column values of 12 and 55 were removed due to on-board GPS device failures. Secondly, the latitude and longitude values of 0, NAN, and duplicate entries in the dataset, totaling about 32 million data, were deleted to improve data quality. Thirdly, outliers were removed based on bus speed exceeding 80 km/h [40]. Fourth, the ROUTEID, PRODUCTID, ACTDATETIME, and BUSRDID columns in the bus GPS trajectory dataset were sorted in ascending order to obtain the running track of the bus during operation. By pre-processing the Fuzhou bus trajectory data, 30 million high-quality data were finally used to quantify the transportation resilience in this study. The pre-processed bus trajectory data are shown in Figure 3.
3. Method

This section introduces the method for evaluating urban transportation performance. First, the deviation of the total displacement of all buses’ GPS trajectories under EWEs are calculated over time, then the transportation resilience is quantified in different subareas based on the transportation performance curve. Figure 4 shows the flowchart of the methodology for evaluating the urban transportation resilience under EWEs.

Figure 3. The bus trajectory data used for calculating transportation resilience.

Figure 4. A flowchart of the evaluation method.
3.1. Evaluate the Transportation Performance under EWEs

When EWEs occur, the performance of urban transportation can change over time. In order to measure the instantaneous perturbations of the transportation performance during EWEs at any moment, the performance indicator (PI) is introduced. The PI is a normalized indicator, which is calculated to evaluate the deviation of the transportation performance from its normal state at any moment during EWEs.

Displacement (d) refers to the change of position and is one of the indicators to measure the change in the human trajectory. By accumulating the continuous displacement of all individuals (here, individual refers to a bus), the total displacement (TD) can be calculated, which is an indicator widely used in transportation. TD is calculated according to Equation (1) [39]:

$$TD = \sum_{j=1}^{m} \sum_{i=1}^{n-1} d_{ij}$$

where $m$ refers to the number of individuals, $n$ refers to the number of locations visited by the $j$th individual in a time span (taken as an hour here), and $d_{ij}$ is the $i$th displacement in the $j$th individual’s trajectory, and is calculated as shown in Equation (2) [41]:

$$d_{ij} = 2rsin^{-1}\left(\frac{\sin^2\left(\frac{\lambda_{i+1,j} - \lambda_{i,j}}{2}\right) + \cos\lambda_{i+1,j} \cos\lambda_{i,j} \sin^2\left(\frac{\xi_{i+1,j} - \xi_{i,j}}{2}\right)}{2}\right)$$

where $r$ is the radius of the earth (6371 km); $\lambda_{i,j}$ and $\lambda_{i+1,j}$ denote the latitude of the first point and the second point, respectively, of the displacement in the individual’s trajectory in radians; $\xi_{i,j}$ and $\xi_{i+1,j}$ denote the longitude of the first and second points, respectively, of the $i$th displacement in the $j$th individual’s trajectory in radians.

A benchmark is needed to evaluate the deviation of bus trajectories from their normal state after TD calculation. The benchmark is denoted as $\overline{TD}$, which refers to the total displacement of all individuals over a time span in the absence of EWEs. $\overline{TD}$ can be calculated based on the TD value under normal conditions following Equation (3) [39].

$$\overline{TD} = \sum_{i=1}^{n} TD_i$$

where $TD_i$ is the TD value of the $i$th time span without EWEs. Based on the $TD_i$ value, PI can be calculated by normalizing TD with $\overline{TD}$, as shown in Equation (4).

$$PI = \frac{TD}{\overline{TD}}$$

3.2. Quantify the Transportation Resilience in Different Subareas under EWEs

The occurrence of EWEs may have varying degrees of impact on transportation resilience across subareas of the city. As the recovery process of transportation varies in each subarea, it is imperative to target the lowest resilience subarea to ensure it returns to its normal state, thereby reducing the impact of EWEs on that subarea. During the EWEs, when different subareas are affected, the transportation performance in each subarea is perturbed, and this perturbation continues for some time until the EWEs gradually cease. Bruneau et al. [42] argued that, with the functionality recovery curve, there is a significant and sudden decrease in functionality due to an extreme event at time instant $t_0$, followed by a gradual recovery of functionality, until the system is fully functional at time instant $t_2$. Motivated by the resilience concept and resilience quantification framework [19], the transportation performance can also be depicted in a curve to illustrate the impacts of EWEs on urban transportation. The transportation performance curve can be analyzed in two phases, the disruption and recovery phases [43], as shown in Figure 5.
Figure 5. Curve showing transportation performance.

