Research Article
Assessing the Dynamic Resilience of Local Roads: A Case Study of Flooding in Wuhan, China

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This study proposed a modified metric inspired by the well-applied “resilience-triangle” framework to integrate the resilience concept within the traffic speed. Firstly, for setting the evolving normal functionality, this study added the concepts of robustness loss and rapidity to characterize and compare the recovery processes of local roads and assess the corresponding resilience under different traffic operation conditions. Secondly, these different evolving resilience patterns provide a quantitative benchmark for detecting the links between resilience and traffic operating conditions and exploring its impact on total resilience. Finally, this study simulated and compared the dynamic evolution of the total resilience of local roads, which accurately captured the weak and poorly resilient road locations. Our findings indicated that the proposed metric was quite efficient and accurate in assisting stakeholders to prioritize the transport planning and the retrofit projects of some specific local roads, which could improve the resilience of overall transport system significantly.

1. Introduction

In the past few decades, the transport system is becoming more interconnected and complex with organizational and technical advances. According to the frequent flooding occurred, the transport system performance has been researched on several different levels. How the transport system could better withstand and recover from disturbances to ensure public safety and the business’s continuity during flooding has been receiving considerable attention from engineers, planners, researchers, and policymakers [1, 2]. Resilience is just a concept that can be considered within transportation domains.

The concept of resilience originated from engineering mechanics in the early 19th century and has been explored in a wide range of areas, such as ecological systems [3–5], economic and environmental systems [6–8], and transport systems [9–11]. Within transport system research, even though the concept of resilience was still struggling for reaching an agreed definition, the main concept defined resilience as “the ability of a transport system to cope with disturbances and recover its normal functionality after a loss of function” [12–15], which defined the transport resilience from an transport-related perspective (i.e., structural resilience), such as the network topology [13, 15]. For example, Goldberg proposed that resilience was associated with two main properties: the degree of disturbance and the speed to recover from the disturbance [16]. Worton offered a much broader sociotechnical framework of resilience, including preparedness, response, recovery, and adaptation [17]. Reggiani cited four dimensions for resilience: robustness, redundancy, resourcefulness, and rapidity [18]. Ganin et al. noted that the resilience of the transportation was “the ability of the road network to maintain its demonstrated level of service or to restore itself to that level of service in a specified timeframe” [19]. Zhang et al. defined transport resilience based on the spatiotemporal clusters of congestion in real traffic, which proposed that the resilience followed a scale-free distribution in 2D city road networks and 1D highways with different exponents but similar exponents on different days and in different cities [20]. Tang et al. proposed that transportation systems were often treated as a functional system whose resilience was often perceived as an integrated system capability. Systemic thinking considered
basic qualities in system resilience and has been applied to transportation studies [21]. Furthermore, many researchers have proposed several qualitative and quantitative frameworks or approaches to measure the transport resilience from a transport-related perspective, such as using mathematical models, general equilibrium tools, and simulation programming [22–25]. For example, Nogal et al. introduced a novel methodology to assess the resilience of a traffic network suffering from a progressive impact. It was based on a macroscopic traffic model that simulates the dynamic response of the network when suffering a disruption, from the beginning of the perturbation to the total recovery of the system [26]. Aydin et al. have combined an intuitive decision-making process for characterizing the enhancement strategies of transportation network resilience with analytic modeling in order to improve the understanding of a road recovery behavior [27]. Calverta and Snelde conducted the Link Performance Index for Resilience (LPIR) to evaluate the resilience level of individual road sections in relation to a wider road network [5]. Simonelli et al. assessed the road network resilience by addressing the reliability and dispersion structure of traffic assignment model, which was conducted through the laboratory experiments in terms of both network/route choice modeling and OD matrix estimation based on the traffic measurements [28]. Mao et al. described a simulation approach for resilience in which an optimum system approach is compared to a user equilibrium approach [29].