As can be seen in Figure 5, the EWEs occur at $t_0$, after which the transportation performance curve begins to show a downward tendency. Usually, it will drop to the threshold value where the transportation performance merely meets the lowest requirements, at which point the negative effects of EWEs are fully released. Subsequently, the transportation performance begins to recover gradually and returns to stability at $t_2$. Among them, $t_0$ indicates the time when the EWEs begin or the time when the transportation performance perturbation begins, $t_1$ indicates the time when the perturbation reaches its lowest point, and $t_2$ indicates the time when the perturbation ends. The disruption phase ranges from the time when the transportation performance perturbation begins to the time it reaches the lowest point. The slope of the disruption phase is denoted by $k_d$, which is calculated as shown in Equation (5). The recovery phase ranges from the time when the perturbation reaches the lowest point to the time when the perturbation ends. The slope of the recovery phase is denoted by $k_r$, which is calculated based on Equation (6).

$$k_d = \frac{PI(t_1) - PI(t_0)}{t_1 - t_0}$$

$$k_r = \frac{PI(t_2) - PI(t_1)}{t_2 - t_1}$$

Particularly, the normalized indicator PI (which ranges from [0, 1]) is used to measure the deviation of the transportation performance from its normal state at any moment under EWEs. The resilience index attempts to comprehensively represent resilience with one parameter, with the value varying between 0 and 1 [44]. It has been widely used for resilience analyses of various infrastructure systems. Thus, the normalized integrating PI over the time span of the EWEs yields the resilience (R) of the transportation, as shown in Equation (7).

$$R = \int_{t_0}^{t_2} \frac{PI}{t_2 - t_0} dt$$

The value of R depends on the magnitude of the PI, and the duration of the impact of EWEs. This duration may exceed the time span of the EWEs and last for a considerable period of time. In this study, $t_0$ is the moment when the PI value first drops below 0.95; $t_2$ is the first point in time when the PI value remains at, at least, 95% during the next 24 h, which is to exclude the deviations of the PI from the specified values caused by factors...
including abnormal road congestion or changes in bus routes by public transportation groups.

4. Case Study in Fuzhou

4.1. Rainstorm Events

Fuzhou is the capital of Fujian Province, China, with a resident population of over 7 million people in 2018 [45]. On the night of 2 May 2018, the city experienced a rainstorm. The China Meteorological Administration (CMA) issued a yellow rainstorm warning, which indicates that the precipitation in Fuzhou city reached more than 50 mm within 6 h of the warning [46]. The rainstorm poured down at 23:00 and did not end until 12:00 the next day, causing waterlogging on some roads in the central area of Fuzhou, slowing down the movement of vehicles, and causing great disturbances.

About a month and half later, the city experienced another more severe rainstorm. It started at 14:00, 20 June 2018, and the CMA issued an orange rainstorm warning soon after, at 16:10. An hour later, the warning level was raised to the highest warning level: red. The rainstorm caused widespread disruptions in transportation and communication, destroyed crops, and also triggered geological disasters such as landslides and mudslides in Fuzhou. The rainstorm lasted for about 10 h, with the total precipitation exceeding 90 mm. Among them, the maximum hourly precipitation reached 46.8 mm. According to the records of the Fujian Meteorological Bureau, the hourly precipitation levels in Fuzhou during the yellow and red rainstorm warnings are shown in Figure 6 and Figure 7, respectively.

![Image of Figure 6](image-url)

**Figure 6.** Hourly precipitation during the yellow rainstorm warning in Fuzhou.
4.2. Division of Subareas

The distribution of bus trajectory data points was visualized and displayed with different brightnesses according to the raster size of 300 m. A brighter raster indicated the highest number of bus trajectory data points, while a darker raster indicated the lowest. The heat map of distribution was drawn based on the bus trajectory data points distribution picture. The picture of bus trajectory data points distribution is shown in Figure 8, and the heat map of bus trajectory data points distribution is shown in Figure 9.

Figure 7. Hourly precipitation during the red rainstorm warning in Fuzhou.