In these previous proposals, the focus tended to be more on static resilience analysis, which assumed “normal functionality” as a non-time dependent and static state, just as other civil infrastructures. However, less attention was paid to the dynamic resilience analysis based on traffic-related domains (i.e., functional resilience). In practice, the normal functionality of the transport system is evolving due to the evolving traffic speed, which could not be captured by static resilience analysis. Therefore, a time-dependent metric is required to quantify transport resilience, which could explore the evolving features of the transport system. In this study, a key differentiation with previous research was that the evolving normal functionality was addressed, which was the first contribution of this study. We used a time-dependent resilience-based metric to measure the evolving process of normal functionality and define the without-event (normal) and within-event functionalities as the dynamic parameters, which provided a novel solution for forming the conceptual framework and mathematical model of transport resilience. Furthermore, most of the current literature was keyed towards road network resilience, which emphasizes the performance of the entire road network rather than only on a road section. Although network performance is crucial and requires evaluation, it eliminates the individual effect of some critical local roads, which are found to be the critical factor, resulting in a performance loss of the road network. Therefore, these critical local roads should be addressed and viewed in more detail, which should be most readily considered for improving the performance of the entire road network, even if the network performance is not directly calculated. The second contribution of this study was to assess the resilience of four selected local roads rather than an exhausting review of road network resilience. The comparative results from the dynamic resilience analysis of these local roads could be used to help road authorities investigate the different evolving patterns of resilience under different traffic operation conditions to identify the weakest local roads with maximum robustness loss and longest recovery time. Furthermore, by extending from previous studies, the last contribution of this study was to propose an indicator “robustness loss (as the difference between the robustness of within-event functionality and without-event functionality)” to measure “the ability of the local road to cope with disturbances (such as the reduced functionality),” rather than using the existing indicator “robustness.” Due to the evolving normal functionality of the local road, it is not sufficient to use the indicator “robustness (as the remaining functionality)” as a critical attribute to measure the dynamic resilience.

2. Study Area

The main focus of our study is Wuhan (latitude 29°58′N to 31°22′N and longitude 113°41′E to 115°05′E), which includes seven administrative regions (Jiangan, Jianghan, Qiaoqou, Hanyang, Wuchang, Hongshan, and Qingshan), and 12 rainwater systems (Chenjiaji, Huangxiao River, Changqing, Hankou along the Yangtze River, Hanyang along the Yangtze River, industrial port, Qingshan Town, Wuchang along the Yangtze River, Gangxi, Dongsha Lake, etc.). Wuhan lies at the intersection of Yangtze and Han rivers, and its general ground elevation is 2.0–8.0 m lower than the average flooding level of the Yangtze River. Therefore, Wuhan’s central area is often hit by flooding due to frequent and concentrated rainfall. Figure 1 shows the flooding risk map of Wuhan’s central area from 2000 to 2015 [30, 31], including 24 high-risk spots (frequency of flooding events > 0.18 times/per year), 18 medium-risk spots (0.18 times/per year > frequency of flooding events > 0.10 times/per year), and 36 low-risk spots (frequency of flooding events < 0.10 times/per year).

Since the 20th century, in Wuhan, a total of 89 lakes from 127 lakes have disappeared due to the lake-filling projects, which caused the area of rivers and lakes to be reduced by 228.9 km², equal to 14.2% of the total area. However, the areas of construction land have increased from 220.22 km² to 694.38 km² in the past decade; most of these areas were lakes and rivers before. 90% or more of the construction land is cement ground and asphalt pavement, almost impervious to block the rain infiltration path or reduce the rain infiltration amount. Therefore, in Wuhan, some local roads, which are located in low-lying areas, are prone to flooding. In this study, we selected four local roads as our study area, which were in the low-lying areas and built by filling rivers and lakes. Most high-risk spots were in or near these four local roads. Moreover, these four local roads were the top four ranked for their importance to the overall road network according to their highest traffic flow during the extended morning peak period (07:00 AM–10:00 AM, 1st July 2016). Figure 2 shows the map of these four selected local roads.
3. Data and Methods

3.1. Data of Rainfall Conditions. Wuhan suffered the most severe flooding in June 2016 due to the effect of the El Niño phenomenon. From 30th June 2016 to 6th July 2016, this heavy rainfall caused the maximum accumulated rainfall to 582.5 mm in Wuhan’s central area, which was more than a third of the annual rainfall in 2016. It was 41 times the size of Dong Lake. The rainfall was more than 200 mm in 65 meteorological monitoring stations, which reached a heavy rain level, particularly on 1st July. This heavy rainfall caused the Yangtze River tunnel to be temporarily closed, Nanhu and Tangshan lakes to be overflowed, and 162 roads to be flooded. Moreover, the airport expressway was collapsed, and 82 bus routes were rerouted or temporarily suspended. In this study, the hourly rainfall data was extracted from the Chinese Automatic Rainfall Station and CMORPH satellite, which was acquired from the National Meteorological Information Center. The dynamic evolution of these extreme rainfall processes was shown in Figure 3, which illustrated the temporal and spatial distribution of the four selected local roads’ rainfall conditions during the extended morning peak period (07:00 AM–10:00 AM, 1st July 2016). The rainfall peak occurred from 07:00 AM to 8:00 AM. In the next two hours, the rainfall moved from northwest to southeast in Wuhan, and the hourly rainfall of most areas maintained a decreasing trend in the range of 0–10 mm/h. Local road 4 experienced the maximum hourly rainfall compared to the other three local roads, which exceeded 10 mm/h in the road sections of Jianghan Bridge and Yingwu Boulevard from 07:00 AM to 8:00 AM. Up to 10:00 AM, the second rainfall peak occurred in the southeast of Wuhan (local roads 2, 3, and 4), including the Second Wuhan Yangtze River Bridge, Yangtze River Tunnel, Sha Lake Bridge, and Yingwu Boulevard.

3.2. Data of Traffic Operating Conditions. In this study, the traffic operating condition of the local road was defined according to the traffic speed. By collecting the traffic data from the road traffic monitoring system, we analyzed the real-time traffic speed of four selected local roads and then divided these local roads into three levels of TPI (Traffic Performance Index). These three levels included smooth (the average traffic speed was greater than 60 km/h), congested (the average traffic speed was between 20 km/h and 60 km/h), and severely congested (the average traffic speed was less than 20 km/h). Therefore, the corresponding traffic operating conditions of these selected local roads were divided into smooth, congested, and severely congested traffic operating conditions. For collecting the traffic data targeted, we split the day into four separate time intervals, namely, morning peak period (7:00 AM–09:00 AM), business hours (9:00 AM–4:00 PM), afternoon peak period (4:00 PM–6:00 PM), and evening/night (6:00 PM–07:00 AM). On 1st July (Friday) 2016, most rains fell from 07:00 AM to 10:00 AM. The Wuhan Traffic Management Bureau indicated that this flooding, which occurred during the morning peak period, caused significant traffic jams, serious traffic incidents, and considerable economic losses. Thus, the traffic operating conditions were simulated just during the morning peak period and extended until 10:00 AM to assess the dynamic resilience of the four selected local roads after this flooding. Moreover, the traffic operating conditions were simulated for 10 minutes each. Figure 4 shows the temporal and spatial dynamic evolution characteristics of the within-event traffic operating conditions of four selected local roads in Wuhan during the extended morning peak period (07:00 AM–10:00 AM, 1st July 2016). For comparative analysis, we selected a total of 30 working days (only on Friday with no rain) from 1st April 2016 to 31st March 2017 to illustrate the without-event traffic operating conditions (as normal functionality) during the extended morning peak period (7:00 AM–10:00 AM), which was shown in Figure 5. At a specific time, the without-event traffic operating condition of a selected local road was simulated by taking the average traffic speed of this local road at the same time during these 30 working days. All information was treated and computed in GIS. The data of traffic operating conditions had a strong time sensitivity, so we used the temporal GIS to simulate and show the dynamic evolution process of within-event and without-event traffic operating conditions of four selected local roads in Wuhan during the extended morning peak period, respectively.
Figure 2: The map of four selected local roads in Wuhan.

Figure 3: The dynamic evolution of four selected local road’s rainfall conditions during the extended morning peak period.
3.3. Defining and Assessing the Dynamic Resilience of Local Road. In civil infrastructure, resilience is defined as its ability to withstand or adapt to external shocks and recover from such shocks efficiently and effectively [21]. The resilience concept is often associated with four attributes: robustness (to withstand an extreme event and deliver a certain level of service even after the occurrence of that event), rapidity (to recover the desired functionality as quickly as possible), redundancy (to be substituted for one another), and resourcefulness (to identify problems, establish priorities, mobilize personnel, and financial resources after an extreme event) as well as technical, organizational, social, and economic dimensions [2]. In this study, in the specific context of the transport system, we defined the resilience of the local roads as “the ability of the local road to cope with disruptive flooding, with the influence of adaptive strategies to ameliorate damage and recover to normal functionality.” Here, the main focus was on engineering or dynamic resilience, referring to the rapidity of this recovery to normal functionality, rather than ecological or static resilience reflecting whether the local road returned to essentially the same functionality after flooding. Therefore, in the engineering resilience perspective, we considered the technical dimension (represented by robustness and rapidity) of resilience. Robustness refers to “the capacity of the local road to withstand the adverse effects of flooding without suffering deterioration or losing functionality.” Rapidity indicated “the ability of the local road to return to an appropriate functionality timely and quickly” [32–34]. Due to defining the normal functionality of the local road as a dynamic parameter, not a static parameter, fluctuations in the traffic operating conditions cause the evolving normal functionality.

By observing and collecting the without-event and within-event traffic operating conditions, respectively, we simulated the local road’s corresponding functionality. Therefore, in Figure 6, the without-event functionality was marked solid green curve, and the within-event functionality was marked orange dotted curve. Moreover, the evolving processes of these functionalities could be divided into two distinct stages: (1) the first stage was a draw-down line. The disrupted state resulted from flooding ($e_j$),
inducing a degraded functionality during a time interval \((t_e - t_f)\). This stage mainly reflects the absorptive capacity of the local road. At a given time \(t_f\), the remaining without-event functionality of the targeted performance curve could be used to assess Robustness_{without-event} of the local road, and the remaining within-event functionality of the real performance curve could be used to assess Robustness_{within-event} of the local road. Therefore, the flooding led to a loss in robustness (by examining the reduced functionality), which could be assessed by the difference between Robustness_{without-event} and Robustness_{within-event}. Moreover, the maximum loss of robustness (MaxRL in Figure 6) describes the maximum reduced functionality during this time interval \((t_e - t_f)\).