Figure 8. Picture showing bus trajectory data points distribution.
As seen in Figures 8 and 9, the distribution of bus trajectory points in the central area of Fuzhou was denser, indicating a higher number of buses. In this study, Cangshan, Gulou, and Jinan as administrative areas in central Fuzhou were selected to study. The Gulou subarea, as the old area of the city, is home to many provincial and municipal government agencies. The Cangshan subarea is a newly developed urban area. The Jinan subarea is the largest area in central Fuzhou. The three subareas of Fuzhou are marked in grey in Figure 10. The administrative level analysis is helpful to formulate an emergency management plan based on the geographical characteristics and development of each subarea.

4.3. Indicator Calculation

The TD in this case study was calculated by the following steps. First, using a time span of one hour as a reference, the trajectory of each bus for a given hour was obtained
from the pre-processed dataset. Second, the $d_{ij}$ was obtained by calculating the displacement between every two adjacent coordinates in the trajectory sequence. Third, the displacement of each bus in the trajectory sequence data of each subarea was accumulated to obtain the hourly displacement of each bus. Fourth, the TD was calculated by accumulating the hourly displacement of all buses in each subarea.

The value of $\overline{TD}$ was determined based on the average TD value for the same hour of the same day in the two weeks before and one week after the EWEs occurred. $\overline{TD}$ was also calculated on an hourly basis, and its calculation process was similar to that of TD. Once TD and $\overline{TD}$ were calculated, PI could be calculated according to Equation (4). The transportation performance curves in each subarea were plotted based on the calculated PI values. The values of $k_d$ and $k_r$, were then calculated in different subareas by using Equations (5) and (6). The normalized integrating PI over the time span of the transportation performance perturbation yielded the values of $R$ in each subarea.

5. Results

Transportation resilience in the Cangshan, Gulou, and Jinan subareas of Fuzhou during yellow and red rainstorm warnings was quantitatively evaluated using the aforementioned indicator and method in this case study. The curves of the transportation performance in each subarea during the yellow and red rainstorm warning are shown in Figure 11. The results of this quantitative evaluation are shown in Table 2. The results are discussed and interpreted from three perspectives, including a comparison between different subareas under the yellow rainstorm warning, a comparison between different subareas under the red rainstorm warning, and a comparison between different rainstorm levels in the same subareas.
Figure 11. Curve showing transportation performance during the yellow and red rainstorm warning in Cangshan, Gulou, and Jinan subareas of Fuzhou. The left side shows the transportation performance curve in the Cangshan, Gulou, and Jinan subareas of Fuzhou during the yellow rainstorm warning, and the right side shows the transportation performance curve in the Cangshan, Gulou, and Jinan subareas of Fuzhou during the red rainstorm warning.

Table 2. Summary of evaluation results.

<table>
<thead>
<tr>
<th></th>
<th>Yellow Rainstorm Warning</th>
<th>Red Rainstorm Warning</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cangshan</td>
<td>Gulou</td>
</tr>
<tr>
<td>Beginning of rainstorms ($t_0'$)</td>
<td>23:00, 2 May 2018</td>
<td>14:00, 20 June 2018</td>
</tr>
<tr>
<td>Beginning of performance perturbation ($t_0$)</td>
<td>0:30, 3 May 2018</td>
<td>23:30, 2 May 2018</td>
</tr>
<tr>
<td>The lowest point of PI ($t_1$)</td>
<td>5:00, 3 May 2018</td>
<td>9:45, 3 May 2018</td>
</tr>
<tr>
<td>End of performance perturbation ($t_2$)</td>
<td>10:05, 3 May 2018</td>
<td>11:15, 3 May 2018</td>
</tr>
<tr>
<td>Disruption phase</td>
<td>4 h 30 min</td>
<td>10 h 15 min</td>
</tr>
<tr>
<td>Slope of the disruption phase ($k_d$)</td>
<td>−0.04</td>
<td>−0.013</td>
</tr>
<tr>
<td>Recovery phase</td>
<td>5 h 5 min</td>
<td>1 h 30 min</td>
</tr>
<tr>
<td>Slope of the recovery phase ($k_r$)</td>
<td>0.035</td>
<td>0.087</td>
</tr>
<tr>
<td>Duration of performance perturbation</td>
<td>9 h 35 min</td>
<td>11 h 45 min</td>
</tr>
<tr>
<td>The lowest PI value</td>
<td>0.77</td>
<td>0.82</td>
</tr>
<tr>
<td>R value</td>
<td>0.93</td>
<td>0.95</td>
</tr>
</tbody>
</table>