The second stage was a draw-up line. It mainly reflects the restorative capacity of the local road. Moreover, the local road reaches an equilibrium state after a time interval \((t_f - t_i)\), which might resemble or equate to the without-event functionality. And the entire time interval \((t_e - t_i)\) indicated one of the recovery processes of the local road after flooding, which could be used to assess the rapidity of the local road.

For assessing resilience, Bruneau et al. proposed a quantitative framework with “Resilience-Triangle” based on functionality, which characterized the resilience by loss of functionality. In light of the transport system, this study, referring to Bruneau et al., assessed the resilience of local roads by considering the traffic speed. A key differentiation with previous proposals was that different traffic operating conditions (including smooth, congested, and severely congested traffic operating conditions) were addressed. We examined and improved the “Resilience-Triangle” framework and adopted the “triangle” idea with a traffic operating condition-oriented approach. Furthermore, our criterion was based on rethinking resilience as an evolving process that consists of multiple recovery processes. The dynamic resilience of the local roads, as functional resilience, rather than the static resilience (or structural resilience), was assessed by calculating the total area of the triangle using time-series functionality, which entailed robustness and rapidity metrics.

The resilience triangle was illustrated in each recovery process by the extent of disruption (represented as robustness loss) and recovery time (represented as rapidity). A
larger area of the triangle denoted a more lost area of functionality, which further indicated a less resilient local road. Therefore, within a time interval \( t_e \) to \( t_j \) (shown in Figure 6), compared with the targeted performance curve of without-event functionality (solid green curve), the recovery process was denoted by the real performance curve of within-event functionality (orange dotted curve). For a local road, during the extended morning peak period, the targeted performance curve could be plotted from the recorded historical data of average traffic speed (a total of 30 working days from 1\(^{st}\) April 2016 to 31\(^{st}\) March 2017, only on Friday with no rain) under without-event traffic operating conditions. The real performance curve could be plotted from the recorded historical data of average traffic speed (1\(^{st}\) July 2016) under within-event traffic operating conditions during the disruptive processes. Therefore, when the time spans from \( t_e \) to \( t_j \) (showed in Figure 6), the resilience was quantified by the total area between the targeted performance curve and the real performance curve (blue shaded area in Figure 6). This metric as the area beneath the performance curves accounted for the dynamic resilience of the local road after flooding. In addition, the targeted and real performance curves were plotted under different traffic operating conditions, respectively. The total resilience score at the time point \( t_i \) could be simulated and computed as follows:

\[
R_{\text{total}}(t_i) = R_{\text{smooth}}(t_i) + R_{\text{congested}}(t_i) + R_{\text{severely congested}}(t_i),
\]

where \( R_{\text{total}}(t_i) \) is the total resilience score of the local road at the time point \( t_i \); \( R_{\text{smooth}}(t_i) \), \( R_{\text{congested}}(t_i) \) and \( R_{\text{severely congested}}(t_i) \) are the resilience scores of the local road at the time point \( t_i \) under smooth, congested, and severely congested traffic operating conditions, respectively; \( t_i \) is the time point during the time span \( t_e \) to \( t_j \); \( R_{\text{smooth}}(t_i) \), \( R_{\text{congested}}(t_i) \) and \( R_{\text{severely congested}}(t_i) \) are assessed as follows:

\[
R_{\text{smooth}}(t_i) = \int_{t_e}^{t_i} f_{\text{smooth-without}}(t) \, dt - \int_{t_e}^{t_i} f_{\text{smooth-within}}(t) \, dt,
\]

\[
R_{\text{congested}}(t_i) = \int_{t_e}^{t_i} f_{\text{congest-without}}(t) \, dt - \int_{t_e}^{t_i} f_{\text{congest-within}}(t) \, dt,
\]

\[
R_{\text{severely congested}}(t_i) = \int_{t_e}^{t_i} f_{\text{severely congested-without}}(t) \, dt - \int_{t_e}^{t_i} f_{\text{severely congested-within}}(t) \, dt,
\]

where \( f_{\text{smooth-without}}(t) \), \( f_{\text{congest-without}}(t) \) and \( f_{\text{severely congested-without}}(t) \) as the targeted performance curves are the without-event functionalities of the local road, which are conventionally defined as the ratio of the average traffic speed of the local...
road at time point \( t_i \) and free-flow speed under without-event smooth, congested, and severely congested traffic operating conditions, respectively; \( f_{\text{simo}}(t), f_{\text{cong}}(t) \) and \( f_{\text{sev}}(t) \) as the real performance curves are the within-event functionalities of the local roads, which are conventionally defined as the ratio of the average traffic speed of the local road at time point \( t_i \) and free-flow speed under within-event smooth, congested, and severely congested traffic operating conditions, respectively. As the speed limits on the local road are 80 and 100 km/h in parts, a reference speed of 80 km/h was selected for free-flow speed. \( t_i \) is the starting time point where flooding occurred. \( t_f \) is the ending time point that the within-event functionalities of the local road returned to the without-event functionality (normal functionality). All these above indicators were standardized (by dimensional analysis, a dimensionless quantity was a quantity without an associated physical dimension) to eliminate the impact of the different units of each indicator.

4. Results

4.1. Analysis of the Recovery Process of the Local Road in Wuhan. During the extended morning peak period, by statistically analyzing the recorded historical data of the average traffic speed of four selected local roads under without-event and within-event traffic operating conditions, respectively, the dynamic evolution of the corresponding functionalities of these local roads were formed and shown in Figure 7. In this figure, the solid curves with green, yellow, and red colors represent the without-event functionalities (targeted performance curves) of four selected local roads under different traffic operating conditions \( (f_{\text{simo}}(t), f_{\text{cong}}(t), f_{\text{sev}}(t)) \), respectively. The dotted curves with green, yellow, and red colors represent the within-event functionalities (real performance curves) of four selected local roads under smooth, congested, and severely congested traffic operating conditions \( (f_{\text{simo}}(t), f_{\text{cong}}(t), f_{\text{sev}}(t)) \), respectively. Each shaded area represents the lost area of functionality of four selected local roads under different traffic operating conditions. Moreover, these dynamic shaded areas indicated the evolving recovery processes of these selected local roads, which could be used to assess their dynamic resilience.

The traffic operating conditions’ specific characteristics were as follows: (1) under smooth traffic operating conditions, four selected local roads’ without-event and within-event functionalities showed draw-down and draw-up cycles under smooth traffic operating conditions during the extended morning peak period. On the contrary, they showed draw-up and draw-down cycles under congested and severely congested traffic operating conditions. (2) Under smooth traffic operating conditions, the rank list according to the without-event functionality was local road 2 > local road 3 > local road 1, and the rank list according to the within-event functionalities was local road 2 > local road 3 > local road 1. Under congested traffic operating conditions, the rank list according to the without-event functionality was local road 1 > local road 3 > local road 2 > local road 4, and the rank list according to the within-event functionality was local road 2 > local road 1 > local road 3 > local road 4. Under severely congested traffic operating conditions, the rank list according to the without-event functionality was local road 3 > local road 2 > local road 1, and the rank list according to the within-event functionality was local road 3 > local road 2 > local road 1. (3) To our surprise, under some traffic operating conditions, the within-event functionalities of some local roads were better than their without-event functionalities. For example, under smooth traffic operating conditions, the without-event functionality of local road 1 was 0.77, while its within-event functionality was 0.79. These results were contrary to our expectations, which might be attributed to the reduced travel demand. Because this flooding made more travelers choose public transport instead of self-driving for safety reasons.

By statistically analyzing the without-event and within-event functionalities of four selected local roads under different traffic operating conditions, Table 1 shows the categorization and description of their recovery processes during the extended morning peak period, quantified by the indicators of time span, \( \text{Max}_{\text{RL}} \) (maximum robustness loss), and rapidity.