5.1. Comparison between Different Subareas under the Yellow Rainstorm Warning

The curves of the transportation performance in the Cangshan, Gulou, and Jinan subareas during the yellow rainstorm warning are shown in Figure 11a–c. The rainstorm began at 23:00, 2 May 2018, as seen in Figure 11a–c. The perturbation of the transportation performance in the Cangshan and Gulou subareas began at 0:30, 3 May, and 23:30, 2 May, and the disruption phase lasted for 4 h 30 min and 10 h 15 min, respectively. The transportation performance curve in the Jinan subarea began to show a downward tendency at 0:05, 3 May, and this trend lasted for 1 h 10 min. The perturbation in the Cangshan, Gulou, and Jinan subareas reached the lowest point around 5:00, 9:45, and 1:15, 3 May, with the lowest point being 0.77, 0.82, and 0.53, respectively. Then, the transportation performance in the Cangshan, Gulou, and Jinan subareas recovered gradually, returning to stability at 10:05, 11:15, and 11:30, 3 May, and this recovery phase lasted for 5 h 5 min, 1 h 30 min, and 10 h 15 min, respectively. The rainstorm temporarily stopped between 6:00.
and 7:00, 3 May, after which the Cangshan, Gulou, and Jinan subareas experienced more precipitation until it ended at 12:00. The curves of the transportation performance in the Cangshan and Gulou subareas oscillated significantly, exhibiting a W-shape from 0:30 to 5:00, May 3, and 23:30, 2 May, to 11:15, 3 May, respectively. The curves of the transportation performance in the Jinan subarea showed a V-shape from 0:05 to 3:00, 3 May. After that, it oscillated significantly, exhibiting a W-shape. Even though the new round of precipitation occurred during the morning rush hour, there was no significant impact on transportation in the Cangshan, Gulou, and Jinan subareas due to the small amount of precipitation. According to Table 2, the duration of the transportation performance perturbation in the Cangshan, Gulou, and Jinan subareas during the yellow rainstorm warning was obtained as 9 h 35 min, 11 h 45 min, and 11 h 25 min, respectively. Based on the curves of the transportation performance in the Cangshan, Gulou, and Jinan subareas during the yellow rainstorm warning and Equations (5)–(7), the values of $k_d$, $k_r$, and R were $-0.04$, $0.035$, and $0.93$ in the Cangshan subarea; the values of $k_d$, $k_r$, and R were $-0.013$, $0.087$, and $0.95$ in the Gulou subarea; the values of $k_d$, $k_r$, and R were $-0.36$, $0.041$, and $0.86$ in the Jinan subarea, respectively.

The following conclusions can be drawn during the yellow rainstorm warning by comparing the transportation performance curves and evaluation results in the Cangshan, Gulou, and Jinan subareas. First, according to Table 2, it can be seen that the lowest points of the perturbation in the Cangshan, Gulou, and Jinan subareas were 0.77, 0.82, and 0.53; the slope of the disruption phase was $-0.04$, $-0.013$, and $-0.36$; the recovery time was 5 h 5 min, 1 h 30 min, and 10 h 15 min; and the transportation resilience was 0.93, 0.95, and 0.86, respectively. This indicates that the transportation performance in the Jinan subarea had the largest decline, the fastest disruption speed and the longest recovery time, and the lowest transportation resilience. The foremost reason for this was the high topography in the northern part of the Jinan subarea and the low topography in the southern part. Waterlogging can easily occur in Dengyun Road, Helin Road, and Chongan Road in the southern part of the Jinan subarea based on the government report.

Secondly, compared with the Cangshan and Jinan subareas, the Gulou subarea suffered the most severe perturbation between 8:00 and 10:00 on 3 May. It was found that the Gulou subarea is home to many provincial and municipal government agencies and companies, and heavy traffic caused serious congestion during the morning rush hour. The PI developed in this study could monitor the transportation performance and capture the perturbation very well. Lastly, the rainstorm ended around 12:00, 3 May, whereas the perturbation in the three subareas returned to stable around 11:00, 3 May. This indicates that the transportation of the three subareas fully recovered before the rainstorm ended.