The specific characteristics of these recovery processes were as follows: (1) as the influence of flooding on four selected local roads, the time span showed a series of disturbances in response to different patterns of recovery processes under different traffic operating conditions, respectively. Three of these selected local roads (local roads 1, 2, and 3) had the greatest number of recovery processes under congested traffic operating conditions, while local road 4 had the greatest number of recovery processes under severely congested traffic operating conditions. The changing time spans of four selected local roads affected their resilience evolving to a different level or state. In local road 2, with an early beginning and an early ending recovery process, the influence of disturbances focused on the time span 7:00 AM to 9:00 AM. In local roads 3 and 4, with a late beginning and a late ending recovery process, the influence of disturbances focused on the time span 7:20 AM to 9:30 AM, and 7:30 AM to 10:00 AM. However, in local road 1, the influence of disturbances almost covered the entire extended morning peak period, which focused on the time span 7:10 AM to 10:00 AM. In each selected local road, stressing the temporal scales of recovery processes under different traffic operating conditions, sometimes spans were the same. For example, in local road 2, under smooth and congested traffic operating conditions, the recovery processes’ time spans were both from 7:00 AM to 7:10 AM, and 7:30 AM to 8:40 AM, respectively. (2) The maximum robustness loss (\( \text{Max}_{\text{RL}} \)) of four selected local roads reflects the maximum reduced functionality after flooding. Unlike fixed robustness losses during the entire extended morning peak period, the robustness losses of selected local roads naturally varied in different recovery processes under different traffic operating conditions, respectively, which further led to the evolving maximum robustness losses. Under all traffic operating conditions, \( \text{Max}_{\text{RL}} \) of most selected local roads gradually
increased over time, except local roads 1 and 3 (under congested traffic operating conditions) and local road 4 (under severely congested traffic operating conditions), in which MaxRL increased firstly and then decreased. The increased MaxRL demonstrated the increased robustness losses of these local roads, which further indicated their increasing reduced functionality. With more than two recovery processes, all selected local roads reached their highest MaxRL in the second recovery process under each traffic operating condition, while the corresponding time spans were significantly different under different operating conditions. In particular, the extent of fluctuation in MaxRL was significantly different among four selected local roads. Under congested traffic operating condition, MaxRL of most selected local roads varied, while MaxRL of local road 3 held steady at the highest values. (3) The rapidity of the four selected roads refers to how fast to recover from a reduced functionality and return to normal functionality after flooding (measured in recovery time). Focused on different recovery processes, the rapidity of these selected local roads has dynamically evolved under different traffic operating conditions. With more than three recovery processes, the rapidity often increased firstly and then decreased under all traffic operating conditions, such as local roads 1, 2, and 3 under congested traffic operating conditions, and local road 4 under severely congested traffic operating conditions. Some local roads only had one recovery process but with the highest rapidity (local road 4 under smooth traffic operating condition), which indicated the longest recovery time after flooding. With less than two recovery processes, the rapidity of some local roads roughly remained stable, such as local roads 1 and 3 under smooth traffic operating conditions, while the rapidity of other local roads significantly altered, such as local road 2 under smooth traffic operating conditions, and local road 4 under congested traffic operating conditions.

Figure 7: The dynamic evolution of the without-event (targeted performance curves) and within-event (real performance curves) functionalities of four selected local roads under different traffic operating conditions during the extended morning peak period.
## Table 1: Categorization and description of the recovery processes of four selected local roads under different traffic operating conditions during the extended morning peak period.

| Recovery process | Indicators | Local road 1 | Local road 2 | Local road 3 | Local road 4 |
|------------------|------------|--------------|--------------|--------------|--------------|
|                  |            | Smooth traffic operating condition | Congested traffic operating condition | Severely congested traffic operating condition | Smooth traffic operating condition | Congested traffic operating condition | Severely congested traffic operating condition | Smooth traffic operating condition | Congested traffic operating condition | Severely congested traffic operating condition |
| 1                | Time span (A.M.) | 07:50–08:00 | 07:10–07:30 | 07:00–07:10 | 07:00–08:30 | 07:30–08:00 | 07:20–08:50 | 07:30–08:00 | 07:30–08:20 | 07:40–09:20 |
|                  | MaxLR      | 0.034 | 0.028 | 0.018 | 0.014 | 0.075 | 0.052 | 0.050 | 0.067 | 0.102 |
|                  | Rapidity (hours) | 0.333 | 0.333 | 0.167 | 0.333 | 0.500 | 0.833 | 0.833 | 1.667 | 0.667 |
| 2                | Time span (A.M.) | 08:10–08:40 | 08:40–09:10 | 07:30–08:40 | 07:30–08:40 | 08:20–08:40 | 08:20–08:40 | 08:20–08:40 | 08:20–08:40 | 08:20–09:30 |
|                  | MaxLR      | 0.036 | 0.092 | 0.049 | 0.072 | 0.115 | 0.104 | 0.109 | 0.109 | 0.667 |
|                  | Rapidity (hours) | 0.500 | 0.833 | 1.167 | 1.167 | 1.167 | 1.167 | 1.167 | 1.167 | 1.167 |
| 3                | Time span (A.M.) | 09:20–09:50 | 08:50–09:00 | 09:00–09:10 | 09:00–09:10 | 09:50–10:00 | 09:20–09:30 |
|                  | MaxLR      | 0.042 | 0.060 | 0.018 | 0.018 | 0.005 | 0.027 |
|                  | Rapidity (hours) | 0.500 | 0.167 | 0.167 | 0.167 | 0.167 | 0.167 |
| 4                | Time span (A.M.) | 09:50–10:00 | 09:20–09:30 |
|                  | MaxLR      | 0.070 | 0.027 |
|                  | Rapidity (hours) | 0.167 | 0.167 |
characterization of the evolving within-event and without-event functionalities (shown in Figure 7) and conversely the identification of their attributes (shown in Table 1) might help investigate the extent to which there is a decrement in the functionalities of the four selected local roads, respectively, and pinpoint the main weaknesses with the most delayed recovery.

4.2. Analysis of the Dynamic Resilience of the Local Road in Wuhan.

Following the resilience assessment approach proposed in equations (2)–(4), Figure 8 shows the dynamic evolution of resilience scores \( R_{\text{smooth}}(t) \), \( R_{\text{congested}}(t) \) and \( R_{\text{severely congested}}(t) \) of four selected local roads under different traffic operating conditions during the extended morning peak period, respectively. By dimensional analysis, these resilience scores were in the range from 0 to 1. Moreover, the different evolving patterns of resilience scores indicated that the same flooding had completely different impacts on these selected local roads. Under a given traffic operating condition, a lower resilience score demonstrated a less lost area of functionality, further indicating a more resilient local road. With a better ability to respond, this more resilient local road could efficiently reduce the magnitude of the impact and rapidly recover from the impact of flooding.

The specific characteristics of these evolving resilience scores were as follows: (1) under all traffic operating conditions, as the total lost area of functionality increased with respect to the total area beneath the performance curves, the resilience scores of all selected local roads increased and finally reached steady values. These steady values marked the time points when the local roads completely returned to their normal functionality. For example, with the shortest recovery time (8:00 AM–08:40 AM), local road 1 was the most effective under smooth traffic conditions, while local road 4 was the least effective under congested traffic conditions, with the longest recovery time (7:40 AM–09:40 AM). (2) With the increase of resilience scores, the final values of the four selected local roads were significantly
different under different traffic operating conditions. For example, local road 2 was the most resilient under severely congested traffic conditions, with the lowest resilience score. On the contrary, local road 1 was the least resilient under congested traffic conditions, with the highest resilience score. (3) Different fluctuation details of resilience scores captured their different sensitivities to the temporal changes in the loss of functionality under different traffic operating conditions. For example, with the greatest loss, some local roads reached their fastest growth rate of resilience scores at the beginning of the extended morning peak period (e.g., local road 3 under smooth traffic operating condition at time point 07:50 AM), and some local roads reached their fastest growth rate of resilience scores at the end of the extended morning peak period (e.g., local road 4 under severely congested traffic operating condition at the time point 09:20 AM). Furthermore, the resilience scores of some local roads had the greatest extent of fluctuation under a specific traffic operating condition (e.g., local road 1 had the highest growth rate of resilience score under congested traffic operating condition), while the resilience scores of the other local roads remained steady with little fluctuation under a specific traffic operating condition (e.g., local road 2 had the lowest growth rate of resilience score under severely congested traffic operating condition).

By defining the total resilience score ($R_{total}(t)$) of four selected local roads as the combination of their resilience scores under different traffic operating conditions, following (1), Figure 9 shows the dynamic evolution of the total resilience scores of four selected local roads during the extended morning peak period. Based on these different evolving patterns, the comparison analysis among the four selected local roads showed that the total resilience score of local road 4 increased most rapidly, which had the highest growth rate. Such severe fluctuation of total resilience score was caused by the evolving resilience scores under congested traffic conditions. Local road 4 finally reached the largest total resilience score at 10:00 AM, indicating the time point to completely return to its normal functionality. With the highest total resilience score and the longest recovery process, local road 4 could be considered as the weakest resilient. With a poor ability to respond, this local road therefore required more attention due to the most significant negative impact of flooding (investigated by the highest Max$_{RL}$ under the congested traffic condition) and slow recovery (investigated by the highest rapidity score under the smooth traffic condition). On the contrary, local road 2 was detected as the most resilient road, with the lowest total resilience score and the shortest recovery process. Until 09:10 AM, local road 2 completely absorbed the impact of flooding and returned to its normal functionality. Comparing the resilience scores of these two local roads under different traffic operating conditions, the results implied that the significantly different evolving patterns of the resilience scores under severely congested traffic operating conditions caused different overall outcomes of the total resilience scores. With lower resilience scores, fewer fluctuations, just a single recovery process, and shorter recovery time under severely congested traffic operating conditions, local road 2 had the higher capacity to reduce the magnitude of the impact and return to its normal functionality more effectively.