**5.2. Comparison between Different Subareas under the Red Rainstorm Warning**

The curves of the transportation performance in the Cangshan, Gulou, and Jinan subareas during the red rainstorm warning are shown in Figure 11d–f. As seen in Figure 11d–f, the rainstorm began at 14:00, 20 June 2018. The transportation performance curves in the Cangshan, Gulou, and Jinan subareas began to show a downward trend at 17:05, 18:30, and 19:00, 20 June, and this trend lasted for 2 h 55 min, 1 h 30 min, and 1 h, respectively. It reached the lowest point around 20:00, 20 June, when the lowest point was 0.5, 0.67, and 0.72. Then, the transportation performance in the Cangshan and Jinan subareas recovered gradually and showed an upward trend, returning to stability at 22:30 and 21:00, 20 June, and this recovery phase lasted for 2 h 30 min and 1 h, respectively. The transportation performance in the Gulou subarea gradually began to recover after reaching its lowest point, returning to stability at 23:00, 20 June, and the recovery phase lasted for 3 h. Overall, the curves of the transportation performance in the Cangshan and Jinan subareas showed a V-shape, and bounced back immediately after reaching the lowest point. During the recovery process, the curve of transportation performance in the Gulou subarea experienced a plateau period from 21:00 to 22:00, 20 June. As seen in Table 2, the duration of the transportation performance perturbation in the Cangshan, Gulou, and Jinan subareas
during the red rainstorm warning was obtained as 5 h 25 min, 4 h 30 min, and 2 h, respectively. Based on the curves of the transportation performance in the Cangshan, Gulou, and Jinan subareas during the red rainstorm warning and Equations (5)–(7), the values of \( k_d \), \( k_r \), and \( R \) were −0.154, 0.18, and 0.69 in the Cangshan subarea; the values of \( k_d \), \( k_r \), and \( R \) were −0.187, 0.093, and 0.82 in the Gulou subarea; the values of \( k_d \), \( k_r \), and \( R \) were −0.23, 0.23, and 0.83 in the Jinan subarea, respectively.

According to Table 2, it can be seen that there was an average delay of 4 h between the occurrence of the rainstorm around 14:00, June 20, and the beginning of the transportation performance perturbation around 18:00, June 20, indicating that the urban transportation exhibited a certain level of resistance to the rainstorm. The duration of the transportation performance perturbation in the Cangshan, Gulou, and Jinan subareas was 5 h 25 min, 4 h 30 min, and 2 h, with the lowest point of perturbation being 0.5, 0.67, and 0.72, and the transportation resilience being 0.69, 0.82, and 0.83, respectively. This indicates that during the red rainstorm warning, the transportation performance perturbation in the Cangshan subarea had the longest duration and the largest decline, and the lowest transportation resilience. This was probably because the Cangshan subarea was a new developing area, lacked experience in dealing with rainstorm events, and had no effective response measures. Additionally, in the recovery process, the Gulou subarea had a plateau period compared with Cangshan and Jinan. The Gulou subarea had the slowest recovery speed of 0.093 and the longest recovery time of 3 h, compared to the recovery speeds of 0.18 and 0.23, and recovery times of 2 h 30 min and 1 h in the Cangshan and Jinan subareas. The reason for this was that the Gulou subarea is an old city with older infrastructure in all aspects. Secondly, the Gulou subarea was connected to the Cangshan and Jinan subareas, which were prone to traffic delays and congestion due to a high traffic flow. Finally, the Gulou subarea had many dead-end highways, causing poor drainage and large areas of waterlogging during a rainstorm.

5.3. Comparison between Different Rainstorm Levels in the Same Subareas

As can be seen in Figure 11, there was a significant difference in the perturbation of the transportation performance caused by different levels of rainstorms in the same subareas. During the red rainstorm warning, the rainstorm occurred during the daytime and there was an average delay of 4 h between the beginning of the rainstorm and the beginning of performance perturbation. In contrast, during the yellow rainstorm warning, the rainstorm occurred during the night and there was an average delay of 1 h. This implies that the urban transportation was more resilient during the day than at night. The reason for this may be that it was easier for transportation managers to mobilize resources during the daytime compared to the night. Second, the night rescue and relief teams were not well-dispatched and implemented.

In addition, it can be seen from Table 2 that the recovery time for the transportation performance in the Cangshan and Jinan subareas during the yellow rainstorm warning was 5 h 5 min and 10 h 15 min, which was significantly longer than the 2 h 30 min and 1 h during the red rainstorm warning. The possible reason for this could be the relatively small number of emergency transportation managers and personnel in the Cangshan and Jinan subareas at night, and the lack of effective countermeasures to mitigate the effects of a rainstorm. Comparing the transportation resilience for different rainstorm levels in the three subareas, it can be seen that the transportation resilience in the Cangshan, Gulou, and Jinan subareas was 0.69, 0.82, and 0.83 during the red rainstorm warning, which was significantly lower than 0.93, 0.95, and 0.86 during the yellow rainstorm warning. This implies that the higher the rainstorm’s level, the lower the transportation resilience in the three subareas.