5. Discussion and Conclusions

By comparatively analyzing the characteristics of the recovery processes of four selected local roads under different traffic operation conditions, and the corresponding dynamic evolution of their total resilience scores, the case of Wuhan clearly showed that (1) the improved overall within-event functionality (by reducing the robustness loss) could improve a local road’s coping capacity, and (2) the improved overall recovery process (by shortening the recovery time) could support recovery actions. This study highlighted these two attributes in improving the dynamic resilience of the local road. Firstly, the maximum robustness loss (Max$_{RL}$) of the four selected local roads varied due to their different topological structures. A local road with a lower Max$_{RL}$ has more alternative routes for all destinations, increasing this local road’s connectivity with the entire road network. Consequently, the richly connected local road with multiple modes and route options would be a critical section of the road network, in which a random failure could not severely degrade its functionality. By measuring the maximum robustness loss of local roads appropriately, such results would help the local governments improve the understanding of the practical application of integrated land use in transportation and the importance of promoting road-oriented planning, which is still a challenge in the case study area, as well as in other cities of China. Secondly, the comparative analysis results of the rapidity of four selected local roads investigated their different evolving patterns of recovery processes under different traffic operation conditions, which showed the corresponding traffic speed reductions differed by recovery time during the extended morning peak period. If most vehicles were stopped by traffic signals on some specific local road, it led to the highest rapidity. Such results
illustrated that an optimized traffic signal could significantly decrease the traffic speed reduction to shorten the recovery time, which further decreased the rapidity of the local road [35, 36]. Moreover, the traffic speed reductions of some selected local roads were somehow less than expected under the severely congested traffic operating condition, due to the significantly decreased travel demand after flooding. This could result in less saturated and discharged processes with the severely congestion patterns being relatively quick. Therefore, forecasting and adjusting the travelers' behavior after flooding could be most effective for minimizing the recovery time of the local road.

By comparing the different evolving patterns of local road resilience after flooding, the significance and challenges were highlighted more clearly to identify the key learning for capacity building, which could improve the resilience of some critical local roads, and further enhance the overall resilience of the transport system, that is, the critical contribution of this study. In summary, firstly, this study addressed some critical local road sections, rather than focusing on a generic description of the road network. The results of the different total resilience scores of these critical local roads allowed road authorities to detect weak and poorly resilient locations after flooding. Secondly, this study presented a new methodology to define the resilience of local roads at a dynamic level, not a static level. This new methodology constructed a metric inspired by the well-applied “resilience-triangle” approach, which considered the resilience of local roads based in part on the traffic speed. Unlike other civil infrastructure, different time-dependent traffic operation conditions could give rise to direct or indirect impacts on the resilience of local roads. Thirdly, the focus of this study was on the technical dimension of engineering resilience. The entailed robustness and rapidity metrics gave a strong indication of the weak and poorly resilient local road sections, allowing the road authorities to act more precisely. In particular, a distinction was made in the robustness metric, utilizing the new term “robustness loss” instead of “robustness.” And the results of the evolving maximum robustness loss (MaxRL) of different local roads under different traffic operating conditions provided a unique and different angle for tackling and comparing the time-varying reduced functionalities.

The detailed findings of this study were as follows: firstly, to characterize these four local roads’ recovery processes quantitatively, the time-dependent metrics assessed the time span, maximum robustness loss (MaxRL), and rapidity under different traffic operating conditions during the extended morning, respectively. The time span could be used to effectively estimate the different influences of flooding on the four selected local roads. The results of time span showed exactly when the recovery processes of these selected local roads occurred under different traffic operating conditions and how long these recovery processes were. The time-dependent MaxRL distribution could be used to effectively quantify the time-varying reduced functionalities of four local roads under different traffic operating conditions, which could be extended to identify the corresponding maximum fragility of these selected local roads. The rapidity referred to the recovery time showed how quickly the four selected local roads could return to their normal functionality after flooding. The different evolving patterns of rapidity gave an overall indication of the time-varying recovery efficiencies of these selected local roads under different traffic operating conditions. Secondly, to effectively assess the dynamic resilience at the traffic level, not just at a higher abstraction level, the analysis concentrated on the time-varying resilience scores of the four selected local roads under different traffic operating conditions, respectively. Compared with the different evolving patterns of these resilience scores, a local road performed poorly (with the highest resilience score or the longest recovery time) under a specific traffic operating condition, which indicated a significant loss of its functionality or its poorly capacity to return to its normal functionality. As part of the total resilience scores, these results offered a deeper insight into explaining the main reasons for the dynamic evolution of these selected local roads’ total resilience scores. Furthermore, a local road with the highest total resilience score accurately contributed to the purpose of identifying the weak and poorly resilient locations in the road network.

A number of limitations regarding this methodology and this particular case study should be highlighted. First, the datasets merely covered the flooding that occurred on 1st July 2016 in Wuhan, leading to an impossible assessment of the dynamic resilience of four selected local roads after another flooding. Second, due to the limitations of the data available, only two attributes (robustness and rapidity) were considered to define and assess the technical dimension of resilience, and further work is required to analyze and evaluate the organizational, social, and economic dimensions of resilience (redundancy, and resourcefulness, etc.). Third, further analysis of the effectiveness of some resilience-inspired strategies is highlighted. It is crucial for selecting and optimizing the most effective restoration strategies and then being combined for enhancing the resilience of the transport system after flooding.

Data Availability
The data used to support the findings of this study have been shown in Data and Methods section of this article.

Conflicts of Interest
The authors declare that there are no conflicts of interest regarding the publication of this study.

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