Notably, during the red rainstorm warning, the slope of the disruption phase and the lowest point of perturbation in the Jinan subarea were −0.23 and 0.72, which were more than those of −0.36 and 0.53 during the yellow rainstorm warning, which indicates that the disruption speed in the Jinan subarea was faster during the yellow rainstorm warning.
Secondly, during the red rainstorm warning, the transportation resilience in the Jinan subarea was the highest among the three subareas, while during the yellow rainstorm warning, it was the lowest among the three subareas. This was probably because the rainstorm caused a large impact on the transportation in the Jinan subarea during the yellow rainstorm warning. The yellow rainstorm event attracted the attention of the Jinan District government, who formulated an emergency plan and took better countermeasures during the red rainstorm warning, such as cleaning the drainage outlet of Dengyun Road and unblocking the drainage pipes, taking traffic restriction control of Helin Road, and filling the drainage pipes on Chongan Road to reduce the impact of the rainstorm on the transportation. This proves that the transportation performance in the Jinan subarea during the red rainstorm warning was improved by 36% compared to the yellow rainstorm warning by formulating an emergency plan and taking mitigation measures.

6. Conclusions and Future Work

The performance indicator and index calculation method introduced in this study could accurately monitor transportation performance and capture the perturbation of the transportation network during a rainstorm. Transportation resilience under various rainstorms in different subareas of Fuzhou, China, is also quantified based on the proposed methodology in this study. The results of the case study validate the effectiveness of the proposed indicator and method, and also present the various degrees of impact from a rainstorm in the Cangshan, Gulou, and Jinan subareas of Fuzhou. The impact of a rainstorm on transportation can be mitigated by developing emergency management plans and prioritizing measures for lower resilience subareas. The approaches and findings in this study could increase our understanding about the complexity of transportation resilience and provide support for developing resilient and sustainable transportation.

Additionally, this study provides valuable information for urban transportation when faced with EWEs. Based on the transportation resilience results obtained in this study, transportation managers can develop emergency plans to mobilize humans and distribute the limited material resources during the life cycle of EWEs, for the purpose of enhancing transportation resilience in different subareas of the city and guaranteeing its sustainable development. Guided by this, government departments can strengthen disaster prevention and mitigation measures, formulate emergency management policies, and pave the way for more informed and effective measures and policies, to improve the urban transportation resilience to withstand EWE-induced impacts in the future.

There are several limitations in this study that need to be noted. The transportation performance and resilience calculations are only analyzed under rainstorm events in the Case Study Section. Future studies will include other EWEs, such as hurricanes [47,48] and tsunamis [49], that can cause more severe damage to urban transportation. In addition, this study uses the baseline method to evaluate the transportation performance of the city. In future studies, the results obtained from the baseline method will be used as a reference, and new methods for evaluating urban transportation performance under EWEs will be developed. The method will be applied to multiple cities to make a comparison at various scales under different EWEs. Finally, future research will also be combined with the resilience response in the three subareas, where some concrete measures are provided for disaster resilience through interviews with disaster prevention and mitigation experts in Fuzhou.

Author Contributions: Methodology, Y.C.; Investigation, H.W. and F.Z.; Writing—original draft, Z.L.; Funding acquisition, P.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the China State Railway Group Co., Ltd. Science and Technology Research and Development Plan Project grant number [N2023B005], National Natural Science Foundation of China grant number [52008110], Natural Science Foundation of Fujian Province.
grant number [2020]05195] and The APC was funded by China State Railway Group Co., Ltd. Science and Technology Research and Development Plan Project.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request. For access to this article’s raw data, please contact the author lzj3082@hotmail.com.

Acknowledgments: This work was produced based on the study supported by the China State Railway Group Co., Ltd. Science and Technology Research and Development Plan Project (Grant No. N2023B005), National Natural Science Foundation of China (Grant No.52008110), and Natural Science Foundation of Fujian Province (Grant No.2020]05195]. The opinions, findings, conclusions, and recommendations expressed in this work are those of the authors and do not necessarily reflect the views of the sponsors.

Conflicts of Interest: Author Fubin Zhou was employed by Fujian Jiuding Construction Group Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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